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Originally published in Review of international economics, 8 (3). pp. 373-396 © 2000 Blackwell Publishing.

Evolving patterns of international trade*

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15th February, 2000

Abstract

Theoretical models of growth and trade suggest that patterns of international specialisation are dynamic and evolve endogenously over time. Initial comparative advantages are either reinforced or gradually unwound with the passage of time. This paper puts forward an empirical framework for modelling international trade dynamics that uses techniques widely employed in the cross-country literature on income convergence. Applying this framework to industry-level data, we find evidence of significant differences in international trade dynamics among the G5 economies.

J.E.L. CLASSIFICATION: C10,F10,030

KEYWORDS: Distribution Dynamics, International Trade, Markov Chains, Revealed Comparative Advantage

*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of England. We would like to thank Mary Amiti, Andrew Bernard, Christopher Bliss, Gavin Cameron, Cecilia Garcia-Penalosa, Nigel Jenkinson, Steve Nickell, Danny Quah, Andrew Scott, Jon Temple, Tony Venables, Peter Westaway, two anonymous referees, and participants in seminars at the Bank of England, the Royal Economic Society, the European Economic Association, and the University of Nottingham for their helpful comments. We are grateful to Jon Temple for first suggesting the use of formal indices of mobility. We are also grateful to Sandra Bulli and Kee Law for excellent research assistance, and to Mark Thirlwell and Colin Webb for their help with the data. We would like to thank (without implicating) Danny Quah for making the TSRF econometrics package available to us. All results, opinions, and errors are the responsibility of the authors alone.

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1 Introduction

Much of the existing empirical trade literature is concerned with patterns of international trade at a point in time. This focus of empirical work stands in marked contrast with the theoretical literature on growth and trade, which emphasises that comparative advantage is dynamic and evolves endogenously over time. This paper proposes an empirical framework for analysing the evolution of patterns of international trade over time, which consists of two main components. First, the extent of a country's specialisation in an individual industry is measured by a modified index of Revealed Comparative Advantage (RCA). A country's pattern of international specialisation at a point in time is then fully characterised by the distribution of RCA across industries. Second, the dynamics of international specialisation correspond to the evolution of this *entire* cross-section distribution over time. We employ a model of distribution dynamics from the cross-country growth literature, that is explicitly suited to the analysis of the evolution of an entire distribution.

Within this empirical framework, it is possible to address a variety of issues relating to international trade dynamics. In particular, we examine changes in countries' overall degree of specialisation (the evolution of the *external shape* of the distribution of RCA) and the extent to which initial patterns of international specialisation persist over time (an issue of *intra-distribution dynamics*). The theoretical literature on trade and growth typically yields ambiguous conclusions concerning both these issues. One strand of the theoretical literature emphasises the role of factor accumulation in determining the evolution of international trade flows over time (see for example Findlay (1970), (1995) and Deardorff (1974)). A second strand of research stresses the endogeneity of technological change (see for example Grossman and Helpman (1991), Krugman (1987), Lucas (1988), and Redding (1999)). A third body of work concerned with economic geography underlines the importance of agglomeration economies (see in particular Krugman (1991) and Fujita et al. (1999)). Each of these strands of theoretical research identifies some forces that lead to persistence in patterns of international trade and others that engender mobility. For example, within the literature on endogenous technological change, sector-specific learning by doing is typically a force for persistence, while knowledge spillovers or technology transfer give rise to mobility. Therefore, whether international trade flows persist or exhibit mobility over time (and whether there is increasing or decreasing specialisation over time) is an empirical question.

The objective of this paper is to propose an empirical framework for modelling international trade dynamics, within which it is possible to address issues such as persistence versus mobility and changes in the degree of international specialisation. The paper is structured as follows. Section 2 presents a theoretical model of international trade and endogenous technological change, that combines elements from Dornbusch et al. (1977), Krugman (1987) and Bernard and Jones (1994, 1996). The objective of this section is to illustrate how a precisely specified economic model yields ambiguous conclusions concerning whether international trade flows exhibit persistence or mobility over time. As such, it provides direct motivation for the empirical analysis that follows. Section 3 introduces the empirical framework: a country's pattern of international specialisation is thought of as a distribution across sectors, and international trade dynamics correpond to the evolution of the entire distribution over time. This very general specification is consistent with a wide range of possible international trade dynamics, and allows us to determine the degree of persistence versus mobility in patterns of international specialisation from the observed data. Later Sections implement the empirical framework using industry-level manufacturing data from the G5 economies.

The dynamics of patterns of international trade are analysed in two stages. First, Section 4 undertakes the preliminary data analysis. Measures of RCA are presented for the manufacturing sectors of France, Germany, Japan, the United Kingdom and the United States. The evolution of patterns of international trade over time is analysed graphically. Second, the model of distribution dynamics is estimated econometrically in Section 5. Transition probability matrices are presented for each of the G5 economies and for the sample formed by pooling observations across economies. The extent of persistence and mobility in patterns of international trade is quantified using formal indices of mobility. We find evidence of significant differences in international trade dynamics among the G5 economies. France exhibits the most mobility and Japan the least. Japan is the only G5 economy to experience an increase in the degree of international specialisation over time. Section 6 summarises our conclusions.

2 Theoretical modelling of trade dynamics

This Section presents a simple theoretical model of international trade and endogenous technological change. The model uncovers some forces that lead to persistence in patterns of international trade and other conflicting influences that tend to induce mobility. Static equilibrium is determined exactly as in the standard Ricardian model with a continuum of goods (Dornbusch et al. (1977)). There are two economies (home and foreign) and A_{ij} denotes the productivity of labour in sector j of economy $i \in \{H, F\}$. Each economy may produce any of a fixed number of goods indexed by $j \in [0, n]$. An individual good j will be produced in home (H) if and only if the unit cost of producing that good in home is below or equal to that in foreign (F),

$$\frac{w_H(t)}{w_F(t)} \leq \frac{A_{Hj}(t)}{A_{Fj}(t)} \tag{1}$$

where w_H and w_F are the home and foreign wage rates respectively. If we denote home productivity relative to foreign by $B_j \equiv A_{Hj}/A_{Fj}$, and index goods so that higher values of j correspond to lower values of home productivity relative to foreign (B_j), then the right-hand side of (1) may be illustrated diagrammatically by the downward sloping curve in Figure 1. Given a value for the home relative wage

w_H/w_F, all goods $j \leq \hat{j}$ in Figure 1 are produced in home and all goods $j > \hat{j}$ are produced in foreign. $\hat{j}$ denotes the limit good such that home's relative wage is exactly equal to home productivity relative to foreign's.

In static equilibrium, home's relative wage is pinned down by the additional requirement that home income equals world expenditure on home goods (or alternatively that trade is balanced). Under the assumption that instantaneous utility is a symmetric, Cobb-Douglas function of the consumption of each good j (with the elasticity of instantaneous utility with respect to the consumption of each good equal to β), a constant fraction β of world income is spent on each good produced in home. Therefore, if the range of goods $[0, \hat{j}]$ is produced in home, the requirement that home income equals world expenditure on home goods is given by,

$$w_H.\bar{L}_H = \hat{j}\beta.[w_H\bar{L}_H + w_F\bar{L}_F]$$

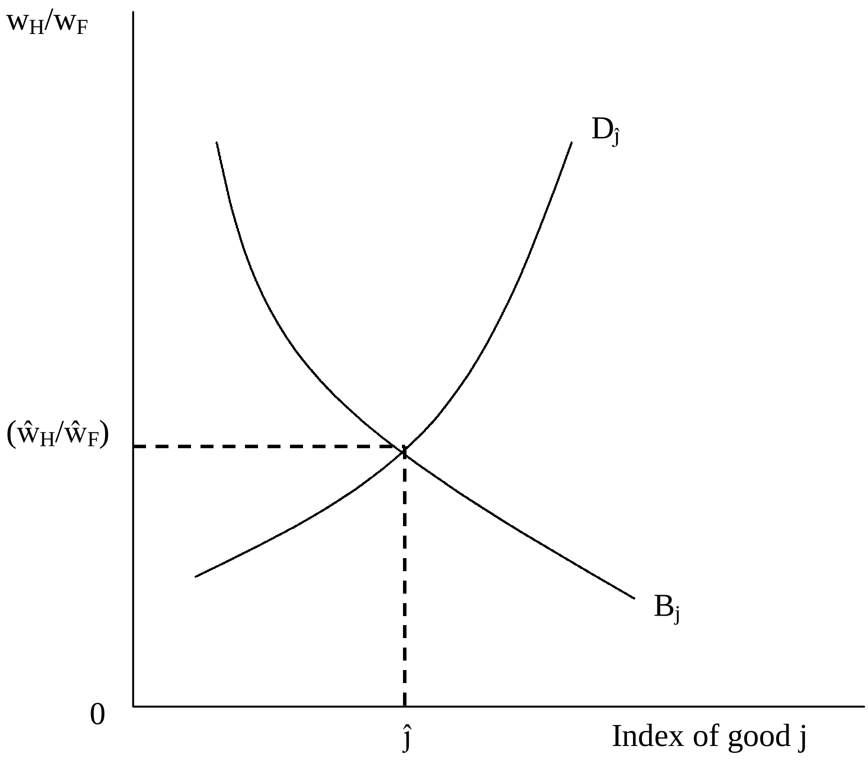
This condition may be re-expressed as,

$$\frac{w_H}{w_F} = D_{\hat{j}}, \qquad \text{where} \qquad D_{\hat{j}} \equiv \frac{\hat{j}.\beta}{1-\hat{j}.\beta}.\frac{\bar{L}_F}{\bar{L}_H} \tag{2}$$

