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Working Paper

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Kiel Working Papers, No. 637

Kieler Arbeitspapiere
Kiel Working Papers

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by

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ISSN 0342 - 0787

The Kiel Institute of World Economics
Düsternbrooker Weg 120
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Kiel Working Paper No. 637

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54544

May 1994

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Abstract

This paper applies Markov chain analysis to examine the empirical dynamics of sectoral specialization in open economies. At issue is here persistence and the hypothesis of hysteresis in national patterns of industrial specialization, often claimed as an implication of strong path dependence in the evolution of high-technologies specific to certain industries. The evidence from twelve OECD member countries' time series of value added in 17 manufacturing industries and from corresponding patent count data does not support the hypothesis of hysteresis based on nationally restricted knowledge spillovers from industrial research and development activities. On the contrary, there seems to be generally lower persistence in patterns of technological specialization than in the corresponding production specialization. Moreover, high persistence in some parts of manufacturing mostly disappears when taking into account changes in countries' relative factor endowments, which form the basis of *dynamic* comparative advantages. These findings cast doubt on the popular belief that a government can — by making cleverly designed and appropriately timed industrial policy interventions — secure a *permanently* larger share of certain industries for the national economy which are supposed to lock in first mover advantages in terms of particularly high rates of technological innovation and productivity growth.

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Financial support given by the Deutsche Forschungsgemeinschaft and helpful comments from Karl-Heinz Paqué on an earlier draft are gratefully acknowledged.

1 Introduction

When economists talk about specialization they usually invoke the theorem of comparative advantage, which has been known at least since David Ricardo. This theorem roughly states that any economic actor — a person, a firm or a country — who is trading his products with others specializes his production in those goods or services in which he has a relative, not necessarily an absolute, cost advantage over his trading partners. One possible reason for international differences in absolute and relative sectoral production costs are the different production technologies that different countries use, as was assumed by Ricardo. Neoclassical economics, by contrast, has usually assumed that production technologies were ubiquitous across countries. Comparative advantages which countries have in certain sectors were then entirely due to factor endowments, and under the assumption of constant returns to scale technologies these comparative advantages alone determined the patterns of specialization and international trade. Implicitly, R&D is seen as a current input needed only to apply ubiquitous technical knowledge in actual production.

Another strand of thought has argued that countries follow idiosyncratic paths of technological development, and that present sectoral patterns of technological specialization do not necessarily reflect present factor endowments, but rather historical leads and lags in certain technologies. These leads and lags are, in turn, thought to have a more powerful influence on specialization in actual production than traditional notions of factor endowment. This view suggests that temporary historical events, like temporary price shocks or industrial and technology policies, can have a lasting effect on a country's pattern of sectoral specialization, and growth rate. In this sense, specialization in technology as well as in production may be independent of factor endowments.[1] Rather than being determinants of specialization the endogenous part of factor endowments, physical and human capital, might change as a result of investment induced by opportunities specific to the particular sectoral strengths and weaknesses an economy has inherited.

[1] This kind of independence is distinct from the sort of indeterminacy of specialization which arises in multi-dimensional neoclassical trade models with more goods than factors and factor price equalization. In these models without externalities it remains true that countries, on average, tend to export goods which make relatively intensive use of relatively abundant factors and that in response to exogenous factor supply changes *some* industries' output must change in certain directions (cf. Ethier, 1984). But idiosyncratic paths of technological development may imply that there are only weak or no responses of output — especially in high technology industries — to changes in factor supplies and that countries do not even on average export goods whose production makes relatively intensive use of relatively abundant factors.

Factor endowments and hysteresis are here considered as competing hypotheses on the determination of technological specialization in open economies.[2] Which of these better explains the dynamics of sectoral patterns of specialization in the real world is an important question for company management as well as for economic policy. It is important for management because it has implications for the choice of R&D strategy including the extent, scope and geographical range of external technology sourcing in highly competitive world markets: Should companies allocate their R&D labs close to established international centres of R&D in their field, betting on beneficial knowledge spillovers in the future, or should they always choose the location that minimizes current costs?

The question *endowments versus hysteresis* is important for economic policy, because it bears on the choice of industrial and technology policy a country should adopt. If factor endowments in the traditional sense were found to be the sole determinant of sectoral patterns of technological specialization, then industrial and technology policies targeted at selected industries in order to change the sectoral mix of a country's pattern of technological leads and lags, could be ruled out to have any lasting, let alone permanent effect. Lasting effects could only be expected from changes in factor endowments, such as educational investment in human capital. If, however, current technological leads and lags were found to be determined by past patterns of technological specialization, then it might pay for a country to use targeted industrial and technology policies to actively influence and shape its future pattern of technological specialization, provided certain technologies promise more growth and higher incomes for those internationally immobile factors, which are used more intensively in the production of the corresponding sector. A country might be well advised to pursue not merely the deepening of technological specialization along established trajectories[3], but also to actively promote the shifting of resources towards

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2 Somewhat related to these competing hypotheses is the controversy of technology push versus demand pull in industrial innovation dynamics, which has remained an important theme in the literature on innovation since Schmookler's (1966) seminal work. If innovation was driven by demand pull only, then idiosyncratic paths of technological development would be unlikely in today's advanced open economies — given the ever more closely-knit web of international trade flows and the overall similarity of final demand in different industrial countries around the world. Technology push, on the other hand, would be consistent with hysteresis whenever the formulation of research programmes and their particular results depend on context factors and the prior knowledge and skills of the scientist or engineer as well as on his serendipity.

3 The term "technological trajectories" was coined by Dosi (1982). He sees continuous technological innovation as progressing along trajectories defined by a technological paradigm akin to "scientific paradigms", while associating discontinuities in technological innovation with the emergence of a new paradigm. He rejects the ideas of the market being the prime determinant of the direction of

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selected newly emerging technological trajectories, provided the government can identify those of the emerging technologies which hold the greatest promise for future development and productivity growth.

Section 2 of this paper reviews some of the recent theoretical discussion on technological change, trade and growth, focusing on the decisive assumptions that yield the competing hypotheses on the (ultimate) determinants of technological and production specialization in open economies. Section 3 uses non-parametric methods to examine the empirical dynamics of specialization, as documented in data on value added in 17 manufacturing industries and corresponding patent count data for twelve OECD member countries. Section 4 attempts to assess empirically the influence of changes in relative factor endowments on the dynamics of specialization. Section 5 suggests directions for further research and concludes.

2 Economic theory on technological change, trade and growth in open economies

The case for factor endowments as the determinants of sectoral patterns of technological and industrial specialization has recently been formalized as a theory of dynamic comparative advantage in international trade. Neo-classical trade theory, based on the seminal work of Heckscher (1919) and Ohlin (1933), is usually exposed as a static theory of resource allocation in open economies that assumes a constant set of goods and ubiquitous production technologies and, thus, does at first sight not have anything meaningful to say about R&D or technological specialization. However, if R&D is interpreted as a current non-tradable input needed to apply ubiquitous technical knowledge in production, a country's sectoral pattern of R&D expenditures — or some other measure of technological specialization — should simply reflect the sectoral composition of its production of tradables due to this country's pattern of comparative advantage vis-à-vis its trading partners. To the extent that R&D output was itself tradable, the allocation of R&D should — at least on average — reflect the relative intensity of factor use in R&D and the country's factor endowment, in other words, the comparative advantage for sectoral R&D just as for any other economic activity (cf. Casson, 1991).

discontinuous technological change. Similar views are held by Rosenberg (1976) and other economic historians.

Heckscher-Ohlin theory remained an essentially static theory for a long time, although a number of authors, notably Bardhan (1970) and Findlay (1973), dealt with the changes in trade equilibria due to *exogenous* productivity growth in the spirit of Solovian growth theory (Solow, 1957). But these did not address the fundamental question how trade, in turn, affects rates of productivity growth in the long run. To do so would have required to do away with one of traditional trade theory's basic assumptions, that the set of goods was given. Recent theoretical work has overcome this shortcoming and has been able to formulate a new theory of dynamic comparative advantage (cf. Grossman/Helpman, 1991). This theory, based on models of endogenous technical change introduced by Romer (1990) and Aghion and Howitt (1992), interprets product and process innovations as the result of purposeful R&D investments made by private, profit-seeking enterprises. Sustained growth of per-capita productivity is feasible whenever the private incentives to accumulate technical knowledge are strong enough and do not weaken over time. The models meet this condition by postulating that the creation of knowledge through private R&D yields positive external effects: part of the new knowledge adds to the public stock of technical knowledge and is accessible to all firms doing R&D themselves. Without these positive externalities, which have the effect of reducing every firm's costs of future R&D, the pioneers of a new technology would be in a position to establish a permanent monopoly that could be defended virtually without further R&D effort.

In this body of theory R&D has — at last — a meaningful role to play, in fact it is seen as the driving force behind long run growth of total factor productivity. Using this theory to understand trade, growth and technological specialization in open economies, it is necessary to make some assumptions about the cross border mobility of R&D output. One important assumption concerns the privately appropriable part of R&D output. This may be either internationally tradable, like most other private inputs in production, or may be largely excluded from international trade, since it is often complementary to specific knowledge and skills available only in the firm or country that has done the R&D. The assumption of international mobility of R&D output is supported by the observation of widespread, and increasing (cf. Vickery, 1986), trade in patents and licences. On the other hand, the assumption of limited international mobility of R&D output is supported by the fact that the recipient of international technology transfers often cannot use the acquired R&D output straight away, but rather has to invest in complementary knowledge and skills and to literally re-search the acquired knowledge to understand its tacit components. Hence, it does not seem so surprising that a large and apparently increasing share of international technology transfers takes place within multinational companies, which are generally in a better position to move not just pure technical knowledge but also complementary human capital resources across borders.

Romer (1990) emphasizes that knowledge has the economic properties of non-rivalry in use and only partial excludability, which distinguish it from most tradable goods. Another important distinction, however, may be in terms of marketability: while tangible assets, which cease to be useful to their owner, can usually be resold at market prices, it is hardly feasible to resell externally acquired knowledge oneself has failed to understand and make use of.[4] While non-rivalry and partial excludability may be powerful forces in support of rapid diffusion of new knowledge, imperfect marketability may work against it. People, firms and countries lacking the necessary complementary skills will not only be unable to benefit from knowledge spillovers, but may even face a much worse cost-benefit ratio in the commercial knowledge trade.

To what extent the privately appropriable part of R&D output, itself an input in other production, is *internationally* tradable has interesting implications for resource allocation and patterns of specialization within the theory of dynamic comparative advantage (cf. Grossman/Helpman, 1991, pp. 197). By extending the international division of labour, trade in new technical knowledge[5] can lead to a more efficient use of resources in knowledge creation and so raise the rate of innovation and growth in the world economy. The crucial assumption, however, which distinguishes the theory of dynamic comparative advantage from the hysteretic theory of technological accumulation, is that the speed, strength and scope, with which the positive *external* effects of knowledge creation through R&D spill over to other firms, are not reduced by international borders, nor by geographical or cultural distance between industry locations.

Some implications of *national* external effects for the dynamics of specialization can be illustrated in their simplest form within a stylized model of a small open Ricardian economy, which has two sectors, a comparative advantage due to higher labour productivity in one of them, but increasing returns to scale in the form of a positive externality in the other sector, and whose reallocation of labour between sectors can be characterized as a stochastic recontracting process (cf. Arthur, 1988).

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4 This is why junior students, before buying a used textbook from a senior student, usually enquire how well this senior student did in his exam on the subject. If the senior student failed, and if alternatives to his textbook are available, he will have difficulty selling, unless he can persuade potential buyers that his failure on the exam was not the textbook's fault, but his own.

5 Either through trade in patents and licences or through technology transfers within multinational companies.

Suppose two new technologies are being introduced, replacing an older technology used in the small open economy, which has been completely specialized in that one old technology as is typical for Ricardian economies with only one factor of production, say, labour. Subsequently the one industry of that economy separates into two, with each branch specializing in the production of only one of the two new differentiated products, which are assumed to sell both at the same constant price in world markets. Each entrepreneur makes an initial random choice for one of the two technologies. But workers frequently change jobs and decide anew with which technology to work. On average they are indifferent between the two technologies, so that in each event of a job change both technologies are chosen with probability ½. The result of workers' never-ending recontracting is that the share of workers in each of the two technologies moves up and down in the form of a Markov random walk[6] with reflecting barriers. Three different cases illustrate how comparative advantages and increasing returns to scale in the form of positive external effects may shape the dynamics of the stochastic process:

(i) First, labour productivity is exogenous and the same in both constant returns to scale technologies. The probability of having a certain number n of workers involved with technology A at time t + 1, which stands here for event time rather than historical time, is defined as:

$$\begin{aligned}P(n,t+1) &= P(n,t)\left(1-p_{AB}(n)-p_{BA}(n)\right)\\ &\quad+P(n-1,t)p_{BA}(n-1)+P(n+1,t)p_{AB}(n+1)\\ &=0.5\,P(n+1,t)+0.5\,P(n-1,t).\end{aligned} \tag{1}$$

The evolution of this probability is described by the Master equation of motion:

$$\begin{aligned}\frac{dP(n,t)}{dt} &= P(n+1,t)p_{AB}(n+1)-P(n,t)p_{AB}(n)\\ &\quad+P(n-1,t)p_{BA}(n-1)-P(n,t)p_{BA}(n).\end{aligned} \tag{2}$$

Approximating the state variable n to a continuous variable would lead to the one-dimensional Fokker-Planck diffusion equation. Both of these equations have the property of finally developing into a long-run stationary probability distribution, irrespective of the initial allocation of workers across industries (cf. Weidlich and

[6] A Markov random walk is a well-known type of a stochastic process in discrete (event or historical) time in which the probabilities of transition of the state variable (here the share of workers in technology A) from any present state to any other state are not only independent of the past (which defines a general Markov process) but also independent of the present state. When the Markov random walk takes place over a discrete state space it is a kind of Markov chain.