where $\bar{L}_H$ and $\bar{L}_F$ are the home and foreign supplies of labour respectively. The right-hand side of equation (2) ($D_{\hat{j}}$) is monotonically increasing in $\hat{j}$, and provides a demand-side relationship between the range of goods produced in home and home's relative wage (w_H/w_F). $D_{\hat{j}}$ is illustrated diagrammatically by the upward sloping curve in Figure 1. Static equilibrium is defined by the intersection of the two curves, where both (1) and (2) are satisfied.

Within this framework, the evolution of patterns of international trade over time is determined by rates of technological progress in each sector of the two economies. In general, rates of technological change will themselves be endogenous, and are determined in part by the existing pattern of international trade. The existing empirical literature suggests a variety of determinants of endogenous technological change; the analysis here focuses on three sets of influences. First, a wide range of empirical evidence exists that learning by doing is an important source of productivity improvement (see, for example, Lucas (1993)). We follow Krugman (1987) in introducing sector-specific learning by doing into the Ricardian model with a continuum of goods. The rate of learning is assumed to depend upon economy i's allocation of labour (the sole factor of production) to sector j (L_{ij}) and a parameter (ψ_j) that may vary across sectors.

Figure 1: Static Equilibrium and International Specialisation



Second, a variety of case study and econometric evidence suggests that transfers of technology or knowledge spillovers are an important source of technological change (see for example Rosenberg (1982), Coe and Helpman (1995), and Keller (1999)). Therefore, we also allow for spillovers of production knowledge across economies. In particular, following Bernard and Jones (1994, 1996), we assume that technology in each sector may be transferred from a leading to a follower economy. Technology transfer is assumed to occur at a constant proportional rate (λ_j), so that economy i's rate of productivity growth in sector j is increasing in the distance between its level of productivity in sector j and the corresponding level in the economy that is the technological leader in sector j.

Third, it is plausible that the rate of productivity growth in sector j or economy i depends upon a variety of other observed and unobserved characteristics. We parameterise these observed and unobserved characteristics by a constant (γ_{ij}), that varies across economies and sectors (a 'fixed effect'). Combining all three sets of influences, the rate of productivity growth in sector j of economy i is given by,

$$\ln\left(\frac{A_{ij}(t)}{A_{ij}(t-1)}\right) = \gamma_{ij} + \psi_j \ln\left(1 + L_{ij}(t-1)\right) + \lambda_j \ln\left(\frac{A_{Xj}(t-1}{A_{ij}(t-1)}\right) \qquad (3)$$
$$\gamma_{ij},\ \psi_{ij},\ \lambda_{ij} \geq 0 \quad \forall i, j$$

where A_{Xj} denotes productivity in sector j in whichever of the two economies $i \in \{H, F\}$ is the world's technological leader. If economy H is the technological leader in sector j, $A_{Hj} = A_{Xj}$ and the third term on the right-hand side of equation (3) is zero. In this case, sector-specific learning by doing and the country-industry characteristics embodied in the fixed effect provide the sole potential sources of productivity growth. Throughout the analysis, technological change is modelled as a pure externality of current production and is therefore consistent with the assumption of perfect competition in the Ricardian model. Equation (3) implies that, in each sector j of the two economies i, the evolution of productivity relative to the world technological leader may be expressed as,

$$\begin{aligned} \triangle \ln\left(\tfrac{A_{ij}(t)}{A_{Xj}(t)}\right) = (\gamma_{ij} - \gamma_{Xj}) + \psi_j \ln\left(\tfrac{1+L_{ij}(t-1)}{1+L_{Xj}(t-1)}\right) \\ -\lambda_j . \ln\left(\tfrac{A_{ij}(t-1)}{A_{Xj}(t-1)}\right) \end{aligned} \qquad (4)$$

The dynamics of international trade patterns are fully characterised by the static equilibrium conditions (1) and (2), together with the specification of productivity growth in equations (3) and (4). Initial levels of productivity determine the pattern of comparative advantage and international specialisation. The pattern of international specialisation (with its associated allocation of labour across sectors) then affects rates of productivity growth and hence the evolution of international trade flows over time.

On the one hand, the presence of sector-specific learning by doing means that initial patterns of international specialisation will tend to be reinforced over time. On the other hand, technological transfer and differences in the exogenous rates of productivity growth across sectors may both be responsible for reversing initial patterns of international specialisation - depending upon the correlation between initial levels of relative productivity and the steady-state levels implicit in equation (4).

For example, consider two special cases. First, suppose that there is a common rate of exogenous technological change across all sectors and economies ($\gamma_{Hj} = \gamma_{Fj} = \gamma$ for all j) and no international knowledge spillovers ($\lambda_j = 0$ for all j). Static equilibrium at time t implies that home will specialise completely in the production of the range of goods $j \in [0, \hat{j}]$ and foreign in goods $j \in (\hat{j}, n]$. It follows immediately, from (3) and the parameter restrictions imposed above, that home productivity relative to foreign will rise in the sectors where home initially specialises and fall in the sectors where home does not initially specialise. As a result, initial patterns of international specialisation persist and will become increasingly locked-in over time (as in Krugman (1987)).

Second, suppose that there is no sector-specific learning by doing ($\psi_j = 0$ for all j); nonetheless, exogenous technological progress occurs at varying rates across sectors and economies ($\gamma_{ij} > 0$ for all i, j, $\gamma_{Hj} \neq \gamma_{Fj}$ for all j) and is accompanied by knowledge spillovers ($\lambda_j > 0$ for all j). Suppose also that those sectors in which home productivity is initially less than foreign are the same sectors in which $\gamma_H > \gamma_F$, and that the converse is also true. Then, from equation (4), sectors where home productivity is initially less than foreign will become - in steady-state - sectors in which home productivity exceeds foreign. This is sufficient (though not necessary) for initial patterns of international specialisation to be reversed over time.

Thus, this model of international trade and endogenous technological change identifies some forces that lead to persistence in patterns of international trade and others that give rise to mobility. Similar results may be obtained within theoretical frameworks that emphasise either factor accumulation (see for example Deardorff (1974) and Findlay (1970), (1995)) or economic geography (see for example Krugman (1991) and Fujita et al. (1999)). Whether international trade flows persist or exhibit mobility over time is ultimately an empirical question, and we require an empirical framework sufficiently general as to encompass both possibilities. This paper proposes such an empirical framework.

3 Empirical modelling of trade dynamics

This Section introduces the empirical framework for analysing the dynamics of international trade flows. The extent of an economy's specialisation in an individual sector is characterised using a modified version of Balassa's (1965) index of Revealed Comparative Advantage (RCA).[1] An economy i's RCA in sector j is given by the ratio of its share of exports in sector j to its average export share in all sectors,[2]

$$RCA_{ij} = \frac{Z_{ij}/\sum_i Z_{ij}}{\frac{1}{N}\sum_j \left(Z_{ij}/\sum_i Z_{ij}\right)} \tag{5}$$

where Z_{ij} denotes the value of economy i's exports in sector j.

RCA yields information about the pattern of international specialisation insofar as it evaluates an economy's export share in an individual sector relative to some benchmark - namely, the economy's average export share in all sectors. The pattern of international specialisation at any one point in time t is characterised by the distribution of RCA across sectors. A value of RCA_{ij} above unity indicates an industry in which economy i's share of exports exceeds its average share in all industries: that is, an industry in which economy i *specialises.*

Evaluating the dynamics of patterns of international specialisation over time involves an analysis of the evolution of the entire cross-section distribution of RCA. Issues such as persistence versus mobility in international trade flows correspond to questions of *intra-distribution dynamics.* What is the probability that a sector moves from one quartile of the RCA distribution to another ? Are the sectors in which $RCA_{ij} > 1$ at time $t+k$ ($k \geq 1$) the same sectors as at time t ? Changes in the overall degree of international specialisation may be evaluated by analysing the evolution of the *external shape* of the RCA distribution. Do we observe an increasing specialisation in a limited subset of industries (a polarisation of the RCA distribution towards extreme values), or has the degree of international specialisation remained broadly unchanged ?

The evolution of the RCA distribution over time may be modelled formally, employing techniques already used in the cross-country growth literature to analyse income convergence (see Quah (1993), (1996a) and (1996c)). Thus, denote RCA by the measure x and its distribution across sectors at time t by $F_t(x)$. Corresponding to F_t, we may define a probability measure λ_t where $\forall\, x \in \Re$, $\lambda_t((-\infty, x]) = F_t(x)$. Following Quah op cit., the evolution of the distribution of RCA over time is then modelled in terms of a stochastic difference equation,

$$\lambda_t = P^*(\lambda_{t-1}, u_t), \qquad \text{integer } t \tag{6}$$

where $\{u_t : \text{integer } t\}$ is a sequence of disturbances and P^* is an operator that maps disturbances and probability measures into probability measures. For simplicity, we assume that this stochastic difference equation is first-order and that the operator P^* is time invariant. Even so, equation (6) is intractable and cannot be directly estimated. However, setting the disturbances u to zero and iterating the stochastic difference equation forwards, we obtain,

$$\begin{aligned} \lambda_{t+s} = P^*(\lambda_{t+s-1}, 0) &= P^*(P^*(\lambda_{t+s-2}, 0), 0) \\ &\vdots \\ &= P^*(P^*(P^* \ldots (P^*(\lambda_t, 0), 0) \ldots 0), 0) \\ &= (P^*)^s \lambda_t \end{aligned} \tag{7}$$

If the space of possible values of RCA is divided into a number of distinct, discrete cells, P^* becomes a matrix of transition probabilities which may be estimated by counting the number of transitions out of and into each cell.[3] From these transition probabilities, one is able to characterise the extent of mobility between different segments of the RCA distribution. Furthermore, by taking the limit $s \to \infty$ in equation (7), one obtains the implied ergodic or stationary RCA distribution. This is simply the eigenvector associated with the largest eigenvalue of the transition probability matrix (see for example Karlin and Taylor (1975)), and provides information concerning the evolution of the external shape of the RCA distribution.

4 Preliminary data analysis

The empirical methodology outlined above is used in the remainder of this paper to analyse the evolution of patterns of international specialisation in the manufacturing sectors of the G5. The techniques used enable a wide range of issues concerning international trade dynamics to be addressed. We consider the extent to which there are changes in patterns of specialisation over time and at what levels of specialisation the greatest degree of mobility is observed. It is possible to examine whether international trade dynamics are different in the US from Japan or the major European economies. We evaluate the degree to which each economy is increasingly specialising in small sub-sets of manufacturing sectors.

This Section presents the RCA data on patterns of specialisation in the G5 economies, and looks informally at changes in international specialisation over time. The following Section estimates the formal model of distribution dynamics econometrically. The source for all the data is the OECD's Bilateral Trade Database (BTD). This provides consistent information on exports to the OECD and 15 trade partners for 22 manufacturing industries for the period 1970-93.[4] We begin by characterising the distribution of RCA at any one point in time in the United Kingdom and the United States, before widening the analysis to encompass the other three members of the G5. Table 1 presents measures of RCA for the United Kingdom in each of the 22 manufacturing industries in the sample for the period 1970-93. For ease of exposition, the data are presented in the form of five-year averages.

Table 1: RCA in the United Kingdom

Industry	1970-4	1975-9	1980-4	1985-9	1990-3
Food and Drink	0.71	0.80	0.87	0.84	0.93
Textiles and Clothing	0.93	0.90	0.84	0.78	0.79
Timber and Furniture	0.22	0.35	0.32	0.28	0.29
Paper and Printing	0.54	0.58	0.62	0.62	0.80
Industrial Chemicals	0.96	1.04	1.16	1.16	1.17
Pharmaceuticals	1.46	1.44	1.54	1.51	1.61
Petroleum Refining	1.10	1.18	1.27	1.27	1.36
Rubber and Plastic	0.96	0.98	1.02	0.91	0.95
Non-metallic Minerals	0.98	0.94	0.84	0.79	0.81
Ferrous Metals	0.58	0.50	0.51	0.69	0.89
Non-ferrous Metals	1.27	1.13	1.21	0.96	0.98
Metal Products	1.12	0.98	0.96	0.83	0.82
Non-electrical Machinery	1.12	1.07	1.12	0.97	0.93
Computers	1.08	1.21	1.19	1.33	1.53
Electrical Machinery	1.03	0.96	0.99	0.86	0.84
Communication	0.72	0.77	0.72	0.77	1.02
Shipbuilding	0.59	0.61	0.52	1.85	0.94
Other Transport	0.72	0.61	0.61	0.42	0.40
Motor Vehicles	0.94	0.78	0.62	0.48	0.67
Aerospace	1.49	1.68	1.98	1.74	1.63
Instruments	1.00	0.97	1.15	1.09	1.07
Other Manufacturing	2.48	2.50	1.93	1.85	1.57
Mean	1.00	1.00	1.00	1.00	1.00

Exactly the same analysis may be undertaken for each of the other four members of the G5. Tables 2 and 3 list the industries in which RCA exceeds one in either or both of the periods 1970-4 and 1990-3 for each of the G5 economies.[5] While the G5 economies' patterns of international specialisation show some similarities, there are also important differences. For example, during the period 1970-4, industries in which the United Kingdom had an RCA and the United States did not were Petroleum Refining, Metal Products, Nonferrous Metals, Pharmaceuticals and Other Manufacturing. During the same period, industries in which the US had an RCA, but the UK did not, were Motor Vehicles and Communication. Tables 2 and 3 also make clear that the identity of industries in which an economy has an RCA changes over time; industries in which an RCA is either acquired or lost during the sample period are denoted by italics.

Table 2: RCA **in the United Kingdom and United States**

Country	**Industry**	**1970-4**	**1990-3**
UK	*Industrial Chemicals*	$\times$	$\surd$
	Instruments	$\surd$	$\surd$
	Electrical Machinery	$\surd$	$\times$
	Computers	$\surd$	$\surd$
	Petroleum Refining	$\surd$	$\surd$
	Non-electrical Machinery	$\surd$	$\times$
	Metal Products	$\surd$	$\times$
	Non-ferrous Metals	$\surd$	$\times$
	Pharmaceuticals	$\surd$	$\surd$
	Aerospace	$\surd$	$\surd$
	Other Manufacturing	$\surd$	$\surd$
	Communication	$\times$	$\surd$
US	Electrical Machinery	$\surd$	$\surd$
	Motor Vehicles	$\surd$	$\times$
	Communication	$\surd$	$\surd$
	Industrial Chemicals	$\surd$	$\surd$
	Instruments	$\surd$	$\surd$
	Non-electrical Machinery	$\surd$	$\surd$
	Computers	$\surd$	$\surd$
	Aeropsace	$\surd$	$\surd$
	Food and Drink	$\times$	$\surd$
	Paper and Printing	$\times$	$\surd$

Note: $\surd$ indicates $RCA_{ij} \geq 1$, $\times$ indicates $RCA_{ij} < 1$

Comparing the periods 1970-4 and 1990-3, the United Kingdom lost its RCA in Electrical Machinery, Non-electrical Machinery, Metal Products and Non-ferrous Metals, but gained an RCA in Industrial Chemicals and Communication. Comparing the same two periods, the United States lost an RCA in Motor Vehicles, but acquired an RCA in Food and Drink and Paper and Printing. Changes in patterns of international specialisation are observed in each of the remaining G5 economies. The case of Japan is particularly worthy of note, where an RCA is lost in Rubber and Plastic, Textiles and Clothing and Other Manufacturing, and an RCA is acquired in Non-electrical Machinery, Electrical Machinery, Motor Vehicles and Computers. From these two tables alone, patterns of international specialisation in France and Germany appear to be less mobile than those in Japan and the United Kingdom.