Haag, 1983, p. 9).[7] In the case considered here, the Markov random walk with reflecting barriers will result in equal stationary probability of all possible allocations of workers, whatever the initial choices of entrepreneurs.

(ii) If workers were more productive in technology B, giving the country a comparative advantage in that industry, and if sector B's firms therefore paid higher wages, the stationary probability distribution of the share of workers in technology A would be highly skewed towards a *low* long-run share of workers in technology A. This is because workers would now be more likely to switch jobs from A to B than the reverse. The p_{AB} and p_{BA} in the Master equation would have to be changed correspondingly.

(iii) For hysteresis to arise, assume that technology A has increasing returns to scale in the form of positive external effects. Since firms are unable to internalize the externality, they remain in perfect competition with each other and pay wages equal to average productivity in their industry. Average productivity and wages in industry A are now an increasing function of industry size, so that the probability of choosing a job there positively depends on the number of workers already involved with technology A — clearly a case of positive feedback. Perhaps the simplest parameterization would be $p_{BA}=n^2/N^2$ and $p_{AB}=1-n^2/N^2$, where n is the number of workers already in technology A and N the total number of workers in the economy. The probability distribution of this Markov process would converge to a bimodal distribution with a high probability of almost complete specialization in either technology A or B. However, the likely allocation of labour resulting from any particular recontracting process of this kind may depend for a long time on the initial (perhaps arbitrary) share of workers in technology A. If that share was small the positive external effects would be weak and wages lower than in industry B so that workers would be more likely to move there. If the initial share of A exceeded a critical level — under the suggested parameterization slightly above 2/3 — the positive external effects would already be sufficiently strong to entice more workers into technology A reinforcing its productivity and wage lead. The resultant Markov process may now look almost like a Markov chain with absorbing barriers, where the economy remains almost completely specialized for long periods of time. But unless complete specialization in one technology is fully absorbing, there always remains the possibility of a transition to the other extreme, however unlikely it may seem.[8]

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[7] In many cases it is possible to work out the stationary probability distribution analytically, but it is often more convenient to get it from computer simulations.

[8] If the time horizon is extended to infinity such radical transitions will certainly happen at some points in time. One may therefore aptly speak of *punctuated equilibria*.

Similar stochastic processes with hysteresis can as well arise in open economy models other than the simple Ricardian, although in more complex models of the Heckscher-Ohlin variety rarely with the result of (almost) complete specialization. In any case, to rationalize the hypothesis of technological accumulation, based on historical leads and lags, in economic terms, the assumptions of the standard neoclassical model of perfectly competitive markets and constant returns to scale production technologies have to to be altered in some way that affects countries asymmetrically. Grossman and Helpman (1991) derive a hysteretic variant of their model of dynamic comparative advantages by simply assuming that knowledge spillovers from R&D are only national in reach. The unintended by-product of private R&D investments then contributes to the national stock of public technical knowledge, thereby enhancing productivity in the R&D of national firms relative to foreign competitors in the same sector.

To summarize, the benchmark model of dynamic comparative advantage assumes both that the privately appropriable part of R&D output is internationally tradable and that knowledge spillovers are not impeded by international borders. Then, disregarding other institutional factors, the international allocation of R&D activities is — at least in principle — not tied to the location of the *users* of R&D output. Moreover, patterns of specialization in technology as well as in actual production would — in the absence of adjustment and transaction costs — be quite mobile over time and independent of each other as they respond to changes in the relative factor endowments of countries. Since the comparative advantages for production and for R&D in an industry would be distinct and might be located in different countries, not even the specialization patterns of those technologies which are confined to single industries need to evolve along the same trends as the corresponding industries.

By contrast, the case for historical events as the determinants of sectoral patterns of technological specialization, based on the theory of technological accumulation, would imply that patterns of specialization in technology as well as in production are much less mobile, especially when a country's industrial structure is already heavily skewed towards certain industries.[9] If knowledge spillovers from R&D were only national in reach, hysteresis could be decisive in the sense that temporary events, like price shocks or industrial and technology policies, can have lasting effects on a country's pattern of

[9] Although related, the theory of technological accumulation is not simply a revamping of earlier technology gap theories. Whereas the latter assumed a single country to be the technological leader in all sectors, and all other countries more or less behind, technological accumulation theory allows for the possibility that technological leads are spread across different countries rather than being all concentrated in one.

technological specialization and trade. Such lasting effects might be recognizable through high persistence of specialization patterns in production and technology despite changes in the relative factor abundance of countries. Persistence would be expected to be particularly pronounced in technological specialization where the positive external effects in the form of knowledge spillovers from R&D would have their most direct and strongest impact. But in general, a close relationship would be expected between the dynamics of countries' specialization in certain technologies and in the production in those industries whose products make intensive use of these technologies.

3 Empirical dynamics of specialization

The stylized model of the stochastic recontracting process and dynamic specialization in the small open Ricardian economy lends itself naturally to an empirical examination. The focus of this will be on questions like: What are the actual dynamics of specialization in technology and industrial production of open economies? Are these dynamics quite similar or rather distinct from each other? Is there any evidence for hysteresis in terms of high persistence of strongly above average or far below average specialization in either technology, production or both?[10]

[10] Research on these questions should be seen as complementary to recent econometric attempts at diagnosing the international range of positive external effects from R&D more directly. A number of empirical studies, surveyed in Griliches (1992), have estimated social rates of return to R&D investments well above the private rates of return. These studies leave little doubt that intra- and intersectoral knowledge spillovers from R&D are pervasive, yet incomplete and often effective only after some time lag. The time series regularly show a strong positive correlation between the productivity growth of a firm or an industry and its own R&D investment. Lichtenberg (1993) extends this line of research and finds that in a number of industrial economies also the *national* productivity growth is significantly and positively correlated with the respective own R&D expenditure of these countries. Under the assumption that R&D expenditures are themselves exogenous with respect to productivity, this result leads to a rejection of the hypothesis that knowledge spillovers from R&D are not at all reduced or slowed down at international borders. Coe and Helpman (1993) find empirical support for the assumption that international spillovers from R&D depend mainly on the intensity of bilateral trade relations and that notably small countries with open markets derive considerable productivity gains from foreign R&D advances.

Despite these findings, it would seem premature to regard the hypothesis of hysteresis in the dynamics of specialization in open economies as confirmed. Sceptics would rightly point out that, although positive externalities may have some influence in the direction of idiosyncratic patterns of specialization, other factors like foreign direct investment and the associated technology transfers might prevent it. A theory of leapfrogging, like that of Brezis, Krugman and Tsiddon (1993), would even argue that it is precisely the temporary exploitation of positive external effects and hysteresis in one country which gives other countries a better starting position in the next round of innovations and productivity advances, because after a change of technological trajectory the old externalities are quickly devalued and new innovators are more likely to look for low wage labour rather than for a location in a high wage country with a fading technology.

The stylized model of the previous section defined the state variable of the recontracting process as the share of workers in industry A. Specialization of the small Ricardian economy was unambiguously measured by the share of industry A in the total labour force. But how can sectoral specialization in industrial production be measured in a multi-country, multi-factor world? To obtain a measure which is comparable across countries and across industries it is suggested to compute — for each industry in each country — an indicator on the basis of value added, the contribution of an industry to Gross Domestic Product:

$$VAI_{i,j}=\left(V_{i,j}\Big/\sum_i V_{i,j}\right)\Big/\left(\sum_j V_{i,j}\Big/\sum_i\sum_j V_{i,j}\right), \tag{3}$$

where $V_{i,j}$ stands for value added in country i and industry j, $\sum_i V_{i,j}$ for total value added in industry j over all countries, $\sum_j V_{i,j}$ for total value added in country i, and $\sum_i\sum_j V_{i,j}$ for total value added in all countries and all industries.[11] This indicator of specialization measures how many times greater or smaller the ratio of a country's value added to the world's value added is in a specific industry as compared with all of manufacturing. In a sense, the indicator compares the relative weight of a certain industry in individual countries with the relative weight of this industry in total world manufacturing. A logarithmic transformation renders the indicator unbounded on both sides, symmetric around zero, the point of no specialization, and relatively sensitive to small deviations from zero, as they are typical for large countries (cf. Grupp, Legler, 1989). Nevertheless, large countries show much less specialization and dynamic variation of this indicator, basically for two reasons: one is the effect of regional evening out and the other is large countries' effect on the normalizing quantity since they themselves make a considerable part of total value added in the world.

Discussing the determinants of specialization in terms of comparative advantage versus hysteresis due to technological accumulation, it is natural to focus on the specialization in those tradables for which the hypotheses are primarily formulated,

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[11] This formula is closely related to the production intensity index suggested by Bowen (1983) as a comparative measure of trade specialization for each industry j within each country i:

$$PII_{i,j}=(T_{i,j}Y_w)/(Y_iQ_{w,j})+1=Q_{i,j}/[(Y_i/Y_w)Q_w],$$

where net trade $T_{i,,j}$ is equivalent to domestic production $Q_{i,j}$ minus domestic consumption $C_{i,j}$, and Y_i and Y_w are gross national and gross world product, respectively. These kinds of pragmatic specialization indicators have their roots in the work of Liesner (1958) and Balassa (1965).

namely manufactures. The limited availability of reliable data on value added by industry, which is taken from the 1992 version of the OECD STAN database, has made it necessary to restrict the scope of this study to only twelve countries — Australia, Canada, Finland, France, West-Germany, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom and the United States — and to the nineteen year period from 1970 through 1988.

Unfortunately, the sample limitation implies that the specialization indicator could not be computed with respect to world value added but only with respect to total value added in the twelve sample countries. This would not matter much if the sectoral composition of value addition in all countries excluded from the sample was on average the same as that of the countries included. In reality, however, the sectoral composition of value addition in the other, mostly less developed countries is likely to be quite different. The absolute values of the specialization indicator as they have been computed for the sample countries are therefore misleading as measures for specialization relative to the world.[12] Anyway, in the present context the absolute values are of little interest compared with the *dynamics* of the relative specialization positions of specific industries in the various countries. So the fact that not all countries of the world are included in the sample may matter far less than the small number of observations at the level of individual industries which is a direct consequence of the small sample size of only twelve countries.

On the other hand, one might argue that the twelve countries considered are responsible for most of the dynamics in specialization, since they command a dominant share in world trade, especially in manufactures: about 85 % of OECD exports and roughly two thirds of world exports in terms of value. The twelve countries also have a dominant share in the world's value added in manufacturing as well as in the resources used intensively in manufacturing — especially in technology and R&D inputs, which are thought responsible for hysteresis.

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[12] Although the omission of other countries may affect not only the absolute levels of the specialization indicator but also the relative position of industries in an individual country, the omission would not affect the relative ranking of countries in individual industries. In any case, the observed relative dynamics in industrial specialization *between* the twelve countries are unlikely to be affected in a fundamental way by the omission of other, mostly developing countries which are of lesser importance in world trade. The dynamics of specialization captured by the indicator are also unlikely to be disturbed by country specific measurement problems. Inflating figures on value added for an entire country or for a particular industry need not alter the dynamics of specialization noticeably unless the figures are treated inconsistently over time, say by being first understated and later overstated.

To measure technological specialization one should ideally use a direct measure of the creation of new technical knowledge, essentially the output of R&D efforts, whose international mobility is crucial for the hypotheses considered here. Direct measurement of intangible R&D output, especially of the part which spills over as a technological externality, is of course infeasible. In view of these difficulties, Soete (1981) suggests as a proxy the index of revealed technological advantage (RTA) which is based on patent count data. This index is defined as the ratio of a country's share of sectoral patenting to the country's overall share of patenting in a particular foreign country. This gives some reassurance that patents granted are of similar "quality" in terms of novelty, since novelty requirements are routinely checked during the nationally standardized approval procedure. Usually the foreign country is chosen to be the United States — the country which has the largest and most important market for technology and, therefore, is most likely to stand high on the patent application agenda of every commercially minded inventor in any country. Moreover, the US Patent and Trademark Office publishes patent count data which are aggregated according to the US Standard Industrial Classification and are thus particularly suitable for economic analysis (see the data appendix for details). The RTA index defines the technological activities of a country as more specialized in those areas where this country gets a larger share of US patents than in the average of all sectors.[13] In its formal structure, this index is analogous to the indicator of industry specialization in terms of value added introduced above, so the RTA is:

$$RTA_{i,j} = \left(G_{i,j} \Big/ \sum_i G_{i,j} G_{i,j} \right) \Bigg/ \left(\sum_j G_{i,j} \Big/ \sum_i \sum_j G_{i,j} \right), \qquad (4)$$

[13] While the RTA index obviously neglects potentially large differences in the economic value of patents (and may thus not be an all too reliable measure), it does have some important advantages, especially over R&D indicators based on input data. In contrast to these, the RTA index values are often directly comparable between countries, across sectors and over time. The index automatically corrects for common industry trends across countries, such as industry-specific propensities to patent, and for common economy-wide trends across industries, such as the documented decline in the ratio of the number of patented innovations to the number of scientists end engineers involved in R&D since 1960 (Evenson, 1991). A problem, however, remains with domestic US patents because individual US inventors are known to file relatively more patent applications in certain fields of technology than in others, while filing very few foreign patent applications at all. Many of the domestic applications of individual inventors cannot be counted as technical advances comparable to patents originating from corporate research laboratories. Therefore, US patents held by individuals have here been deducted before computing the technology specialization indicator in order to avoid biasing figures for the United States towards those sectors in which leisure inventors were most active.

where $G_{i,j}$ stands for the number of US patents, by date of application, which are of practical use mainly in industry j and granted to inventors resident in country i.