While tables 2 and 3 provide one means of analysing the dynamics of international specialisation and yield some interesting information, the conclusions that may be drawn are necessarily limited. First, the analysis is concerned with only two of the five-year periods. Second and more importantly, by restricting attention to movements of RCA above or below the value of one, one loses a vast amount of information on changes in the degree of specialisation in individual industries. Movements between other segments of the RCA distribution are also of interest. For example, between 1970-4 and 1980-4, RCA in the US Textiles and Clothing rose to 173% of its original value, while that in the US Ferrous Metals industry fell to 64% of its initial value. Neither of these substantial changes in patterns of international specialisation enters into Table 2.

Table 3: *RCA* in France, Germany, and Japan

Country	Industry	1970-4	1990-3
France	Metal Products	$\surd$	$\surd$
	Industrial Chemicals	$\surd$	$\surd$
	Electrical Machinery	$\surd$	$\surd$
	Motor Vehicles	$\surd$	$\times$
	Pharmaceuticals	$\surd$	$\surd$
	Ferrous Metals	$\surd$	$\surd$
	Non-metallic Minerals	$\surd$	$\surd$
	Textiles and Clothing	$\surd$	$\surd$
	Food and Drink	$\surd$	$\surd$
	Other Transport	$\surd$	$\times$
	Rubber and Plastic	$\surd$	$\surd$
	Aerospace	$\times$	$\surd$
Germany	Rubber and Plastic	$\surd$	$\surd$
	Computers	$\surd$	$\times$
	Pharmaceuticals	$\surd$	$\surd$
	Ferrous Metals	$\surd$	$\surd$
	Non-metallic Minerals	$\surd$	$\surd$
	Instruments	$\surd$	$\surd$
	Industrial Chemicals	$\surd$	$\surd$
	Metal Products	$\surd$	$\surd$
	Motor Vehicles	$\surd$	$\surd$
	Electrical Machinery	$\surd$	$\surd$
	Non-electrical Machinery	$\surd$	$\surd$
	Textiles and Clothing	$\times$	$\surd$
Japan	*Rubber and Plastic*	$\surd$	$\times$
	Textiles and Clothing	$\surd$	$\times$
	Other Manufacturing	$\surd$	$\times$
	Instruments	$\surd$	$\surd$
	Ferrous Metals	$\surd$	$\surd$
	Communication	$\surd$	$\surd$
	Shipbuilding	$\surd$	$\surd$
	Other Transport	$\surd$	$\surd$
	Non-electrical Machinery	$\times$	$\surd$
	Electrical Machinery	$\times$	$\surd$
	Motor Vehicles	$\times$	$\surd$
	Computers	$\times$	$\surd$

Note: $\surd$ indicates $RCA_{ij} \geq 1$, $\times$ indicates $RCA_{ij} < 1$

The econometric techniques employed in this paper analyse the evolution of the entire distribution of RCA over time, and therefore overcome both limitations. Before proceeding to the econometric estimation, we present the results of an informal graphical analysis of the evolution of the entire distribution of RCA. This is undertaken for the United Kingdom in Figures 2-7. In Figure 2, UK industries are ordered in terms of increasing five-year averaged RCA for the period 1970-4, and deviations of RCA from the value of 1 are graphed. A value of zero on the y-axis therefore corresponds to an RCA of 1, while industries in which the United Kingdom specialises are shown by positive deviations of RCA from the value 1. Figure 2 simply presents the information in Table 1 graphically, and corresponds to the cross-section distribution of RCA during 1970-4. Figures 3, 4, 5 and 6 preserve the same ordering of industries and graph deviations of RCA from 1 for the periods 1975-79, 1980-4, 1985-9 and 1990-3 respectively. Figure 7 re-orders industries in terms of increasing RCA for the period 1990-3, and again graphs the cross-section distribution of RCA in the form of deviations from a value of 1.

Taken together, Figures 2-6 yield information concerning *intra-distribution dynamics*. If patterns of international specialisation in the United Kingdom exhibited persistence, one would expect the distribution of RCA to remain similar across successive time periods. Industries with high values of RCA in 1970-4 would also have high values of RCA in 1990-3. In fact, what one observes, as one moves between the figures, is considerable mobility in the United Kingdom's pattern of international specialisation. This is particularly true in the middle of the distribution. For example, between 1970-4 and 1985-9, the UK's RCA in Motor Vehicles fell from 0.94 to 0.48, before rising to 0.67 in 1990-3. The same exercise can be undertaken for each of the G5 economies: industries are ordered in terms of increasing RCA for the period 1970-4, and the cross-section distribution of RCA in successive time periods is graphed. In each case, we find evidence of changes in the distribution of RCA over time - a finding that will be confirmed in the econometric analysis to follow.

We also examine changes in countries' overall degree of international specialisation (the evolution of the *external shape* of the RCA distribution). One way of addressing this issue is to analyse the evolution of the sample standard deviation of RCA over time.[6] Table 4 presents sample standard deviations of five-year averaged RCA data across industries for each of the G5 economies and the pooled sample. A complete absence of specialisation corresponds to an equal share of exports in all sectors: that is, an RCA of 1 in all sectors with zero standard deviation. In four of the five G5 economies and the pooled sample, we observe a decline in the sample standard deviation of RCA over time, while the latter remains roughly constant in France. In itself, this suggests there was a decline in the degree of international specialisation during the sample period. However, the sample standard deviation of RCA is not, in general, a summary statistic for the external shape of the entire distribution. An analysis of the evolution of the sample standard deviation of RCA over time may therefore yield misleading conclusions about changes in economies' overall degree of international specialisation.

Table 4: Standard Deviations of five-year averaged RCA

	1970-4	**1975-9**	**1980-4**	**1985-9**	**1990-3**
Pooled Sample	0.60	0.59	0.56	0.56	0.51
France	0.32	0.26	0.29	0.31	0.32
Germany	0.38	0.31	0.30	0.33	0.29
Japan	0.92	0.96	0.94	0.87	0.85
United Kingdom	0.45	0.43	0.43	0.44	0.36
United States	0.74	0.73	0.65	0.70	0.57