A general model of the stochastic process of the evolving cross-section distributions of measures of specialization is given by the stochastic difference equation (cf. Stokey and Lucas, 1989, pp. 234, and Quah, 1993a, p. 13):

$$\lambda_t = T^*\left(\lambda_{t-1}, u_t\right), \tag{5}$$

where T* is an operator which maps the probability measures λ in period t-1, together with a disturbance u, to probability measures in period t. Ignoring the disturbance u leaves a difference equation in probability measures, a model of the law of motion in industrial specialization[14], which can be used, by iteration, to "predict" future cross-section distributions:

$$\lambda_{t+s} = (T^* * T^* * \cdots * T^*)(\lambda_t) = \left((T^*)^s\right)(\lambda_t). \tag{6}$$

Taking this iteration to the limit as s → ∞, gives a characterization of the likely long-run distribution of the cross-country, cross-industry specialization indicator. Analogously to the conclusions from the small open Ricardian economy, hysteresis would imply that the probability measure $\{\lambda_{t+s}$: s > 0$\}$ tends towards a bimodal distribution in the long-run, with very little or virtually no measurable mobility of individual industries between the two modes. The alternative hypothesis would be that the future degree of specialization of a certain industry in a certain country is only temporarily dependent on that industry's starting position, but entirely independent in the long-run, provided there is either virtual equality of relative factor endowments across countries, or else enough *mobility* in relative factor endowments to undermine established comparative advantages over time. The probability measure would then tend towards a uniform distribution in the long run.

One way of estimating such a model of evolving cross-section distributions in terms of probability measures, recently used by Quah (1993a) in a different context, is to specify the operator T* as a stochastic kernel[15], which maps the product of the real

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[14] As Quah (1993b) points out such a model of dynamically evolving distributions is like an autoregression, except that its values are distributions rather than scalars or vectors of numbers.

[15] The difference equation in probability measures then becomes: $\lambda_t(H) = \int M(x,H)\, d\lambda_{t-1}(x)$ for all H on the real line.

line with its Borel sets to the unit interval, and to estimate this by appropriately rescaling a nonparametric density estimate of transitions, to obtain a conditional probability for each fixed neighbourhood in the continuous state space of degrees of industrial specialization. While a proper judgement on the hypothesis of hysteresis will have to take into account the actual movements in relative factor endowments, unconditional estimation may still give valuable insights into the nature of specialization dynamics. Indeed, the unconditional dynamics should not be overlooked since the exogeneity of changes in relative factor endowments may be in doubt.

Figures 1 and 2 graph stochastic kernel estimates[16] of one-year and five-year transitions in the industry specialization indicator. Figures 3 and 4 do the same for the corresponding technology specialization transitions. These graphs make clear that there is high persistence in specialization in the short run — probability mass is concentrated on and closely around the 45°-diagonal. But there seems to be considerably less persistence over longer time horizons, particularly in the case of technological specialization: probability mass leaks out and flows away from the diagonal, and apparently more so at the ends of extreme specialization.[17] Comparing Figures 2 and 4 suggests that over a five-year period there is less persistence in technology than in industry specialization measured in terms of value added — just the contrary of what would presumably be needed to establish causality from hysteresis in technological development to hysteresis in industrial specialization patterns.

Although these graphic results give a rather impressive picture of the overall dynamics in sectoral specialization, as documented in the data, they do not allow to draw proper statistical inferences, nor to calculate the expected long-run stationary distributions, should they exist. But these kinds of inferences would be essential for a sound judgement on the hypothesis of hysteresis.[18]

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[16] Using the squared Epanechnikov kernel, as described in Silverman (1986).

[17] In Figure 2 the spikes at the positive end of specialization are merely a consequence of outliers in non-parametric density estimation and should not distract from the more relevant other parts of the picture.

[18] One should emphasize here that simple parametric autoregressions also fail to be informative on the hypothesis of hysteresis formalized here in terms of a probability model of evolving cross section distributions. An estimated slope coefficient greater than one from regressing an indicator of specialization on its lagged values cannot be taken as evidence that past specialization in a certain sector would give this sector an advantage for future growth. A linear regression of the logarithmic industry specialization indicator in 1988 on a constant and the industry specialization indicator in 1970 (lagged 18 years) yields an estimated slope coefficient of 0.70, a t-value of 20.2 and an adjusted R^2 of 0.67, which seems to imply that past specialization does *not* give countries much of an advantage in particular sectors for the future. Instead, the sectoral strengths of countries seem to erode over time; measured specialization seems to converge to neutrality. Similarly, a regression of the technology specialization indicator in 1989 on a constant and the technology specialization indicator

... continued

Therefore, an alternative approach to estimation may be preferable, in which the operator T* is approximated by a finite Markov chain transition matrix for a discretized state space. An empirical estimate of the transition matrix can give useful information on the intra-distributional mobility of individual industries between different degrees of specialization over time and can be used to calculate long-run stationary distributions of the specialization indicator — provided they exist — according to the Chapman-Kolmogorov equation:

$$P^s = P^r \cdot P^{s-r} \qquad \text{with } s \to \infty, \tag{7}$$

where P denotes the transition probability matrix; its rows contain the conditional probabilities that a transition beginning in a certain discrete state (row i) will end after one step (in event time) or one period (in historical time) at a certain state (column j). P^r consequently has the probabilities of moving from initial states to intermediate states after r steps or periods of time.

To discretize the continuous state space of the logarithmic specialization indicator six states are defined, somewhat arbitrary, by setting upper boundaries at µ-sd, µ-sd/3, µ, µ+sd/3, µ+sd, and at ∞, where µ stands for the sample mean, sd for the standard deviation of the indicator realizations over all years from 1970 to 1988. The corresponding 6 × 6 Markov chain transition matrix is estimated by maximizing the log-likelihood function

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in 1972 (lagged 17 years) gives a slope estimate of 0.49, which suggests there was even less long-term influence of past specialization in technology. But this interpretation is merely an example of the so-called Galton's regression fallacy, which often arises when the dependent and the independent have a bivariate normal distribution and are measured as deviations from their means. The conditional distribution of the dependent variable is then also normal around the mean m: $E(Y|X=x) = m(y) + \rho\sigma(y)/\sigma(x)(x - m(x))$. If the variances of the two marginal distributions $\sigma^2(.)$ are very similar, the regression coefficient *must* be smaller than unity because the correlation coefficient ρ always is. This does not reveal any useful information about the relationship between the two variables (cf. Maddala, 1992, pp. 104). — Moreover, taking the negative slope estimates from above at face value would imply that the distributions of the specialization indicators must converge to a single point at the mean. But as can be seen from comparing non-parametric density estimates for selected years (Figures 5 and 6), the distributions of the specialization indicators do not seem to be collapsing. Instead, excess kurtosis, made visible in Figure 6 by graphing — in addition to the density estimates — the normal density for the sample mean and sample variance of the technology specialization indicator, seems to be decreasing over time, and that for both the technology and the industry specialization indicator. The density estimates in Figures 5 and 6 are based on the Gaussian kernel with window width selected automatically as suggested in Silverman (1986), pp. 45.

$$\log L = \log p_i(1970) + \sum_{i,j} h_{ij} \log p_{ij} \tag{8}$$

with respect to p_{ij} and subject to the restriction $\sum_j p_{ij} = 1$,
where $p_i(1970)$ are the initial probabilities of having a realization of the specialization indicator in state i, p_{ij} are the probabilities of having a realization in state j after a specified transition period, conditional upon a prior realization in state i, and h_{ij} are the observed frequencies of transitions from state i to state j in that period. Ignoring any information about transition probabilities which may be contained in the initial probability distribution[19] and assuming the transition probabilities to be invariant with respect to time as well as across industries and countries, the Maximum Likelihood estimator can be readily computed as:

$$\hat{p}_{ij} = h_{ij}/h_i, \text{ where } h_i = \sum_j h_{ij}. \tag{9}$$

This estimator can be shown to be consistent and to have an asymptotic normal distribution (cf. Basawa and Prakasa Rao, 1980, pp. 54).

Table 1 presents estimates of first-order, time-stationary transition probabilities over periods of one, five and ten years for the entire data set of industry specialization in terms of value added, including all twelve countries and the seventeen industries described in the appendix. The first panel gives the one-step annual transition matrix, whose (i, j) entry is the conditional probability that the degree of specialization of a certain industry in a certain country has transited from state i to state j after one year. The first column gives the total number of observed transitions from all starting states i, which are arranged in increasing order of indicator values. Entries on the main diagonal are the probabilities that the degree of specialization of an industry observed in a certain interval of the state space will not have moved out of that interval after one year. Entries to the right of the main diagonal give the probabilities that an industry increases its relative weight in a certain country compared with that industry's weight in the world, whereas entries to the left of the main diagonal are the probabilities for an industry to loose ground in a certain country, compared with the overall share of this industry in the world.[20]

The first panel shows high persistence at the extremes, with diagonal entries of 89 % at the low and 90 % at the high end of specialization states. Entries in the middle of

[19] This is warranted for large h but may be problematic in other cases.
[20] Entries are rounded to two decimal places; non-entries indicate that both decimal places are zero after rounding.

the diagonal are much lower, indicating substantial mobility of industries in those countries in which they have a relative weight similar to the world average. In rows 2 and 3 the sum of entries to the right of the main diagonal is greater than the sum of entries to the left, which indicates that below average specialization is more likely to be followed by an increase than by a decline. In rows 4 and 5 the reverse is true for above average specialization. These estimates thus do not indicate perfect persistence, but considerable inertia in patterns of specialization. Not surprisingly then, the long-run stationary distribution — computed according to the Chapman-Kolmogorov equation and reported in panel 1 along with the sample distribution — is ergodic and does not show any concentration of probability mass at the extreme ends of specialization.

The second and third panel give estimates of five- and ten-year transition matrices, respectively. The entries on the main diagonal are here much lower, indicating much less persistence over longer periods of time. Qualitatively, however, the overall picture remains basically unchanged from the one-year transitions. The only interesting difference is in the third panel where the stationary distribution computed from the ten-year transition matrix does seem to show slightly higher concentration of probability at the extremes than the sample distribution. But this may merely indicate a mild general trend towards increasing specialization rather than high persistence, because the off-diagonal entries in the ten-year transition matrix again show convergence of countries' shares in industries' value added to the world average.[21]

A very similar picture emerges from estimates of six-state Markov chain transition matrices for the RTA-index of technological specialization, reported in Table 2. The major difference to the results for industry specialization in terms of value added seems to be that almost all entries on the main diagonal (in all panels) are much smaller than the corresponding entries in Table 1.[22] There appears to be considerably less persistence in technological specialization than in production, which casts doubt on the hypothesized causality from technological externalities in the form of

[21] To illustrate consistency of short- and long-run estimates, the one-year transition matrix has been iterated ten times, the result of which is reported in the fourth panel. Since the entries on the main diagonal are much smaller than the corresponding entries in the directly estimated ten-year transition matrix, this comparison suggests that persistence may actually be higher than estimated by first-order Markov chain models.

[22] As a caveat, one should note that part of the higher mobility in technology may be due to measurement problems: Because the patent count data are integer-constrained, small countries with often very few patents per year in some industries will show spuriously high mobility, so for instance when a year with two recorded patents, assigned for a small country to a particular industry, is followed by a year with only one patented application from the same country in that particular industry.

knowledge spillovers from R&D to hysteresis in production. The high mobility in technological specialization is underlined by the speedy convergence of the iterated one-year transition matrix to its stationary distribution, which seems to be almost completed after only ten iterations (panel 4, Table 2).

Although these estimation results on the overall dynamics of specialization in value added and technology do not seem to support the hypothesis of hysteresis, the picture may be different at the level of individual industries. After all, the claim of hysteresis is made mostly in view of those industries which make intensive use of technological innovation and which are therefore rightly classified as high-technology industries. Separate estimates of five-year transition matrices for a number of industries, selected for the high technology content of their typical products, are presented in Table 3, and that both for the industry and the technology specialization indicators.

Empirical research on positive external effects from innovation at the industry level has repeatedly found evidence for their existence in parts of the chemical industry, in pharmaceuticals, machinery, microelectronics and in the professional instruments industry (cf. Mohnen, 1990). Particular attention will therefore be paid to the specialization dynamics in these and the closely related industries of the sample.[23] In *chemicals* (excluding drugs and medicines) persistence in terms of entries on the main diagonal appears to be even lower than in the five-year transition matrix for all industries, except at the extreme end of above average specialization, where the estimated probability of remaining in the highest state is 94 %. The off-diagonal entries suggest that the degree of specialization tends to converge towards the average whenever a national chemical industry is over- or under-represented in its home country compared with the share of chemicals in total world manufacturing.

In the *technological* specialization indicator of chemicals, on the other hand, persistence on the main diagonal is higher for almost all states than in the five-year technology transition matrix for all industries. Moreover, the entries in the second, third and fourth row suggest that transitions may often be away from the average share of chemical patenting in total patents granted in all fields of technology. However, the bulk of observations, entries in row five, do not show divergence from the mean. And overall, the chemical technology transition matrix does not look very different from the transition matrix of specialization in terms of value added.

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[23] See the data appendix for a listing of all sample industries and their ISIC codes.

For the industry specialization indicator in *drugs and medicines*, generally less persistence is estimated on the main diagonal than in chemicals and in all industries together. This holds too for the extreme states of the technology specialization indicator. Moreover, only the third row of the technology transition matrix suggests slightly higher probability of the indicator moving away from the mean. In the five-year transition matrix for the *rubber and plastics* industry, by contrast, persistence appears to be high at the extreme ends of industrial specialization, with a tendency in the second, third and fourth row to move further away from the mean. The technology transition probabilities appear to be more in line with those of all industries, except for the fourth row, where a trend away from the mean is estimated.

In the *office machinery and computer* industry generally less persistence is observable — in both value added and technology (except for the high end of technology transitions) — than in all industries together, and no tendency of divergence can be detected. Also the *electrical machinery* industry seems to have generally lower persistence than the specialization indicators for all industries. But divergence is observed in the second and, albeit only some, in the fifth row of the value added transition matrix as well as in the fourth row of the technology transition matrix. The transition matrix estimated for value added in the *motor vehicles* industry is rather irregular and difficult to interpret — due to the unfortunate clustering of most observations in the fifth interval of the discretizing grid. The technology transition matrix is characterized by low persistence in the middle states and high persistence at the ends; but only the third row has an entry that signals a trend away from the mean.

High persistence at the end states is again characteristic for the estimated technology transitions in *ship building*, but the transition matrix in terms of value added is quite similar to that of all industries together. Finally, both the *aircraft* industry and the *professional instruments* industry have very high persistence at the exremes in their value added specialization indicator, but much less so in their technology specialization indicator.

Except for the value added specialization indicator in the *motor vehicle* industry and for the technology indicator in the radio, television and communication equipment (RTV) industry[24], the estimated transition dynamics of industrial and technological specialization in individual industries are all ergodic with unique stationary

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24 The MOTV industry and the RTV technology indicator transitions matrices are divided in two ergodic sets. In the case of RTV technology, the highest state appears to be absorbing, no transitions out of this state are observed. In the case of MOTV value added, one ergodic set is comprised of the two lowest states, the other of the remaining four states.

distributions. But only for DRUG industry and technology transitions and for AIRC, ELMA and, arguably, non-metallic minerals (SCG) technology transitions do the stationary distributions resemble the corresponding sample distribution, as would be expected in the *absence* of any path dependence or hysteresis. On the other hand, only the stationary distributions for MOTV and PROF technology and value added in the non-metallic mineral industry (SCG) turn out really bimodal, as would be expected in the case of hysteresis. Most stationary distributions rather have a concentration of probability mass in the middle states (CHEM, COMP, ELMA value added and AIRC technology) or at one end only (RTV and PROF value added, CHEM and COMP technology and both indicators for FOOD, RAP, IRON, NFM, FABM, MACH and SHIP).

These observations, however, must neither be taken as evidence against nor in support of high persistence pointing to hysteresis. Instead they are likely to be an unfortunate consequence of including countries of vastly different sizes in one and the same transition matrix. When the biggest or a few of the biggest economies increase their share in total value added in a certain industry, then more of the smaller economies must be loosing shares in this industry. Consequently, the Maximum Likelihood estimator assigns a larger weight to the more frequently observed losses of the more numerous smaller economies than to the corresponding gains of one or very few big economies. A stationary distribution with a concentration at one end may thus often reflect a montone trend in the specialization dynamics in the largest economy in the sample, the United States.[25]

One way of dealing with the inconvenience caused by the great disparity in the sizes of countries in the sample is to estimate transition matrices for *fractile* Markov chains as proposed by Geweke, Marshall and Zarkin (1986) and recently applied by Quah (1993c) in another context. Instead of using an arbitrary grid to discretize the continuous state space of the specialization indicators, one can fix a set of increasing, non-redundant probabilities, equally spaced on the open unit interval, say P = {1/6, 1/3, 1/2, 2/3, 5/6, 1}, and let this determine for each period t a corresponding set

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[25] Similarly, a stationary distribution with a concentration in the middle may lend spurious support to the hypothesis of convergence in specialization indicators. In fact, it may indicate that the two largest economies, the United States and Japan, have monotonically moved in opposite directions away from the middle states, pulling many of the smaller, perhaps initially more specialized economies inwards from the end states. In theory, the move of two dominating economies in opposite directions may even be the consequence of hysteresis when one of them is winning a path-dependent technological race in a certain industry where positive externalities have a strong impact on productivity.

of quantiles.[26] The sequence of quantile sets {Q(t): integer t} then parametrizes movements in the entire distribution, while the estimated fractile transition probability matrix — named so by Quah (1993c) — parametrizes intradistribution mobility.

The simple Maximum Likelihood estimator is again based on the assumption of invariance of the transition probabilities with respect to time and the relevant cross section dimension — countries, industries or both. If the estimated fractile matrix is ergodic, its stationary distribution will be uniform relative to the quantiles Q (cf. Quah, 1993c, p. 15). Estimates of intradistribution mobility will here be less disturbed by a trend movement of a large country since the fractile method basically implies a redefinition of the grid discretizing the state space in each period of time. In order to relate the stationary distribution to the original state space one would have to consider — in addition to intradistributional mobility — movements in the entire distribution as estimated in the sequence of quantile sets {Q(t): integer t}.[27]

In the present context, it will suffice to examine whether the interquantile range increases, decreases or remains constant over time. This can be done by running a simple linear regression of the interquantile range on time and testing for significance of the slope coefficient. Within this approach, a significant positive time trend in the interquantile range combined with high persistence in terms of large entries on the main diagonal — especially at the ends — of the estimated fractile matrix would point to hysteresis, whereas a negative or no time trend in the interquantile range and low persistence in the transitions matrix would appear to contradict the hypothesis of hysteresis.

Estimates of the ten-year *fractile* Markov chains for specialization in value added and technology taking all industries together (reported in Table 4) reveal almost the same degree of persistence on the main diagonal as observed in the previously reported non-fractile Markov chain estimates. Again, persistence appears to be lower in technology than in value added. But for both, a positive time trend in the interquantile range, albeit a mild one, is found to be significant at the 5 % level.

[26] Experimenting with different ways of dicretizing the state space is generally recommended as a test for robustness of Markov chain estimates, regardless of any specific problems like varying country sizes. Arbitrary and inappropriate discretization without considering alternatives often is a source of spurious results.

[27] But any attempt at forecasting the stationary distribution of individual industries' specialization on the corresponding original sate space may bear the danger of reintroducing the stated problems associated with vastly differing country sizes.

Looking at fractile Markov chain transition estimates for individual industries (Table 5) generally confirms the picture that has emerged from the estimates of non-fractile Markov chain transitions. However, more persistence at the end states of specialization is observed in *chemicals*, *electrical machinery* and *professional instruments*, while the RTV industry divides into two ergodic sets of three states each. But in *machinery* as well as *office and computing equipment* persistence at the end states appears less pronounced when estimating fractile Markov chains. In the fractile estimates of five-year *technology* transition matrices for individual industries, more persistence at the ends is noticeable in *drugs and medicines* and *electrical machinery*, less persistence in RTV and *motor vehicles*.

But only for the technology transitions of *ship building*, *machinery* and *professional instruments* are positive time trends in the interquantile range detected which are significant at the 5 % level. Of these three industries, machinery also has a significant positive time trend in the interquantile range of its industry specialization indicator in terms of value added, whereas the corresponding interquantile range for professional instruments is significantly negative, and that of ship building not significantly different from zero. The evidence of high persistence in the estimated fractile transition matrices of specialization in terms of value added is again undermined by a negative time trend in the interquantile range in the case of *chemicals*, *electrical machinery*, *motor vehicles* and *aircrafts*.

Where a *positive* time trend coincides with high persistence at the end states of value added specialization — as in RAP, SCG and NFM — this can still not justify a hysteretic explanation based on knowledge externalities, because no time trend and low persistence are observed in the corresponding *technology* specialization indicators. It appears that the estimated fractile transition matrices for both technology and value added specialization are jointly supportive of the hypothesis of hysteresis only in the case of machinery.

4 The impact of changes in factor endowments

Although the preceding discussion has described the observable dynamics of technological and industrial specialization for twelve OECD countries in some detail, this is still a long way from giving *conclusive* evidence on hysteresis. Methodological questions — such as robustness of the non-parametric estimates — apart, the main shortcoming of the preceding analysis is its lack of accounting for relative factor endowments in the sample countries and changes thereof during the sample period. If factor endowments have any impact at all on the international allocation of sectoral economic activities, they might — in the case of monotonic time trends in the dynamic comparative advantages of countries — even be responsible for patterns of specialization dynamics which point to a bimodal stationary distribution, just like hysteresis would.[28] It is surely important to account for the influence of changes in the relative factor supplies of countries when analysing the dynamics of specialization with a view to testing hysteresis, although this will — admittedly — be a very difficult task.

A first attempt is made by simply regressing the familiar value added indicator of an industry's specialization in the sample countries on conceptually similar indicators of countries' relative factor endowments, and by subsequently estimating fractile Markov chain transition matrices on the residuals. Provided all relevant endowments are appropriately considered, this procedure eliminates that part of the specialization dynamics which can be accounted for by the dynamics of comparative advantages. The residual dynamics would then lend support to the hypothesis of hysteresis, if they showed high persistence at the end states of specialization and a positive time trend in the interquantile range. They would, on the other hand, cast doubt on hysteresis if there was low persistence or a negative time trend in the interquantile range.

The factor endowments considered here for each of the twelve countries are: Physical capital, R&D capital, the number of R&D scientists and engineers in the business enterprise sector, the labour force, and the years of schooling in the labour force. While R&D capital, using cumulative R&D expenditures as a proxy for the national stock of technical knowledge, and physical capital are both stocks from which input services flow, the other three factors are more direct measures of input flows, although years of schooling and the number of R&D scientists and engineers stand for facets of human capital in labour services.[29] On theoretical grounds one might argue that these factor endowments should not be given equal weight as conditioning factors for sectoral specialization, because they are likely to possess quite different degrees of international mobility. Only fully immobile factor endowments should ideally be treated as country-specific characteristics, but this issue is neglected here. To avoid implicitly regressing on country size, yearly factor supplies have been normalized dividing each country's share in the total supply of all twelve countries by the country's share in the sum of the Gross Domestic Products of all twelve countries. As with the

[28] This can already be seen from the stylized Ricardian model with stochastic recontracting discussed in section 2.
[29] For sources and methods see the data appendix.

industry specialization indicators, a logarithmic transformation is made to obtain more symmetrically distributed variables.

The separate regressions of each industry's indicator of specialization in value added on the indicators of relative factor endowments have been done by ordinary least squares, pooling time series across countries. By design, no attempt has been made to correct the estimation for the substantial autocorrelation (over time) which is evident in the residuals. After all, it is precisely the structure of this autocorrelation which is subsequently to be analysed in terms of fractile Markov chain transition probabilities. A general tendency of divergence in the autocorrelated residuals away from their theoretical mean of zero could be interpreted as evidence in support of hysteresis, whereas substantial non-monotonic mobility of the residuals, or even convergence to the mean, would lend support to the alternative hypothesis of dynamic comparative advantages as an adequate explanation of industrial specialization dynamics.[30]

Results of the regressions are reported in Table 6. But the estimated parameters should not be interpreted as revealing any specific economic causality — for several reasons. First, there is substantial collinearity between the factor endowment indicators. Some bivariate correlations between the exogenous variables are higher than bivariate correlations with the dependent variable in many of these regressions; the variance inflation factors are all around two in magnitude. Second, the regressions are, by ordinary standards, misspecified since the hypothesis of no country fixed effects, which is implicit in using only one common intercept for each industry regression, is clearly rejected at any conventional level of significance.[31] And third, the estimation of pooled data by simple ordinary least squares ignores that in reality adjustment costs are likely to have an important impact on the relationship between changing relative factor endowments and the industrial specialization in open economies.

Nevertheless, the residuals from these "naive" regressions may be of use in Markov chain analysis where they are simply taken to be that part of the specialization

[30] Notice that neither divergence nor convergence in the residuals is predisposed by the chosen regression method. But the assumption of exogeneity of factor endowments with respect to industrial specialization patterns is fundamental to the interpretations advanced. This assumption may, of course, be open to question.

[31] Similarly, the hypothesis of structural stability across time is rejected at the 1 % level of significance in the case of RAP, IRON, NFM, MACH, COMP, ELMA, RTV and at the 5 % level of significance in the case of CHEM, SCG, MOTV, SHIP and AIRC. These inferences are based on a general Wald-test for the joint significance of an intercept and slope dummies for the subperiod 1980 through 1988. In the case of the PROF industry, slope dummies for the specified subperiod are significant at the 5 % level for the schooling and the research scientists and engineers endowment indicators.

dynamics which is *statistically* unexplained by movements in countries' relative factor endowments. The regressions are merely used to filter out those components of the industry specialization dynamics which are *not* orthogonal to relative factor endowments. It would therefore be misleading to include dummies to capture country specific effects in these regressions. Although such dummies would surely account for much of the variation in the specialization indicators and greatly improve the fit of the regressions reported in Table 6, they would spoil those characteristics in the residuals which bear on the hypothesis of hysteresis. After all, it is precisely the persistence of country specific effects in the residuals' autocorrelation structures which is here to be analysed in terms of fractile Markov chains.

A glance at Table 6 suggests that the factor endowments considered here do not account at all well for the variation in measured specialization in food, beverages and tobacco, nor in fabricated metals. Most other regressions, however, have an acceptable coefficient of determination, adjusted for degrees of freedom. So the residuals from these regressions are likely to have dynamics quite distinct from those of the unconditioned indicators of industrial specialization in the sample countries.

Estimation of a six-state, five-year *fractile* Markov chain transition matrix on the residuals from all industries together reveals clearly less persistence on the main diagonal than in the corresponding *unconditioned* fractile transition matrix.[32] Moreover, there is no significant time trend. This evidence against hysteresis is in fact confirmed by most fractile transition probability estimates for individual industries' residuals: Less persistence than in the unconditional specialization dynamics is observed in the residuals from drugs and medicines, professional instruments, aircrafts, ship building, rubber and plastics, electrical machinery, office and computing machinery as well as from the RTV industry. The RTV residuals also loose their previously striking division of the five-year fractile transition matrix into two ergodic sets.