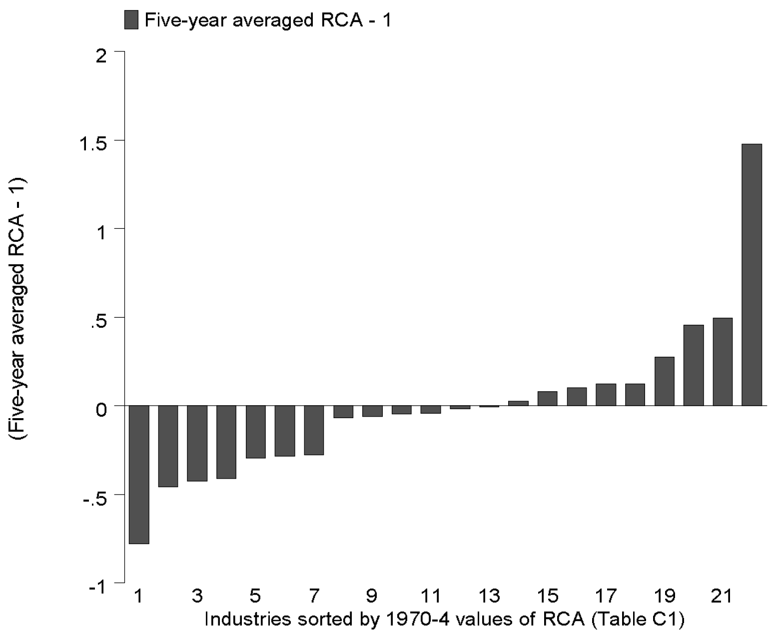


Figure 2: Deviations of RCA from 1, UK 1970-4

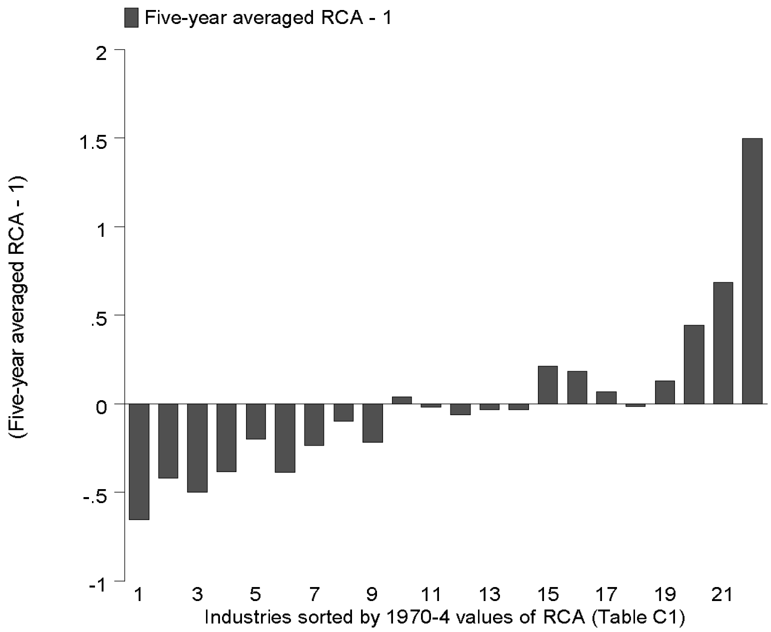


Figure 3: Deviations of RCA from 1, UK 1975-9

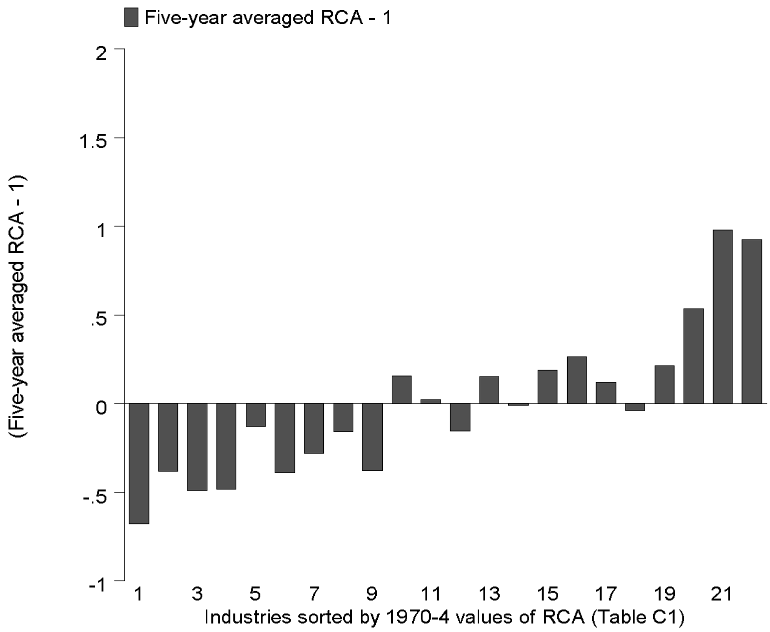


Figure 4: Deviations of RCA from 1, UK 1980-4

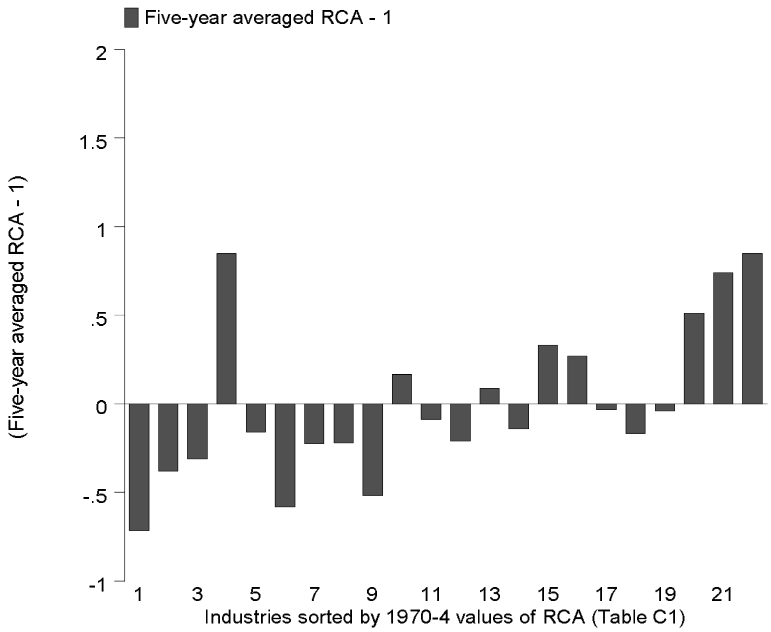


Figure 5: Deviations of RCA from 1, UK 1985-9

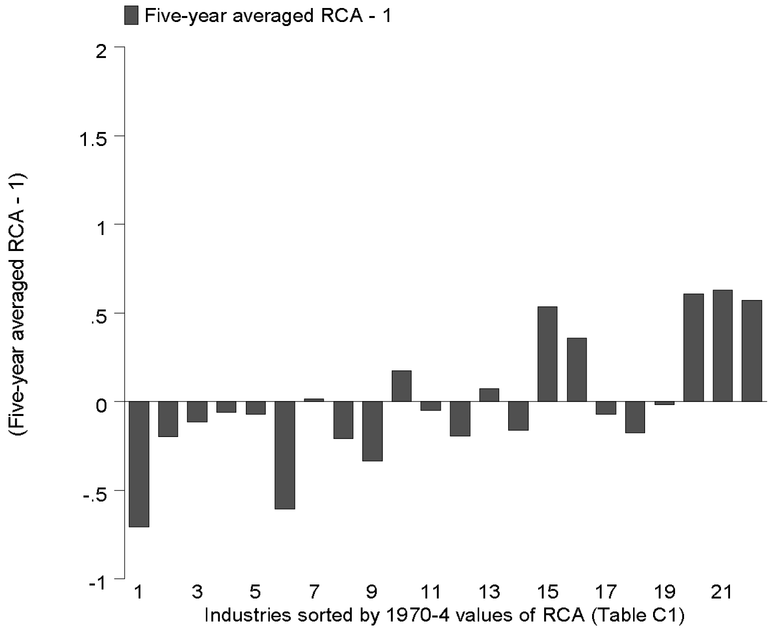


Figure 6: Deviations of RCA from 1, UK 1990-3

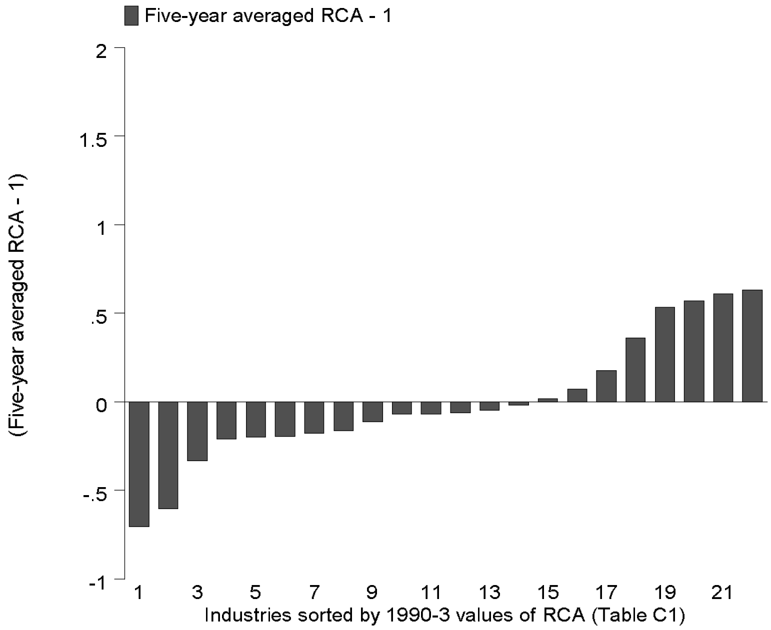


Figure 7: Deviations of RCA from 1, UK 1990-3

A more complete - although again informal - analysis may be carried out for the United Kingdom using Figures 2-7. If the United Kingdom were increasingly specialising in a subset of industries, one would observe RCA systematically increasing in specific sectors and systematically decreasing in others. The distribution of RCA would therefore exhibit an increasing mass at extreme values of RCA. A comparison of Figures 2 and 7 reveals that there is no evidence of an increase in the degree of international specialisation in the United Kingdom. The same conclusion holds for each of the other G5 economies, with the exception of Japan. Only in the latter do we find evidence of an increase in the overall degree of international specialisation; an increase that was not revealed by the analysis of sample standard deviations in Table 4.

In Figure 8, Japanese industries are ordered in terms of increasing five-year averaged RCA for the period 1970-4, and deviations of RCA from the value of 1 are graphed. Figure 9 re-orders industries in terms of increasing RCA for the period 1990-3, and again graphs the cross-section distribution of RCA in the form of deviations from a value of 1. At the beginning of the sample period, there were a large number of Japanese industries with values of RCA close to 1. Thus, during 1970-4, there were 8 industries with an RCA between 0.8 and 1.2, and only 4 industries with an RCA above 1.2.

Over time, RCA systematically moves away from values of 1, as Japan progressively specialises in one set of industries and reduces its specialisation in another set of industries. Thus, during 1990-3, there were only 2 industries with an RCA between 0.8 and 1.2, and 8 industries with an RCA above 1.2. This increase in Japan's degree of international specialisation is seen in Figures 8 and 9 by a decrease in the mass of the distribution concentrated around the x-axis. This trend was obscured in the analysis of sample standard deviations by the decline in the value of RCA in the two industries where Japan has the highest levels of RCA in both 1970-4 and 1990-3: Shipbuilding and Other Transport Equipment.

The next Section conducts a more formal econometric analysis of both the degree to which initial patterns of international specialisation persist over time and the extent to which we observe changes in economies' overall degree of international specialisation over time.

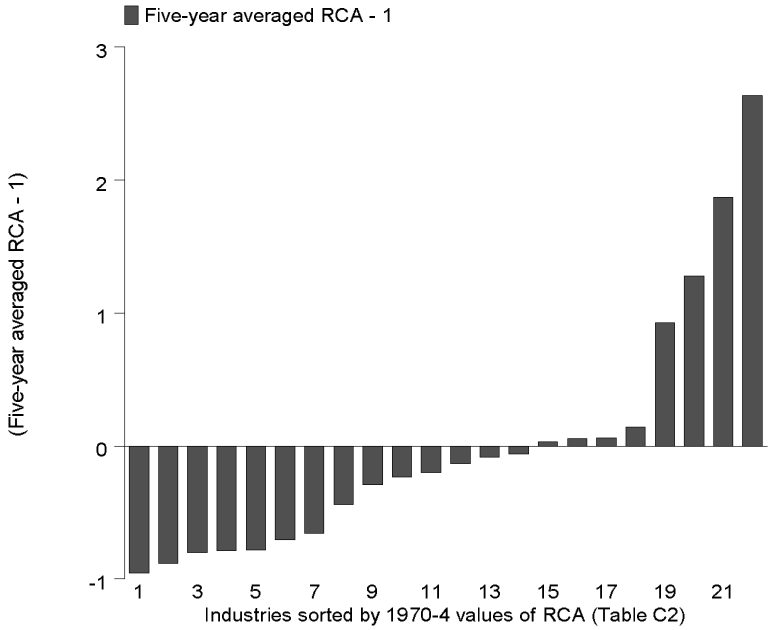


Figure 8: Deviations of RCA from 1, Japan 1970-4

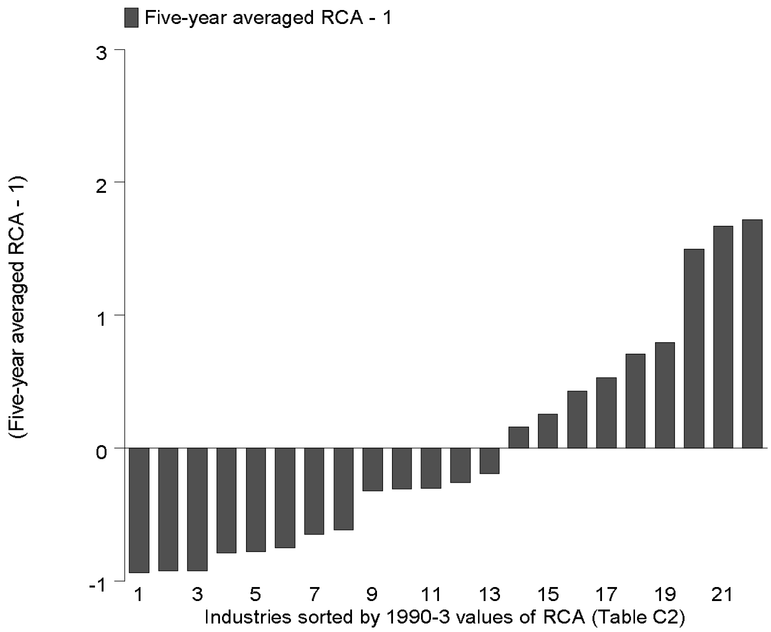


Figure 9: Deviations of RCA from 1, Japan 1990-3

5 Econometric estimation

This Section estimates the formal model of distribution dynamics econometrically. If the space of possible values of RCA is divided into m discrete cells, the operator P^* in equations (6) and (7) becomes an $m \times m$ matrix of transition probabilities,

$$\lambda_t = P^*.\lambda_{t-1} \tag{8}$$

The matrix P^* contains elements p_{kl}, each of which denotes the probability that an industry moves from cell k to cell l (where $k, l \in \{1, ..., m\}$) and which may be estimated by counting the number of transitions out of and into each cell. All empirical estimation was undertaken using Danny Quah's TSRF econometrics package.[7] In each case, the boundaries between cells were chosen such that industry-year observations are divided roughly equally between the grid cells.

In order to provide a benchmark against which to compare the results for individual economies, we begin by pooling observations across economies. In so doing, we assume that the stochastic process determining the evolution of RCA in each economy is the same - an assumption that will be relaxed below. Table 5 presents the estimated transition probability matrix for the pooled sample. The interpretation of this table is as follows. The numbers in parentheses in the first column are the total number of industry-year observations beginning in a particular cell, while the first row of numbers denotes the upper endpoint of the corresponding grid cell. Thereafter each row denotes 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 fifth column) the probability of remaining in the lowest RCA state and then the probability of moving into the lower-intermediate, higher-intermediate and highest RCA states successively. The final row of the upper section of the table gives the implied ergodic distribution. In the lower section of the table, the one-year transition probability matrix is iterated five times.

Transition probability matrices are also estimated for each of the G5 economies individually. Here, we allow the stochastic process shaping the evolution of RCA to vary across economies. The results of this estimation are presented in Table 6. The interpretation of the tables is directly analogous, except that the one-year transition probability matrix iterated five times is now omitted. Since the boundaries between grid cells are chosen such that industry-year observations are divided roughly equally between the cells, each grid cell corresponds approximately to a quartile of the distribution of RCA across industries and over time. The values of estimated transition probabilities characterise the degree of mobility between different quartiles of this distribution. Estimated values of transition probabilities close to one along the diagonal are indicative of persistence in RCA distribution, while large off-diagonal terms imply greater mobility.

Table 5: Transition probabilities, one-year transitions

Pooled sample	*Upper endpoint*			
Number	0.670	0.915	1.223	∞
(609)	0.90	0.10	0.00	0.00
(604)	0.09	0.83	0.09	0.00
(607)	0.00	0.08	0.84	0.07
(600)	0.00	0.00	0.06	0.94
Ergodic	0.234	0.249	0.244	0.273
	1 $\times$ *transitions iterated 5* $\times$			
	0.6518	0.2928	0.0574	0.0049
	0.2635	0.4928	0.2320	0.0421
	0.0459	0.2062	0.4892	0.2271
	0.0033	0.0321	0.1946	0.7655

Table 6: Transition probabilities, one-year transitions

France	*Upper endpoint*			
Number	0.743	1.047	1.245	∞
(114)	0.83	0.17	0.00	0.00
(116)	0.16	0.73	0.10	0.00
(118)	0.01	0.09	0.79	0.11
(114)	0.00	0.01	0.11	0.89
Ergodic	0.266	0.258	0.242	0.234
Germany	*Upper endpoint*			
Number	0.740	0.994	1.270	∞
(121)	0.86	0.14	0.00	0.00
(123)	0.14	0.80	0.07	0.00
(120)	0.00	0.06	0.88	0.07
(120)	0.00	0.00	0.07	0.93
Ergodic	0.233	0.237	0.265	0.265
Japan	*Upper endpoint*			
Number	0.222	0.768	1.446	∞
(122)	0.97	0.03	0.00	0.00
(119)	0.05	0.84	0.11	0.00
(124)	0.00	0.13	0.83	0.04
(119)	0.00	0.00	0.03	0.97
Ergodic	0.325	0.211	0.179	0.286
United Kingdom	*Upper endpoint*			
Number	0.739	0.942	1.176	∞
(123)	0.90	0.09	0.00	0.01
(119)	0.08	0.78	0.13	0.00
(123)	0.00	0.15	0.72	0.12
(119)	0.01	0.00	0.12	0.87
Ergodic	0.253	0.269	0.235	0.243
United States	*Upper endpoint*			
Number	0.608	0.878	1.143	∞
(118)	0.88	0.12	0.00	0.00
(114)	0.11	0.79	0.11	0.00
(115)	0.00	0.10	0.81	0.10
(115)	0.00	0.00	0.10	0.90
Ergodic	0.217	0.245	0.269	0.269

In France, the probability of moving out of one grid cell after one year ranges from 11%-27%, while in the United States the same probability varies from 10%-21%. Iterating the one-year transition matrix five times (not shown in Table 7), the extent of mobility is brought out more strongly: for France, the probability of remaining in the same grid cell over a five-year period ranges from 64% to 37%. Thus, the estimates in Table 6 imply that, if an industry begins in the second quartile of the French RCA distribution, there is a 37% probability that the industry will remain in this quartile of the RCA distribution after five years. This provides evidence of mobility in patterns of international specialisation and confirms the results of the informal analysis in the previous Section.