Furthermore, testifying against the case of hysteresis are the significant negative time trends in the interquantile range — mostly higher in absolute terms than in the unconditioned dynamics — which are estimated for several industries. But a significant positive time trend in the interquantile range remains in machinery as well as in rubber and plastics. Nevertheless, hysteresis on the basis of knowledge spillovers is most unlikely in the case of rubber and plastics — not only because the residual

32 See Table 7 for the estimated overall residual transition probabilities and for separate estimates of selected industries' residual transition matrices.

dynamics show so little persistence, but also because low persistence is as well characteristic for the technology dynamics, as estimated in terms of either fractile or non-fractile, five-year Markov chains transitions (reported above). In the case of machinery, the degree of persistence in technology and in the residual dynamics is quite similar to that of all industries together — no special case here either. So it seems that the hypothesis of hysteresis in industrial specialization, based on positive knowledge spillovers from R&D, finds little support in the available data, once they are subjected to a close and careful examination.

5 Concluding remarks

This paper has discussed new work, using an approximation in terms of finite Markov chains, to assess the empirical dynamics of specialization in advanced open economies — with an eye on the controversial hypothesis of hysteresis allegedly caused by path dependence and national idiosyncracies in sectoral technological accumulation. The evidence from the non-parametric estimates of Markov chain transition probabilities presented here does not point to hysteresis or serious inertia in the dynamics of industrial specialization. This finding appears to be fairly robust since it is confirmed both when considering all industries together and when scrutinizing individual industries separately. Conditioning on five factor endowments, assumed to be of particular relevance in technological development and modern manufacturing, has not overturned the findings. On the contrary, conditioning — although done here in a crude, preliminary fashion — has strengthened the case for dynamic comparative advantages (the alternative hypothesis) as an adequate explanation of observable specialization dynamics.

As a caveat, one should note that these conclusions are arrived at without having considered the possibility that the observed specialization dynamics have in part been shaped by specific industrial policies, which governments of individual countries may have undertaken in the past. Moreover, the conclusions drawn from the residual dynamics hinge on the exogeneity of changes in factor supplies, including physical and R&D capital, with respect to changing patterns of specialization. This exogeneity is likely to be disputed by advocates of path dependence in technological change and industrial specialization dynamics.

A number of other important problems also remain unresolved in this paper. One of these is how to take the great variation in the size of national economies properly into account. This problem might be alleviated if a larger cross section of countries became available, in which the specialization dynamics of more countries of similar size could be compared with each other. Another possibility to come to terms with size might be to apply the methodology explored here to regional data sets, where hysteresis would again be a serious hypothesis to confront, and where the biggest region might not be as dominant as the United States are in the world economy. Alternatively, instead of trying to avoid the statistical problems stemming from vastly differing country sizes, one could address the issue more directly; an important question would be whether hysteresis might become effective only when a certain industry, or the pertinent R&D activities of a country, had passed a certain threshold in terms of absolute size.

Another important question relates to the level of industry aggregation used in this paper. The hypothesis of hysteresis based on path dependence in technological dynamics may actually be more relevant at lower levels of sectoral aggregation. Besides, potentially interesting information may surface from technology measures other than patent count data. Quantitative information on R&D inputs, for instance, may reveal how intensively the R&D activities in different industries make use of scarce factors, like specialized human capital. Finally, the incorporation of conditioning information needs to be improved upon, and more powerful methods of statistical inference need to be devised and applied in future work on this subject.

Data Appendix

Data on sectoral value added for the industry specialization indicator has been taken from the 1992 version of the "OECD STAN Database for Industrial Analysis", an estimated database, not composed of OECD member countries' official data, but geared towards compatibility with national accounts and towards international comparability. This database covers the twelve countries Australia, Canada, Finland, France, West-Germany, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom and the United States for the years 1970 to 1988. For these countries data on patents granted by the US patent office, by date of application, is available from the Office of Technology Assessment and Forecasting at the US Department of Commerce, for the years 1972 to 1989. The data used are re-classified according to the US Standard Industrial Classification (SIC) according to a concordance between the US Patent Classification System (USPCS) and 55 product fields based on the SIC. The data are so-called fractional counts, which eliminate multiple counting by dividing each patent count by the number of product fields to which it is assigned and adding the resulting fraction to each assigned product field.

Time series on countries' relative factor endowments have been obtained from various sources: Capital stocks are computed, for the beginning of each period, on the basis of annual investment data in Heston and Summers (1991), using the perpetual inventory method, assuming a rate of depreciation of 13.3 % as would be implied by an average asset life of 15 years. R&D capital stocks are taken from Coe and Helpman (1993), who have used R&D expenditure data from the OECD's Main Science and Technology Indicators. Their computations are again based on a perpetual inventory model, with the assumption of a 5 % rate of depreciation or obsolescence. For further details see the appendix in Coe and Helpman (1993). Data on the size of labour forces and on national employment of research scientists and engineers (in the business enterprise sector) are taken from the OECD Science and Technology Statistics (1992). Missing figures for research scientists and engineers have been filled in from linear trend regressions in the case of Canada, the Netherlands, Norway and Sweden, by intrapolation in the case of Australia, Germany and France. For Finland, a trend regression on university graduates of science and engineering studies in the business enterprise sector has been used. In the case of the United Kingdom, a trend has been extracted from figures on scientists and engineers employed by industry as well as by government, published by the US National Science Board (1991) in its annual "Science and Engineering Indicators", p. 301. Figures on years of schooling in the labour force are based on linear trend regressions for the five-yearly data on average years of schooling attained by adults over 25 years of age, which have recently been compiled by Barro and Lee (1993).

To normalize relative factor endowments, the different shares of each country in the total factor endowments of all twelve countries have been divided by the country's share in the sum of all countries' Gross Domestic Product (GDP). A logarithmic transformation has then been made to assure symmetry of the factor endowment indicators. GDP figures are from the chain index series of real GDP per capita in constant dollars at 1985 international prices in Heston and Summers (1991). Purchasing power parities are from the OECD Science and Technology Statistics (1992).

The table on the next page lists the seventeen industries included in the study and indicates how patent data, based on the concordance between the US patent classes and product fields of the US standard industrial classification, have been assigned to the International Standard Industrial Classification of the United Nations (ISIC), on which the OECD STAN data on industries' value added is based. An adjustment to the source data has been made when patent count data for a small country was zero in a particular industry for one or several consecutive years. In these cases, the sum of patented applications recorded for the preceding and subsequent year has been evenly distributed across the years. The purpose of this is to avoid realizations at minus infinity in the logarithmic transformation of the technology specialization indicator.

Industries included in the analysis:

ISIC-CODE	INDUSTRY	US-SIC	OTAF Sequence Number	Abbreviation in tables
31	Food, Beverages, Tobacco	20	1	FOOD
351 & 352 (excl. 3522)	Chemicals excluding drugs	281, 282, 284, 285, 286, 287, 289	4	CHEM
3522	Drugs and Medicines	283	14	DRUG
355 & 356	Rubber and Plastics	30	16	RAP
36	Non-Metallic Mineral Products	32	17	SCG
371	Iron and Steel	331, 332, 3398	19	IRON
372	Non-Ferrous Metals	333, 334, 335, 336 3399	20	NFM
381	Fabricated Metal Products	341, 342, 343, 344, 345, 3466, 3469, 347, 3493-9	21	FABM
382 (excl. 3825)	Machinery nec (except office & computing)	348-3492, 351-356, 358-3594, 3599, 3631-33	22 minus 27	MACH
3825	Office and Computing Machinery	3571, 3572, 3575, 3577-3579	27	COMP
383 (excl. 3832)	Electrical Machinery (except radio, tv & com. equ.)	3612-3, 362, 364, 369	34	ELMA
3832	Radio, TV and Communication Equipment	3651-2, 3661, 3663, 3669, 3671-2, 3674-9, 3844-5	41	RTV
3841	Shipbuilding and Repair	373	49	SHIP
3843	Motor Vehicles	371	46	MOTV
3845	Aircraft	372, 376	47, 54	AIRC
3842, 3844, 3849	Other Transport Equipment	374-5, 379	48 minus 49	OTRA
385	Professional Goods (Instruments)	38, except 384	55	PROF

Missing values for the Netherlands' value added in NFM in 1988 and for Italy's value added in the DRUG, COMP, SHIP and AIRC industries in 1988 have been added from extrapolations by the author. In a number of cases time series of individual industries' value added are not reported at all in the 1992 STAN database. These cases are therefore omitted from the analysis: MACH, COMP, ELMA and RTV in France, AIRC in the Netherlands, OTRA in the United Kingdom and PROF in Canada.

References

Aghion, Philippe and Peter Howitt (1992), "A Model of Growth Through Creative Destruction". *Econometrica*; Vol. 60, No. 2, pp. 323-351.

Arthur, W. Brian (1988), Self-Reinforcing Mechanisms in Economics. In: Philip W. Anderson, Kenneth J. Arrow and David Pines (eds.), The Economy as an Evolving Complex System. Redwood City 1988.

Basawa, Ishawa V. and B.L.S. Prakasa Rao (1980), Statistical Inference for Stochastic Processes. London.

Balassa, Bela (1965), "Trade Liberalization and 'Revealed' Comparative Advantage". *The Manchester School of Economic and Social Studies*, Vol. 23, No. 2, pp. 99 - 123.

Bardhan, P.K. (1970), Economic Growth, Development and Foreign Trade. New York.

Barro, Robert J. and Jong-Wha Lee (1993), International Comparisons of Educational Attainment. Harvard University Working Paper. Cambridge.

Bowen, Harry P. (1983), "On the Theoretical Interpretation of Indices of Trade Intensity and Revealed Comparative Advantage". *Weltwirtschaftliches Archiv*, Vol. 119, pp. 464 - 472.

Brezis, Elise, Paul Krugman and Daniel Tsiddon (1993), "Leapfrogging in International Competition: A Theory of Cycles in National Technological Leadership". *American Economic Review*, Vol. 83, pp. 1211 - 1219.

Casson, Mark (1991), Comparative Advantage and Location of R&D. In: Mark Casson (ed.), Global Research Strategy and International Competitiveness. Oxford.

Coe, David T. and Elhanan Helpman (1993), International R&D spillovers. NBER Working Paper No. 4444. Cambridge, MA.

Dosi, Giovanni (1982), "Technological Paradigms and Technological Trajectories". *Research Policy*, Vol. 11, pp. 147-162.

Ethier, Wilfried J. (1984), Higher Dimensional Issues in Trade Theory. In: R.W. Jones, P.B. Kenen (eds.), Handbook of International Economics, Vol. I. Amsterdam.

Evenson, R.E. (1991), Patent Data by Industry: Evidence for Invention Potential Exhaustion? In: OECD (ed.), Technology and Productivity: The Challenge for

Economic Policy. Paris.

Findlay, Ronald (1973), International Trade and Development Theory. New York.

Geweke, John, Robert C. Marshall and Gary A. Zarkin (1986), "Mobility Indices in Continuous Time Markov Chains". *Econometrica*, Vol. 54, pp. 1407 - 1423.

Griliches, Zvi (1992), "The Search for R&D Spillovers". *Scandinavian Journal of Economics*, Vol. 94, Supplement, pp. 29 - 47.

Grossman, Gene M. and Elhanan Helpman (1991), Innovation and Growth in the Global Economy. Cambridge, MA.

Grupp, Hariolf and Harald Legler (1989), Strukturelle und technologische Position der Bundesrepublik Deutschland im internationalen Wettbewerb. Hannover.

Heckscher, Eli (1919), "The Effects of Foreign Trade on the Distribution of Income". *Economisk Tidskrift*, Vol. 21, pp. 497 - 512.

Heston, Alan and Robert Summers (1991), The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950 - 1988". *Quarterly Journal of Economics*, Vol. 106, pp. 327 - 368.

Hippel, Eric von (1976), "The Dominant Role of Users in the Scientific Instrument Innovation Process". *Research Policy*, Vol. 5, pp. 213 - 239.

Hippel, Eric von (1988), The Sources of Innovation. Oxford.

Lichtenberg, Frank R. 1993, R&D Investment and International Productivity Differences. In: H. Siebert (Hrsg.), Economic Growth in the World Economy. Symposium 1992. Tübingen.

Liesner, H.H.(1958), "The European Common Market and British Industry". *The Economic Journal*, Vol. 68, pp. 306 - 316.

Maddala, G.S. (1992), Introduction to Econometrics. New York.

Mohnen, Pierre (1990), "New Technologies and Interindustry Spillovers". *STI-Review*, No. 7, pp. 131 - 147.

National Science Board (1991), Science and Engineering Indicators - 1991 Tenth Edition. Washington, DC.

OECD (1992a), The OECD STAN database for industrial analysis. Paris.

OECD (1992b), OECD Science and Technology Statistics. Paris.

Ohlin, Bertil (1933), Interregional and International Trade. Cambridge.

Quah, Danny (1993a), Dependence in Growth and Fluctuations Across Economies with Mobile Capital. LSE Working Paper. London.

Quah, Danny (1993b), "Empirical cross-section dynamics in economic growth". *European Economic Review*, Vol. 37, pp. 426 - 434.

Quah, Danny (1993c), "Galton's Fallacy and Tests of the Convergence Hypothesis". *Scandinavian Journal of Economics*, Vol. 95, pp. 427 - 443.

Romer, Paul M. (1990), "Endogenous Technological Change". *Journal of Political Economy*, Vol. 98, pp. 71 - 102.

Rosenberg, Nathan (1976), Perspectives on Technology. Cambridge.

Rosenberg, Nathan (1994), Exploring the black box. Cambridge.

Schmookler, Jacob (1966), Invention and Economic Growth. Cambridge, MA.

Silverman, B.W. (1986), Density Estimation for Statistics and Data Analysis. London.

Soete, Luc L.G. (1981), "A General Test of Technological Gap Trade Theory". *Weltwirtschaftliches Archiv*, Vol. 117, pp. 638 - 660.

Solow, Robert M. (1957), "Technical Change and the Aggregate Production Function". *Review of Economics and Statistics*, Vol. 39, pp. 312 - 320.

Stokey, Nancy L. and Robert E. Lucas, Jr. (1989), Recursive Methods in Economic Dynamics. Cambridge, MA.

Vickery, Graham (1986), "International Flows of Technology: Recent Trends and Developments". *STI-Review*, No. 1, pp. 47 - 84.

Weidlich Wolfgang and Günter Haag (1983), Concepts and Models of a Quantitative Sociology. Berlin.

US Patent and Trademark Office (1991), Patenting Trends in the United Sates 1963 - 1990. Washington, DC.

Table 1

Six-state Markov chain estimates for the industry specialization indicator 1970 — 1988

First-order, time-stationary estimates of the one-year transition probabilities:

	Transition end state — upper boundary					
Observations	μ - sd	μ - sd/3	μ	μ + sd/3	μ + sd	> μ + sd
441	0,89	0,11				
497	0,08	0,78	0,12	0,01		
493		0,11	0,64	0,23	0,02	
643		0,02	0,18	0,63	0,17	
1151				0,10	0,86	0,03
321					0,10	0,90
Stationary distribution	0,116	0,142	0,143	0,185	0,323	0,093
Sample distr.	0,124	0,140	0,139	0,181	0,325	0,090

First-order, time-stationary estimates of the five-year transition probabilities:

340	0,78	0,19	0,03			
385	0,17	0,6	0,14	0,07	0,02	
381		0,15	0,46	0,24	0,15	
518		0,05	0,23	0,47	0,24	
886			0,04	0,15	0,76	0,05
248					0,17	0,82
Stationary distribution	0,113	0,135	0,139	0,172	0,337	0,103
Sample distr.	0,123	0,139	0,138	0,188	0,321	0,099

First-order, time-stationary estimates of the ten-year transition probabilities:

212	0,77	0,17	0,03		0,02	
257	0,21	0,49	0,15	0,10	0,06	
234	0,04	0,18	0,37	0,25	0,16	
342		0,09	0,25	0,35	0,31	0,01
572		0,01	0,07	0,15	0,69	0,08
156		0,01	0,03	0,02	0,17	0,77
Stationary distribution	0,149	0,134	0,138	0,152	0,315	0,113
Sample distr.	0,119	0,145	0,132	0,193	0,323	0,088

One-year transitions, iterated ten times:

0,44	0,29	0,13	0,08	0,05	
0,24	0,27	0,18	0,16	0,14	0,01
0,09	0,17	0,19	0,22	0,28	0,04
0,05	0,12	0,17	0,23	0,37	0,06
0,02	0,06	0,12	0,21	0,47	0,11
	0,02	0,05	0,12	0,40	0,40

Table 2

Six-state Markov chain estimates for the technology specialization indicator 1972 — 1989

First-order, time-stationary estimates of the one-year transition probabilities:

	Transition end state — upper boundary					
Observations	μ - sd	μ - sd/3	μ	μ + sd/3	μ + sd	> μ + sd
424	0,54	0,25	0,08	0,04	0,06	0,03
661	0,17	0,50	0,16	0,08	0,06	0,02
631	0,04	0,21	0,44	0,19	0,90	0,02
777	0,02	0,06	0,17	0,56	0,16	0,02
892	0,03	0,05	0,06	0,13	0,63	0,09
355	0,04	0,02	0,05	0,05	0,21	0,64
Stationary distribution	0,116	0,181	0,163	0,201	0,236	0,102
Sample distr.	0,113	0,177	0,169	0,208	0,239	0,095

First-order, time-stationary estimates of the five-year transition probabilities:

315	0,51	0,25	0,07	0,04	0,08	0,03
501	0,18	0,48	0,18	0,07	0,07	0,02
487	0,06	0,22	0,38	0,22	0,09	0,03
590	0,03	0,08	0,18	0,50	0,18	0,02
692	0,03	0,06	0,08	0,15	0,56	0,12
275	0,05	0,03	0,04	0,06	0,23	0,59
Stationary distribution	0,125	0,191	0,164	0,192	0,222	0,105
Sample distr.	0,110	0,175	0,170	0,206	0,242	0,096

First-order, time-stationary estimates of the ten-year transition probabilities:

200	0,45	0,24	0,09	0,07	0,07	0,07
294	0,21	0,43	0,13	0,10	0,08	0,03
296	0,07	0,26	0,31	0,24	0,08	0,02
366	0,05	0,11	0,18	0,42	0,20	0,08
444	0,02	0,08	0,11	0,17	0,48	0,14
160	0,03	0,06	0,09	0,04	0,26	0,52
Stationary distribution	0,132	0,205	0,156	0,189	0,206	0,112
Sample distr.	0,114	0,167	0,168	0,208	0,252	0,090

One-year transitions, iterated ten times:

0,12	0,18	0,16	0,19	0,23	0,10
0,12	0,19	0,16	0,19	0,23	0,09
0,12	0,18	0,16	0,20	0,23	0,09
0,11	0,18	0,16	0,20	0,24	0,10
0,11	0,18	0,16	0,20	0,24	0,10
0,11	0,17	0,16	0,21	0,25	0,11

Table 3

Six-state Markov chain estimates for the industry and technology specialization indicators of individual industries

(First-order, time-stationary estimates of the five-year transition probabilities)

	Transition end state - upper boundary					
Observations	μ-sd	μ-sd/3	μ	μ+sd/3	μ+sd	>μ+sd
			FOOD — industry specialization:			
35	0,51	0,31	0,09	0,06		0,03
35	0,23	0,54	0,17		0,03	0,03
17		0,59	0,18	0,18		0,06
40	0,05	0,08	0,07	0,55	0,20	0,05
13	0,23	0,08	0,08	0,23	0,31	0,12
28					0,04	0,96
Station. distr.	0,126	0,193	0,065	0,072	0,059	0,484
Sample distr.	0,208	0,208	0,101	0,238	0,077	0,166
			FOOD — technology specialization:			
35	0,43	0,26	0,06	0,11	0,11	0,03
25	0,28	0,28	0,12	0,04	0,20	0,08
19	0,16	0,11	0,32	0,16	0,16	0,11
30	0,13	0,13	0,10	0,33	0,30	
39	0,08	0,08	0,03	0,18	0,39	0,26
21	0,10		0,05	0,05	0,24	0,57
Station. distr.	0,189	0,132	0,083	0,142	0,248	0,206
Sample distr.	0,207	0,148	0,112	0,178	0,231	0,124
			CHEM — industry specialization:			
30	0,67	0,17	0,17			
26	0,04	0,58	0,31	0,07		
33		0,27	0,54	0,15	0,03	
14		0,14	0,36	0,28	0,21	
48		0,04	0,06	0,06	0,77	0,06
17					0,05	0,94
Station. distr.	0,027	0,237	0,272	0,099	0,177	0,188
Sample distr.	0,178	0,154	0,196	0,083	0,285	0,101
			CHEM — technology specialization:			
32	0,72	0,16	0,06	0,03	0,03	
22	0,27	0,59	0,05	0,09		
10	0,30	0,10	0,40		0,20	
19	0,05	0,16	0,16	0,26	0,37	
68	0,02	0,03	0,02	0,12	0,71	0,12
18					0,39	0,61
Station. distr.	0,279	0,177	0,071	0,082	0,301	0,091
Sample distr.	0,189	0,13	0,059	0,112	0,402	0,107

Table 3 continued

DRUG — industry specialization:

27	0,63	0,11	0,15	0,07	0,04	
17	0,12	0,53	0,24		0,12	
24	0,04	0,29	0,29	0,08	0,29	
10		0,20	0,40		0,30	0,10
70			0,07	0,07	0,80	0,06
20					0,50	0,50
Station. distr.	0,055	0,123	0,139	0,055	0,554	0,074
Sample distr.	0,161	0,101	0,142	0,059	0,416	0,119

DRUG — technology specialization:

14	0,14	0,29	0,14	0,29	0,07	0,07
36	0,14	0,53	0,16	0,14		0,03
39	0,03	0,33	0,41	0,18	0,03	0,03
33	0,09	0,16	0,28	0,42	0,06	
38	0,03	0,03	0,05	0,21	0,53	0,16
9		0,11			0,67	0,22
Station. distr.	0,082	0,296	0,22	0,226	0,125	0,051
Sample distr.	0,083	0,213	0,231	0,195	0,225	0,053

RAP — industry specialization:

18	1,00					
16	0,56	0,19	0,13		0,13	
27	0,19	0,31	0,11	0,07	0,33	
24		0,13	0,13	0,33	0,42	
60		0,08	0,13	0,17	0,53	0,08
23				0,04	0,35	0,61
distribution	1					
Sample distrib.	0,107	0,095	0,161	0,143	0,357	0,137

RAP — technology specialization:

20	0,50	0,25	0,10	0,05	0,05	0,05
21	0,29	0,10	0,29	0,05	0,24	0,05
18	0,06	0,28	0,17	0,28	0,22	
16	0,13	0,13	0,06	0,13	0,50	0,06
84	0,04	0,06	0,11	0,08	0,69	0,02
10	0,20			0,10	0,50	0,20
Station. distr.	0,16	0,127	0,127	0,103	0,444	0,039
Sample distr.	0,118	0,124	0,107	0,095	0,497	0,059

SCG — industry specialization:

23	0,78	0,17	0,04			
40	0,25	0,47	0,12	0,07	0,05	0,03
39	0,03	0,36	0,41	0,15	0,05	
24		0,08	0,29	0,33	0,29	
22			0,09	0,23	0,36	0,32
20					0,20	0,80
Station. distr.	0,207	0,167	0,122	0,098	0,149	0,257
Sample distr.	0,137	0,238	0,232	0,143	0,131	0,119

Table 3 continued

SCG — technology specialization:

24	0,25	0,21	0,08	0,13	0,17	0,17
22	0,36	0,05	0,14	0,18	0,27	
25	0,04	0,08	0,24	0,48	0,16	
41	0,49	0,12	0,20	0,39	0,20	0,05
40	0,03	0,20	0,05	0,20	0,43	0,10
17	0,06	0,12	0,06		0,47	0,29
Station. distr.	0,106	0,137	0,128	0,258	0,287	0,084
Sample distr.	0,142	0,13	0,148	0,243	0,237	0,101

IRON — industry specialization:

28	0,46	0,32	0,14		0,07	
38	0,07	0,39	0,28	0,08	0,16	
30	0,07	0,27	0,30	0,07	0,30	
10	0,20	0,50	0,10		0,20	
38		0,18	0,18	0,13	0,32	0,18
24					0,17	0,83
Station. distr.	0,078	0,233	0,177	0,059	0,215	0,237
Sample distr.	0,167	0,226	0,178	0,059	0,226	0,142

IRON — technology specialization:

17	0,47	0,18	0,18	0,18		
39	0,03	0,46	0,28	0,05	0,10	0,08
29	0,17	0,31	0,17	0,14	0,14	0,07
28	0,11	0,18	0,39	0,07	0,25	
23	0,12	0,15	0,21	0,15	0,24	0,12
23	0,09	0,04	0,09	0,09	0,26	0,43
Station. distr.	0,101	0,231	0,172	0,166	0,195	0,136
Sample distr.	0,157	0,266	0,224	0,111	0,146	0,095

NFM — industry specialization:

28	0,46	0,32	0,14		0,07	
38	0,07	0,39	0,28	0,08	0,16	
30	0,07	0,27	0,30	0,07	0,30	
10	0,20	0,50	0,10		0,20	
38		0,18	0,18	0,13	0,32	0,18
24					0,17	0,83
Station. distr.	0,078	0,233	0,177	0,059	0,215	0,237
Sample distr.	0,167	0,226	0,178	0,059	0,226	0,142

NFM — technology specialization:

18	0,67	0,17	0,06	0,06	0,06	
44	0,14	0,50	0,18	0,05	0,14	
19	0,05	0,16	0,53	0,16	0,11	
30	0,03	0,10	0,17	0,47	0,13	0,10
36		0,14	0,14	0,17	0,36	0,19
22	0,05	0,09	0,05	0,18	0,32	0,32
Station. distr.	0,15	0,214	0,218	0,176	0,168	0,074
Sample distr.	0,107	0,26	0,112	0,176	0,213	0,13

Table 3 continued

FABM — industry specialization:

32	0,63	0,31	0,06			
33	0,15	0,57	0,24	0,03		
11	0,27	0,18	0,18	0,27	0,09	
15		0,07	0,07	0,34	0,47	0,07
55		0,02		0,07	0,64	0,27
22					0,41	0,59
Station. distr.	0,066	0,094	0,039	0,067	0,434	0,300
Sample distr.	0,191	0,196	0,065	0,089	0,327	0,131

FABM — technology specialization:

25	0,64	0,20	0,08		0,04	0,04
41	0,17	0,39	0,27	0,15	0,02	
29	0,07	0,14	0,66	0,10		0,03
10			0,30	0,20	0,10	0,40
36	0,03	0,03	0,03	0,03	0,64	0,25
28	0,04	0,04	0,04	0,07	0,21	0,61
Station. distr.	0,141	0,122	0,237	0,08	0,185	0,235
Sample distr.	0,148	0,242	0,172	0,059	0,213	0,166

COMP — industry specialization:

21	0,48	0,48	0,05			
31	0,06	0,65	0,16	0,03	0,1	
13	0,08	0,31		0,23	0,38	
6		0,33	0,17	0,17	0,33	
58		0,09	0,12	0,09	0,55	0,16
25					0,40	0,60
Station. distr.	0,054	0,313	0,105	0,075	0,326	0,127
Sample distr.	0,136	0,201	0,084	0,039	0,377	0,162

COMP — technology specialization:

19	0,42	0,42			0,16	
25	0,32	0,32	0,24	0,20		
20	0,10	0,25	0,25	0,20	0,20	
14	0,14	0,29	0,21	0,14	0,21	
70	0,06	0,09	0,16	0,09	0,57	0,04
21	0,05				0,29	0,67
Station. distr.	0,223	0,266	0,16	0,097	0,225	0,029
Sample distr.	0,112	0,148	0,118	0,828	0,414	0,124

MACH — industry specialization:

43	0,84	0,07	0,05	0,05		
8	0,25		0,13	0,38	0,25	
10		0,10		0,80	0,10	
33		0,06	0,09	0,30	0,55	
45			0,02	0,16	0,58	0,24
15					0,20	0,80
Station. distr.	0,016	0,010	0,021	0,115	0,378	0,416
Sample distr.	0,279	0,052	0,065	0,214	0,292	0,097

Table 3 continued

MACH — technology specialization:

22	0,55	0,32	0,09	0,45		
55	0,15	0,67	0,15	0,02	0,02	
18	0,11	0,39	0,17	0,17	0,11	0,06
30	0,03	0,10	0,10	0,43		
18				0,06	0,39	0,56
26			0,04	0,04	0,19	0,73
Station. distr.	0,083	0,188	0,07	0,078	0,169	0,412
Sample distr.	0,13	0,325	0,107	0,178	0,107	0,154

ELMA — industry specialization:

13	0,54	0,46				
15	0,47	0,47		0,07		
23		0,13	0,35	0,30	0,22	
37		0,11	0,22	0,54	0,14	
59		0,03	0,07	0,03	0,69	0,17
7					0,86	0,14
Station. distr.	0,331	0,328	0,048	0,092	0,168	0,033
Sample distr.	0,084	0,097	0,149	0,240	0,383	0,045

ELMA — technology specialization:

22	0,36	0,23	0,05	0,09	0,18	0,09
14	0,14	0,36	0,29	0,07	0,07	0,07
20		0,35	0,20	0,15	0,30	
30	0,03	0,10	0,03	0,43	0,33	0,07
73	0,03	0,05	0,04	0,10	0,67	0,14
10	0,30	0,00	0,20		0,30	0,20
Station. distr.	0,084	0,17	0,152	0,144	0,437	0,044
Sample distr.	0,13	0,083	0,118	0,178	0,432	0,059

RTV — industry specialization:

25	0,84	0,16				
33	0,39	0,48	0,12			
13		0,77	0,15		0,08	
1					1,00	
61				0,11	0,70	0,18
21					0,19	0,81
Station. distr.				0,056	0,485	0,459
Sample distr.	0,162	0,214	0,084	0,006	0,396	0,136

RTV — technology specialization:

29	0,62	0,24	0,10	0,03		
25	0,24	0,52	0,20	0,04		
24		0,38	0,38	0,17	0,08	
10	0,40	0,10	0,30	0,00	0,20	
55	0,02		0,04	0,04	0,91	
26						1,00
Station. distr.	0,238	0,262	0,166	0,057	0,277	
Sample distr.	0,172	0,148	0,142	0,059	0,325	0,154

Table 3 continued

MOTV — industry specialiation:

36	0,86	0,14				
6	0,50	0,50				
1					1,00	
6				0,50	0,50	
113			0,03	0,12	0,79	0,07
6					0,33	0,66
	0,783	0,217				
Station. distr.			0,018	0,170	0,685	0,127
Sample distr.	0,214	0,036	0,006	0,036	0,673	0,036

MOTV — technology specialization:

23	0,61	0,26	0,04		0,09	
25	0,24	0,44	0,12	0,04	0,16	
14	0,07	0,57	0,14	0,07	0,14	
18		0,28	0,22	0,16	0,28	0,06
71	0,01	0,07	0,07	0,20	0,18	0,17
18		0,06	0,06		0,17	0,72
Station. distr.	0,187	0,264	0,094	0,074	0,227	0,153
Sample distr.	0,136	0,148	0,083	0,107	0,42	0,107

AIRC — industry specialization:

29	0,86	0,14				
25	0,04	0,44	0,52			
20		0,20	0,65		0,15	
1			1,00			
47		0,02	0,06	0,02	0,77	0,13
32					0,19	0,81
Station. distr.	0,032	0,111	0,252	0,008	0,355	0,242
Sample distr.	0,188	0,162	0,130	0,006	0,305	0,208

AIRC — technology specialization:

29	0,52	0,21	0,10	0,07	0,03	0,07
18	0,22	0,22	0,22	0,22	0,11	
21	0,19	0,14	0,24	0,19	0,24	
22	0,09	0,09	0,23	0,41	0,18	
58	0,02	0,03	0,07	0,16	0,53	0,19
21	0,05				0,67	0,29
Station. distr.	0,157	0,102	0,135	0,185	0,321	0,100
Sample distr.	0,172	0,107	0,124	0,130	0,343	0,124

SHIP — industry specialization:

32	0,56	0,44				
54	0,16	0,64	0,2			
12		0,25	0,17	0,50	0,08	
24		0,83	0,25	0,42	0,25	
24		0,04	0,08	0,29	0,17	0,42
31					0,19	0,81
Station. distr.	0,087	0,244	0,120	0,164	0,122	0,263
Sample distr.	0,190	0,268	0,071	0,143	0,143	0,185

Table 3 continued

SHIP — technology specialization:

19	0,37	0,47		0,05	0,11	
51	0,25	0,45	0,16	0,06	0,08	
31	0,06	0,19	0,39	0,06	0,19	0,10
13	0,08	0,08	0,23	0,31	0,23	0,08
30			0,27	0,10	0,33	0,30
25	0,04	0,04	0,04	0,08	0,16	0,64
Station. distr.	0,125	0,2	0,18	0,095	0,181	0,219
Sample distr.	0,112	0,302	0,183	0,077	0,178	0,148

PROF — industry specialization:

19	0,79	0,05	0,16			
36	0,08	0,61	0,19	0,03	0,08	
23	0,09	0,09	0,35	0,09	0,39	
5		0,20	0,40	0,20		
42	0,05	0,05	0,17	0,05	0,60	0,1
29					0,03	0,97
Station. distr.	0,116	0,076	0,112	0,025	0,178	0,492
Sample distr.	0,123	0,234	0,149	0,032	0,272	0,188

PROF — technology specialization:

19	0,42	0,32	0,05	0,05	0,11	0,05
32	0,31	0,25	0,28		0,16	
28	0,07	0,32	0,07	0,04	0,50	
8			0,50	0,13	0,38	
61	0,03	0,07	0,16	0,05	0,66	0,03
21	0,10				0,19	0,71
Station. distr.	0,144	0,163	0,154	0,039	0,425	0,075
Sample distr.	0,112	0,189	0,166	0,047	0,361	0,124

Table 4

Fractile Markov chain estimates for the specialization indicators

(First-order, time-stationary estimates of the ten-year transition probabilities)

Industry specialization in value added (1970 — 1988):

	Transition end state — quantile					
Observations	1/6	1/3	1/2	2/3	5/6	1
288	0,73	0,19	0,06	0,01	0,01	
297	0,23	0,38	0,23	0,10	0,07	
297	0,02	0,29	0,35	0,23	0,08	0,02
297	0,01	0,10	0,23	0,37	0,22	0,06
297		0,03	0,09	0,26	0,48	0,13
297		0,02	0,04	0,02	0,14	0,78

A regression of the interquantile range on time (in years) yields a slope coefficient of 0.005 with a t-value of 2.31 and an adjusted R^2 of 0.194.

Technology specialization (1972 — 1989):

	Transition end state — quantile					
Observations	1/6	1/3	1/2	2/3	5/6	1
264	0,50	0,20	0,10	0,06	0,06	0,06
272	0,24	0,36	0,17	0,11	0,08	0,04
272	0,12	0,19	0,31	0,25	0,08	0,05
272	0,05	0,11	0,19	0,33	0,23	0,08
272	0,04	0,08	0,14	0,19	0,31	0,25
272	0,04	0,06	0,08	0,06	0,25	0,51

A regression of the interquantile range on time (in years) yields a slope coefficient of 0.006 with a t-value of 2.43 and an adjusted R^2 of 0.224.

Table 5

Fractile Markov chain estimates for the specialization indicators of individual industries

(First-order, time-stationary estimates of the five-year transition probabilities)

	Transition end-state — quantile					
	1/6	1/3	1/2	2/3	5/6	1
CHEM	0,82		0,14	0,03		
value added	0,11	0,53	0,25	0,11		
	0,04	0,28	0,39	0,25	0,04	
	0,04	0,14	0,18	0,43	0,21	
		0,04	0,04	0,18	0,75	
						1
CHEM	0,62	0,23	0,11	0,04		
technology	0,27	0,46	0,27			
	0,12	0,23	0,35	0,31		
		0,08	0,27	0,42	0,15	0,08
				0,19	0,35	0,46
				0,03	0,33	0,64
DRUG	0,64	0,28	0,07			
value added	0,32	0,46	0,07	0,11	0,04	
	0,04	0,21	0,46	0,11	0,11	0,07
		0,04	0,21	0,25	0,25	0,25
			0,17	0,42	0,28	0,11
				0,11	0,32	0,57
DRUG	0,27	0,08	0,31	0,19	0,12	0,04
technology	0,35	0,42	0,12	0,04	0,04	0,04
	0,12	0,27	0,15	0,23	0,19	0,04
	0,11	0,15	0,35	0,12	0,27	
	0,12	0,08	0,08	0,35	0,15	0,23
	0,02			0,05	0,15	0,77
RAP	0,75	0,21				0,03
value added	0,17	0,43	0,11	0,18	0,07	0,04
	0,04	0,18	0,43	0,25	0,04	0,07
	0,04	0,15	0,28	0,17	0,25	0,11
		0,04	0,14	0,35	0,32	0,14
			0,04	0,04	0,32	0,61
RAP	0,35	0,31	0,19	0,04		0,12
technology	0,27	0,38	0,04	0,19	0,08	0,04
	0,15	0,12	0,31	0,12	0,15	0,15
		0,08	0,23	0,19	0,23	0,27
	0,08		0,08	0,19	0,35	0,31
	0,10	0,08	0,10	0,18	0,13	0,41

Table 5 continued

SCG value added	0,61	0,28	0,04	0,04	0,04	
	0,28	0,28	0,21	0,17		0,04
	0,04	0,32	0,42	0,11	0,11	
	0,04	0,11	0,21	0,35	0,28	
	0,04		0,11	0,32	0,39	0,14
					0,18	0,82
SCG technology	0,27	0,19	0,08	0,15	0,12	0,19
	0,31	0,27	0,08	0,12	0,12	0,12
	0,23	0,12	0,19	0,15	0,23	0,08
	0,04	0,04	0,35	0,15	0,19	0,23
	0,08	0,15	0,12	0,23	0,08	0,35
	0,05	0,15	0,13	0,13	0,18	0,36
IRON value added	0,71	0,14	0,11	0,04		
	0,07	0,28	0,21	0,35	0,07	
	0,07	0,36	0,25	0,25	0,07	
		0,17	0,25	0,18	0,39	
	0,14	0,03	0,18	0,18	0,18	0,28
					0,28	0,71
IRON technology	0,35	0,23	0,08	0,12	0,12	0,12
	0,08	0,31	0,38	0,12	0,08	0,04
	0,15	0,12	0,27	0,15	0,19	0,12
	0,08	0,15	0,04	0,27	0,19	0,27
	0,12	0,12	0,08	0,12	0,31	0,27
	0,15	0,05	0,10	0,15	0,08	0,46
NFM value added	0,93	0,07				
	0,07	0,64	0,17	0,11		
		0,21	0,39	0,25	0,14	
		0,07	0,28	0,5	0,14	
			0,14	0,14	0,64	0,07
					0,07	0,92
NFM technology	0,46	0,27	0,04	0,12	0,04	0,08
	0,27	0,27	0,27	0,04	0,15	
	0,08	0,15	0,38	0,19	0,08	0,12
	0,04	0,12	0,12	0,35	0,23	0,15
	0,04	0,12	0,12	0,15	0,23	0,35
	0,08	0,05	0,05	0,10	0,18	0,54
FABM value added	0,61	0,32	0,07			
	0,32	0,46	0,21			
	0,07	0,17	0,57	0,14	0,04	
		0,03	0,11	0,57	0,17	0,11
				0,17	0,46	0,35
			0,04	0,11	0,32	0,54

Table 5 continued

FABM technology	0,62	0,15	0,15		0,04	0,04
	0,19	0,38	0,19	0,15	0,04	0,04
	0,08	0,31	0,35	0,27		
	0,04	0,04	0,27	0,31	0,23	0,12
	0,04	0,04		0,15	0,38	0,38
	0,03	0,05	0,03	0,08	0,21	0,32
MACH value added	0,5	0,42	0,07			
	0,21	0,67	0,11			
	0,04	0,11	0,21	0,5	0,11	0,04
			0,46	0,39	0,11	0,04
			0,14	0,11	0,43	0,32
			0,03		0,36	0,61
MACH technology	0,62	0,15	0,15		0,04	0,04
	0,19	0,38	0,19	0,15	0,04	0,04
	0,08	0,31	0,35	0,27		
	0,04	0,04	0,27	0,31	0,23	0,12
	0,04	0,04		0,15	0,38	0,38
	0,03	0,05	0,03	0,08	0,21	0,32
COMP value added	0,36	0,57	0,07			
	0,07	0,46	0,43	0,04		
	0,18	0,18	0,21	0,39		0,04
	0,07	0,04	0,25	0,46	0,14	0,04
		0,04		0,07	0,54	0,41
			0,07	0,04	0,32	0,57
COMP technology	0,46	0,35	0,08	0,04		0,08
	0,27	0,23	0,23	0,15	0,08	0,04
	0,08	0,23	0,15	0,38	0,08	0,08
	0,08	0,12	0,27	0,19	0,23	0,12
	0,08	0,04	0,12	0,08	0,38	0,31
	0,03	0,03	0,10	0,10	0,15	0,59
ELMA value added	0,64	0,28		0,07		
	0,17	0,39	0,25	0,18		
		0,39	0,53	0,07		
		0,07	0,21	0,67	0,03	
				0,03	0,89	0,07
					0,07	0,92
ELMA technology	0,50	0,04	0,15	0,12	0,04	0,15
	0,15	0,38	0,23	0,08		0,15
	0,15	0,08	0,31	0,08	0,15	0,23
	0,04	0,08	0,19	0,31	0,27	0,12
	0,04	0,15	0,04	0,27	0,15	0,35
	0,08	0,18	0,05	0,10	0,26	0,33