Comparing the estimated transition probability matrices across countries and with the results of the pooled estimation provides a further way of evaluating the degree of mobility in international specialisation patterns of individual G5 countries. A comparison of the diagonal and off-diagonal terms in the six estimated transition probabilities reveals that France and the United Kingdom exhibit the greatest mobility, while Japan displays the least. This conclusion would not be drawn from Tables 2 and 3 alone, and confirms the limitations of the informal analysis that were pointed out earlier. By restricting attention solely to whether RCA rises above or falls below a value of one, one rules out of consideration a wide range of interesting international trade dynamics.

The finding that mobility is highest in France and the United Kingdom, and lowest in Japan is confirmed with the use of formal indices of mobility (see, for example, Bartholomew (1973), Shorrocks (1978), Geweke et al. (1986) and Quah (1996b)). These seek to reduce information about mobility in the matrix of transition probabilities (P^*) to a single statistic, and Table 7 presents the values of three mobility indices for the pooled sample and the G5 economies separately. The first of these mobility indices (M_1, following Shorrocks (1978)) evaluates the trace (tr) of the matrix; the second (M_2, after Bartholomew (1973)) presents information on the average number of class boundaries crossed by a sector originally in state k weighted by the corresponding proportions π_k of the ergodic distribution; the third (M_3, following Shorrocks (1978)) evaluates the determinant (det).[8]

Table 7: Mobility Indices for the G5

Country	M_1	M_2	M_3
Pooled	0.163	0.121	0.426
UK	0.243	0.187	0.590
US	0.207	0.161	0.518
France	0.253	0.196	0.607
Germany	0.177	0.135	0.460
Japan	0.130	0.083	0.360

$M_1 = \frac{m-tr[P]}{m-1}$, $M_2 = \sum_k \pi_k \sum_l p_{kl} \, |k-l|$, and $M_3 = 1 - |\det(P)|$.

A key advantage of the present approach is that, by analysing the evolution of the *entire* distribution of RCA, we are able to evaluate the degree of mobility through all possible values of RCA. Thus, it is not only the overall degree of mobility in a transition probability matrix that is interesting, but also the pattern. In each of the G5 economies and in the pooled sample, the off-diagonal elements of the matrix are largest in the lower- and upper-intermediate grid cells, corresponding to greater mobility in the middle of the RCA distribution.

The pattern of mobility is particularly important for understanding the evolution international specialisation in Japan. The estimated probabilities of moving out of the lower- and upper-intermediate grid cells in Japan (characterising the degree of mobility in the middle of distribution) are not dissimilar to those estimated for the United States. What is noteworthy about Japan is the immobility in the lower and upper grid cells of the estimated transition probability matrix. Thus, mobility in the centre of the distribution is combined with immobility at the extremes. There is a relatively high probability of industries moving out of the lower- and upper-intermediate grid cells, but, once industries move into the lower and upper grid cells, they are extremely likely to remain there. It is this combination of mobility in the centre of the distribution and immobility at the extremes, that is driving some of movements in RCA above and below the value of one in Table 3. This is confirmed if one repeats for Japan the analysis undertaken earlier for the United Kingdom in Figures 2-6.

The empirical finding of mobility in patterns of international specialisation contrasts with the results of a number of theoretical models of trade and growth. In the absence of international knowledge spillovers, models of endogenous technological progress through either sector-specific learning by doing (eg Krugman (1987)) or research and development (R&D) (eg Grossman and Helpman (1991), Chapter 8) predict that initial specialisation patterns will become locked-in over time. This corresponds to no potential for technology transfer in the theoretical model of Section 2 ($\lambda_j = 0$). However, the prediction of persistence in patterns of specialisation is clearly at variance with the data. This suggests the importance of incorporating into theoretical models economic forces capable of inducing changes in international specialisation over time. These include knowledge spillovers, which correspond to $\lambda_j > 0$ in the theoretical model of Section 2 (see also Grossman and Helpman (1991) (Chapter 7)). In models of international trade based on cross-sector differences in factor intensity and cross-country differences in factor abundance, factor accumulation provides an additional explanation for changes in international specialisation over time (see, for example, Findlay (1970), (1995), and Deardorff (1974)).

The econometric techniques implemented in this Section also yield information about changes in economies' degree of international specialisation over time (the evolution of the *external shape* of the RCA distribution). Iterating the estimated transition probability matrix forwards in time, and allowing the number of iterations to tend towards infinity, one obtains the implied ergodic or stationary RCA

distribution towards which patterns of international specialisation are evolving. This corresponds to the unconditional probability of an industry being in a particular grid cell. If economies are increasingly specialising in a subset of industries, this will be reflected in a polarisation of RCA towards extreme values and the emergence of a bimodal distribution of RCA.

The final row of each panel of Tables 5-6 reports the ergodic distribution implied by each transition probability matrix. In the pooled sample and four of the five G5 economies (France, Germany, the United Kingdom, and United States), the ergodic distribution is approximately uniform. For these economies, there is no evidence of an increase in the degree of international specialisation over time. The exception to this pattern is Japan. The high persistence in the lower and upper grid cells noted above is responsible for a polarisation of RCA towards extreme values and implies a bimodal ergodic distribution. The results of the econometric estimation therefore confirm the earlier informal analysis of the changing external shape of the RCA distribution in Figures 2-9. Formal and informal analyses of the evolution of the *entire* distribution of RCA only reveal evidence of an increase in the degree of international specialisation in Japan.

The techniques implemented in this Section may also be used to examine whether the stochastic process determining the evolution of RCA across industries is the same in each of the G5 economies. Anderson and Goodman (1957) show that, for each state k, under the null hypothesis $p_{kl} = \tilde{p}_{kl}$,

$$\sum_{l=1}^{m} n_{k}^{*}.\frac{(p_{kl} - \tilde{p}_{kl})^2}{\tilde{p}_{kl}} \sim \chi^2(m-1), \qquad n_k^* \equiv \sum_{t=0}^{T-1} n_k(t) \tag{9}$$

where p_{kl} are the estimated transition probabilities, $\tilde{p}_{kl}$ are the probabilities of transition under the (known) null and $n_k(t)$ denotes the number of sectors in cell k at time t.

The test statistic in equation (9) may be used to test the hypothesis that the transition probabilities estimated for an individual G5 economy are the result of a Data Generation Process (DGP) given by the transition probabilities estimated for the pooled sample. From equation (9), this test may be undertaken for each state $k = 1, ..., m$. Furthermore, since the transition probabilities are independently distributed across states, we may sum over states and test the hypothesis that, for *all* states $k = 1, ..., m$, the estimated transition probabilities are equal to those under the null. The resulting test statistic is asymptotically distributed $\chi^2(m(m-1))$.

Implementing this test procedure for the G5 economies, the null that the DGP is given by the matrix of transition probabilities estimated for the pooled sample is rejected at the 5% level in France and the United Kingdom (the two most mobile economies). The same hypothesis is not rejected at conventional levels of statistical significance in Germany, Japan and the United States (though the hypothesis is close to rejection at the 10% level in Japan). These results suggest that, as well as there being considerable mobility in patterns of international specialisation in each economy, there are significant differences in international trade dynamics across economies.[9]

Finally, we undertake a whole series of econometric robustness tests.[10] Our results are robust to all of these tests. First, the space of values of RCA was divided into five cells rather than four and transition probability matrices were re-estimated. Second, the transition probabilities were estimated allowing transitions to occur over five-year rather than one-year periods. The probabilities estimated over five-year transition periods exhibit some differences from the one-year transition probabilities iterated five times, suggesting that the evolution of RCA is not fully characterised by a first-order, time homogenous model. However, in both cases, the results suggested a broadly similar interpretation to that given above.

Third, we examine the stability of the econometric estimates over time. Transition probability matrices were estimated separately for the periods 1970-81 and 1982-93. For both the pooled sample and each of G5 economies, the null hypothesis that the matrix of transition probabilities estimated during either (a) 1970-81 or (b) 1982-93 is the result of a DGP given by the matrix of transition probabilities estimated for the full sample (1970-93) cannot be rejected at the 5% level. Fourth, we consider measurement error and the sensitivity of the results to observations from any single industry. An industry in all G5 countries was sequentially excluded from the sample and transition probability matrices were re-estimated. For both the pooled sample and each of the G5 economies, the sample mean of each element of the transition probability matrix across the 22 sets of estimation results lies close to the value estimated for the full sample in Tables 5-6. The sample standard deviation of each element of the transition probability matrix is an order of magnitude smaller than the estimated transition probabilities.

Fifth, to address the sensitivity of the results to the exact level of sectoral disaggregation employed, we aggregate the four-digit industries in the sample to the three-digit level. This yields 16 industries, compared with the 22 industries classification used in the analysis above (see Table A1 in Appendix A). For both the pooled sample and each of the G5 economies, there is little change in the estimated transition probabilities. The null hypothesis that the matrix of transition probabilities estimated for the 16 industry classification is the result of a DGP given by the matrix estimated for the 22 industry classification cannot be rejected at the 5% level.

6 Conclusion

The theoretical literature on trade and growth emphasises the dynamic nature of comparative advantage. However, much of the existing empirical literature is concerned with static patterns of international trade. This paper proposes an empirical framework for analysing the dynamics of international specialisation. The extent of a country's specialisation in an individual industry is measured by a modified index of Revealed Comparative Advantage (RCA). A country's pattern of international specialisation at a point in time is then fully characterised by the distribution of RCA across industries. The dynamics of international specialisation correspond to the evolution of this *entire* cross-section distribution over time. We employ a model of distribution dynamics, introduced into the cross-country growth literature by Quah (1993), (1996a), and (1996c), and that is explicitly suited to an analysis of the evolution of an entire distribution.

The paper examines two main issues relating to international trade dynamics: the extent to which initial patterns of specialisation persist over time (an issue of *intra-distribution dynamics*) and changes in countries' overall degree of specialisation (the evolution of the *external shape* of the distribution of RCA). A number of different strands of the theoretical literature on dynamic comparative advantage yield ambiguous conclusions concerning whether patterns of international specialisation exhibit persistence or mobility over time. This is therefore an empirical question. The empirical framework presented in the paper is consistent with a wide range of possible international trade dynamics, and allows the degree of persistence versus mobility to be determined from observed trade data.

The empirical model of international trade dynamics is implemented using industry-level data from the G5 economies. Transition probability matrices were estimated for both the pooled sample (pooling observations on RCA across economies) and for each of the individual G5 countries. We find evidence of substantial mobility in patterns of international specialisation, and the extent of mobility in individual G5 countries was quantified using formal indices of mobility. Overall mobility was found to be highest in France and the United Kingdom and lowest in Japan.

The empirical finding of substantial mobility in patterns of international specialisation contrasts with the results of a number of theoretical models of trade and growth. In the absence of international knowledge spillovers, models of endogenous technological progress through either sector-specific learning by doing or research and development (R&D) predict that initial specialisation patterns will become locked-in over time. The fact that this prediction is at variance with the data suggests the importance of incorporating into theoretical models forces such as knowledge spillovers and factor accumulation, which are capable of generating changes in international specialisation over time (see, for example, Grossman and Helpman (1991) (Chapter 7), Findlay (1970), (1995), and Deardorff (1974)).

If countries are increasingly specialising in subsets of sectors, we would expect to observe RCA

systematically increasing in some industries and systematically decreasing in others. That is, we would expect to observe a polarisation of the RCA distribution towards extreme values. Both a formal and informal analysis of the evolution of the *entire* distribution of RCA revealed no evidence of an increase in international specialisation in France, Germany, the United Kingdom and the United States. Only in Japan, is there evidence of an increase in international specialisation over time, directly linked to the extreme immobility observed in the tails of the Japanese RCA distribution.

Appendix A

The data source for the indices of Revealed Comparative Advantage is the OECD's Bilateral Trade Database (BTD). This provides information on the value of exports and imports between the 23 OECD countries and 15 partner economies. The partner countries are: Argentina, Brazil, China, Czech and Slovak Republics, Hong Kong, Hungary, India, Indonesia, Malaysia, Mexico, Philippines, Singapore, Korea (South), Taiwan and Thailand. Although OECD imports from and OECD exports to these partner countries are included in the database, trade entirely outside the OECD area (eg from one partner country to another) is not. The OECD estimates that 90%-95% of world trade in goods is included in the database. Information is available for the 22 industries listed in Table A1.

Table A1: Industrial Classification

Industry	ISIC Classification
1. Food, Drink and Tobacco	31
2. Textiles, Footwear and Leather	32
3. Wood, Cork and Furniture	33
4. Paper, Print and Publishing	34
5. Industrial Chemicals	351+352-3522
6. Pharmaceuticals	3522
7. Petroleum Refining	353+354
8. Rubber and Plastic Products	355+356
9. Non-metallic Minerals	36
10. Ferrous Metals	371
11. Non-ferrous Metals	372
12. Metal Products	381
13. Non-electrical Machinery	382-3825
14. Computers and Office Machinery	3825
15. Electrical Machinery	383-3832
16. Communication Equipment	3832
17. Shipbuilding	3841
18. Other Transport Equipment	3842+3844+3849
19. Motor Vehicles	3843
20. Aerospace	3845
21. Instruments	385
22. Other Manufacturing	39

Appendix B: Measuring RCA

Balassa (1965) defines an economy i's measure of 'Revealed Comparative Advantage' ($\widetilde{RCA}_{ij}$) in sector j as follows,

$$\widetilde{RCA}_{ij} = \frac{Z_{ij}/\sum_i Z_{ij}}{\sum_j Z_{ij}/\sum_i \sum_j Z_{ij}}, \tag{10}$$

$\widetilde{RCA}$ suffers from the disadvantage that its arithmetic mean across sectors is not necessarily equal to one. The numerator in equation (10) is unweighted by the proportion of total exports accounted for by a given sector, while the denominator is a weighted sum of export shares in all manufacturing sectors. Thus, if an economy's pattern of trade is characterised by high export shares in a few sectors, each of which accounts for a small share of total world exports (as is generally true for small economies), this implies high values for the numerator and low values for the denominator in equation (10). As a result, the economy will be characterised by a mean value of $\widetilde{RCA}$ of above one.[11] Furthermore, mean values of $\widetilde{RCA}$ may change over time, so that, as measured by $\widetilde{RCA}$, an economy exhibits changes in its average extent of specialisation over time.

This paper adopts an alternative measure of Revealed Comparative Advantage (RCA), in which an economy's export share in a given sector is evaluated relative to its *average* export share in all manufacturing sectors. By construction, the mean value of RCA is constant and equal to one. It is straightforward to show that $RCA_{ij} = \widetilde{RCA}_{ij}/\frac{1}{N}\sum_j \widetilde{RCA}_{ij}$. Thus, an alternative interpretation of the present analysis is that, at each point in time, we normalise Balassa's measure by its cross-section mean in order to abstract from the changes in the average extent of specialisation that this measure is subject to.

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Endnotes

[1] For a more recent application of Balassa's original index, see Dollar and Wolff (1993).

[2] Balassa (1965)'s actual measure of RCA is the ratio of economy i's export share in sector j to its share of total exports of all sectors. This measure suffers from the disadvantage that its arithmetic mean is not necessarily equal to one, and may vary both across economies and over time. The measure used in this paper is formally equivalent to normalising Balassa's measure by its cross-sectional mean. See Appendix B for further discussion.

[3] More generally, if we continue to treat RCA as a continuous variable, one may estimate the stochastic kernel associated with P^* (see for example Quah (1996c)). However, in the present application, there are too few cross-sectional units to permit such estimation.

[4] Further details concerning the data used, including an industrial classification, are contained in Appendix A.

[5] In the interests of brevity, actual values of RCA are not reported. A data appendix containing this information is available from the authors on request.

[6] See also Amiti (1997). Since the mean of RCA across industries is 1, the standard deviation equals the coefficient of variation.

[7] Responsibility for any results, opinions and errors is, of course, solely the authors'.

[8] For the exact relationship between these indices and the circumstances under which they yield transitive rankings of transition probability matrices see Shorrocks (1978) and Geweke et al. (1986).

[9] It is also possible to test the null hypothesis for one G5 economy that the DGP is given by the matrix of transition probabilities estimated for another G5 economy. For a more detailed analysis of international trade dynamics in Germany and the UK, see Proudman and Redding (1997).

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

[11] For example, suppose there are two economies (the UK and France) and two goods (beer and wine). The total value of the UK's exports is £500 (£400 Beer and £100 Wine) and the total value of France's is £10,100 (£100 Beer and £10,000 Wine). It is straighforward to show that the UK's mean RCA is considerably above one (it is in fact 8.59) and France's considerably below one (it is in fact 0.63).