Table 5 continued

RTV	0,29	0,71				
value added	0,36	0,61	0,04			
		0,04	0,96			
				0,82	0,14	0,04
				0,14	0,61	0,25
				0,04	0,25	0,71
RTV	0,50	0,04	0,15	0,12	0,04	0,15
technology	0,15	0,38	0,23	0,08		0,15
	0,15	0,08	0,31	0,08	0,15	0,23
	0,04	0,08	0,19	0,31	0,27	0,12
	0,04	0,15	0,04	0,27	0,15	0,35
	0,08	0,18	0,05	0,10	0,26	0,33
	I					
MOTV		0,75	0,07	0,11	0,04	0,04
value added		0,18	0,5	0,21	0,04	0,07
		0,07	0,28	0,21	0,21	0,21
			0,07	0,36	0,39	0,18
			0,07	0,11	0,32	0,5
MOTV	0,50	0,31	0,08	0,04	0,04	0,04
technology	0,31	0,42	0,15	0,04	0,04	0,04
	0,04	0,12	0,42	0,19	0,12	0,12
	0,04	0,08	0,12	0,31	0,27	0,19
		0,08	0,12	0,35	0,19	0,27
	0,08		0,08	0,05	0,23	0,56
SHIP	0,71	0,28				
value added	0,17	0,46	0,32	0,04		
	0,11	0,21	0,46	0,11	0,11	0
			0,14	0,61	0,25	
		0,04	0,07	0,25	0,43	0,21
					0,21	0,79
SHIP	0,38	0,42	0,08	0,04		0,08
technology	0,38	0,31	0,23	0,04	0,04	
	0,08	0,19	0,23	0,19	0,23	0,08
	0,15	0,04	0,23	0,23	0,19	0,15
			0,15	0,27	0,15	0,42
		0,03	0,05	0,15	0,25	0,51
AIRC	0,86	0,14				
value added	0,07	0,68	0,25			
		0,25	0,71	0,04		
			0,04	0,68	0,28	
				0,28	0,61	0,11
					0,11	0,89

Table 5 continued

AIRC	0,46	0,31	0,12			0,12
technology	0,31	0,27	0,27	0,08	0,04	0,04
	0,15	0,19	0,27	0,23	0,15	
		0,15	0,23	0,46	0,08	0,08
	0,04	0,08	0,08	0,12	0,41	0,38
	0,03		0,03	0,08	0,28	0,59
PROF	1,00					
value added		0,50	0,43	0,07		
		0,28	0,32	0,36	0,04	
		0,21	0,07	0,43	0,28	
			0,18	0,14	0,68	
						1,00
PROF	0,62	0,12	0,08	0,08	0,04	0,08
technology	0,23	0,38	0,27	0,08	0,04	
	0,08	0,19	0,23	0,23	0,15	0,19
	0,04	0,08	0,27	0,31	0,08	0,23
		0,19	0,11	0,15	0,46	0,08
	0,03	0,03	0,03	0,10	0,15	0,67

Table 5 continued

Regressions of interquantile range in industry specialization on time:

	coefficient	t-value	adj.R^2
All industries	0,00	2,31	0,194
CHEM	-0,02	-6,75	0,710
DRUG	-0,02	-1,64	0,085
RAP	0,02	8,73	0,807
SCG	0,01	3,19	0,337
IRON	0,00	-0,84	-0,016
NFM	0,02	2,28	0,190
FABM	0,00	2,09	0,158
MACH	0,02	5,85	0,649
COMP	-0,12	-8,04	0,779
ELMA	-0,06	-1,61	0,081
RTV	0,01	1,63	0,085
MOTV	-0,01	-2,31	0,195
SHIP	0,01	0,32	0,052
AIRC	-0,01	-1,68	0,091
PROF	-0,02	-2,43	0,215

Table 5 continued

Regressions of interquantile range in technology specialization on time:

	coefficient	t-value	adj.R^2
All industries	0,01	2,43	0,224
CHEM	0,01	0,65	0,035
DRUG	-0,01	-0,43	-0,05
RAP	-0,02	-0,36	-0,054
SCG	-0,01	-1,25	0,033
IRON	0,00	0,23	-0,059
NFM	0,00	-0,11	-0,062
FABM	0,01	1,83	0,122
MACH	0,02	5,36	0,620
COMP	0,02	1,26	0,034
ELMA	-0,01	-1,76	0,111
RTV	-0,01	-0,57	-0,041
MOTV	-0,01	-0,61	-0,039
SHIP	0,04	3,09	0,336
AIRC	-0,02	-1,27	0,035
PROF	0,01	2,75	0,278

Table 6

Regressions of Specialization in Value Added on Relative Factor Endowments

(Annual data 1970 — 1988, twelve countries (eleven countries for MACH, COMP, ELMA, RTV, AIRC and PROF). Figures in italics are t-values.)

Industry	Constant	Capital	R&D Capital	R&D Scientists & Engineers	Labour	Schooling	Adjusted R^2
FOOD	**0,06**	**0,16**	**-0,05**	**-0,04**	**-0,41**	**0,07**	**0,16**
		1,82	*-2,29*	*-0,89*	*-4,07*	*1,04*	
CHEM	**0,01**	**0,59**	**0,38**	**-0,22**	**-0,39**	**-0,01**	**0,43**
		4,79	*11,53*	*-3,06*	*-2,78*	*-0,12*	
DRUG	**-0,13**	**-1,71**	**-0,19**	**0,65**	**1,63**	**-1,16**	**0,54**
		-11,42	*-4,67*	*7,48*	*9,52*	*-9,36*	
RAP	**-0,03**	**-0,36**	**-0,10**	**0,43**	**0,31**	**-0,75**	**0,47**
		-4,99	*-5,20*	*10,18*	*3,69*	*-12,43*	
SCG	**-0,09**	**-0,25**	**-0,17**	**-0,05**	**0,92**	**-0,65**	**0,64**
		-4,02	*-9,91*	*-1,53*	*12,88*	*-12,53*	
IRON	**-0,10**	**-0,18**	**-0,22**	**0,71**	**0,23**	**-0,50**	**0,41**
		-1,69	*-7,88*	*11,58*	*1,93*	*-5,68*	
NFM	**0,12**	**0,46**	**-0,35**	**0,80**	**-2,42**	**0,30**	**0,39**
		1,98	*-5,59*	*5,95*	*-9,04*	*1,56*	
FABM	**-0,02**	**-0,21**	**-0,04**	**-0,06**	**-0,15**	**-0,15**	**0,26**
		-3,15	*-2,15*	*-1,46*	*-1,99*	*-2,71*	
MACH	**-0,05**	**-0,04**	**0,19**	**-0,05**	**0,92**	**0,23**	**0,44**
		-0,36	*5,96*	*-0,74*	*6,82*	*1,93*	
COMP	**-0,15**	**-0,84**	**-0,16**	**1,44**	**-0,99**	**-1,07**	**0,37**
		-2,81	*-1,99*	*8,47*	*-2,96*	*-3,65*	
ELMA	**-0,24**	**-0,69**	**-0,36**	**0,51**	**2,06**	**-1,03**	**0,33**
		-2,93	*-5,84*	*3,78*	*7,85*	*-4,51*	
RTV	**0,11**	**0,87**	**0,66**	**0,49**	**-1,34**	**-0,14**	**0,72**
		5,36	*15,56*	*5,30*	*-7,42*	*-0,92*	
MOTV	**-0,07**	**-2,64**	**-0,45**	**1,09**	**1,29**	**-1,91**	**0,47**
		-10,29	*-6,49*	*7,36*	*4,38*	*-8,97*	
SHIP	**0,06**	**2,07**	**0,36**	**-0,60**	**-0,40**	**2,13**	**0,39**
		6,55	*4,22*	*-3,29*	*-1,11*	*8,16*	
AIRC	**-0,27**	**-2,58**	**0,30**	**-0,79**	**-1,27**	**0,14**	**0,73**
		-10,24	*4,30*	*-5,60*	*-4,48*	*0,71*	
PROF	**-0,29**	**-1,21**	**0,07**	**0,27**	**0,55**	**-0,89**	**0,30**
		-4,68	*0,97*	*1,86*	*1,93*	*-4,27*	

See explanations in section 4 of the main text.

Table 7

Fractile Markov chain estimates for the industry residual specialization indicator 1970 — 1988

(First-order, time-stationary estimates of the five-year transition probabilities)

	Transition end-state-quantile					
	1/6	1/3	1/2	2/3	5/6	1
All industries	0,57	0,2	0,1	0,06	0,05	0,02
	0,21	0,34	0,23	0,1	0,07	0,03
	0,09	0,23	0,32	0,21	0,11	0,04
	0,06	0,13	0,19	0,31	0,24	0,08
	0,04	0,08	0,14	0,21	0,33	0,2
	0,02	0,03	0,03	0,09	0,2	0,63
CHEM	0,93	0,04	0,04			
	0,07	0,29	0,29	0,21	0,11	0,04
		0,29	0,32	0,18	0,11	0,11
		0,25	0,14	0,29	0,29	0,04
		0,07	0,18	0,18	0,39	0,18
		0,07	0,04	0,14	0,11	0,64
DRUG	0,46	0,18	0,21	0,11	0,04	
	0,29	0,36	0,04	0,18	0,04	0,11
	0,11	0,18	0,21	0,11	0,25	0,14
	0,07	0,11	0,29	0,14	0,18	0,21
	0,07	0,14	0,11	0,05	0,32	0,11
		0,04	0,14	0,21	0,18	0,43
RAP	0,46	0,14	0,11	0,21	0,07	
	0,18	0,25	0,29	0,11	0,04	0,14
	0,14	0,21	0,18	0,11	0,14	0,21
	0,07	0,18	0,14	0,18	0,21	0,21
	0,04	0,11	0,11	0,18	0,32	0,25
	0,11	0,11	0,18	0,21	0,21	0,18
MACH	0,57	0,43				
	0,21	0,11	0,36	0,11	0,18	0,04
		0,36	0,29	0,29	0,04	0,04
		0,25	0,25	0,28	0,14	0,07
		0,07	0,11	0,25	0,36	0,21
				0,07	0,29	0,64
COMP	0,36	0,43	0,07	0,14		
	0,07	0,39	0,07	0,29	0,14	0,04
	0,14	0,18	0,25	0,18	0,25	
	0,04	0,14	0,46	0,21	0,04	0,11
	0,07	0,07	0,14	0,21	0,21	0,29
			0,04	0,04	0,36	0,57

Table 7 continued

ELMA	0,14	0,21	0,36		0,21	0,07
	0,25	0,39	0,21	0,11		0,04
	0,11	0,09	0,21	0,18	0,18	0,04
	0,04	0,04	0,14	0,32	0,35	0,11
		0,11	0,25	0,21	0,18	0,25
	0,04	0,07		0,18	0,18	0,54
RTV	0,21	0,43	0,21	0,14		
	0,29	0,43	0,18	0,07	0,04	
	0,11	0,21	0,18	0,19	0,21	
		0,11	0,25	0,25	0,36	0,04
		0,04	0,14	0,25	0,29	0,29
			0,14	0,07	0,11	0,67
MOTV	0,79	0,11	0,11			
	0,11	0,46	0,39	0,04		
	0,04	0,32	0,04	0,14	0,14	
	0,04	0,11	0,07	0,36	0,29	0,14
	0,04		0,07	0,39	0,39	0,11
				0,07	0,18	0,75
SHIP	0,61	0,07	0,18	0,11	0,04	
	0,18	0,36	0,25	0,11	0,11	
	0,14	0,29	0,21	0,29	0,07	
	0,04	0,21	0,14	0,25	0,32	0,04
	0,04	0,07	0,21	0,18	0,43	0,07
				0,07	0,04	0,89
AIRC	0,43	0,14	0,21	0,21		
	0,11	0,21	0,5	0,11	0,07	
	0,14	0,57	0,11	0,18		
	0,04	0,07	0,29	0,32	0,14	0,14
		0,07		0,18	0,43	0,32
				0,11	0,36	0,54
PROF	0,71	0,29				
	0,07	0,50	0,36	0,04	0,04	
	0,07	0,32	0,36	0,21	0,04	
			0,21	0,64	0,14	
			0,04	0,07	0,54	0,36
		0,04	0,04	0,04	0,25	0,64

Table 7 continued

Regressions of interquantile range in residuals on time:

	coefficient	t-value	adj.R^2
All industries	0,00	-0,72	-0,028
CHEM	0,00	-0,75	-0,025
DRUG	-0,02	-7,65	0,762
RAP	0,01	3,18	0,336
MACH	0,01	3,21	0,340
COMP	-0,11	-6,36	0,687
ELMA	-0,07	-1,77	0,106
RTV	-0,01	-1,52	0,068
MOTV	-0,01	-0,06	-0,059
SHIP	0,01	0,84	-0,017
AIRC	-0,04	-5,35	0,600
PROF	-0,02	-2,11	0,161

Figure 1

Stochastic kernel estimate for industry specialization transitions after one year

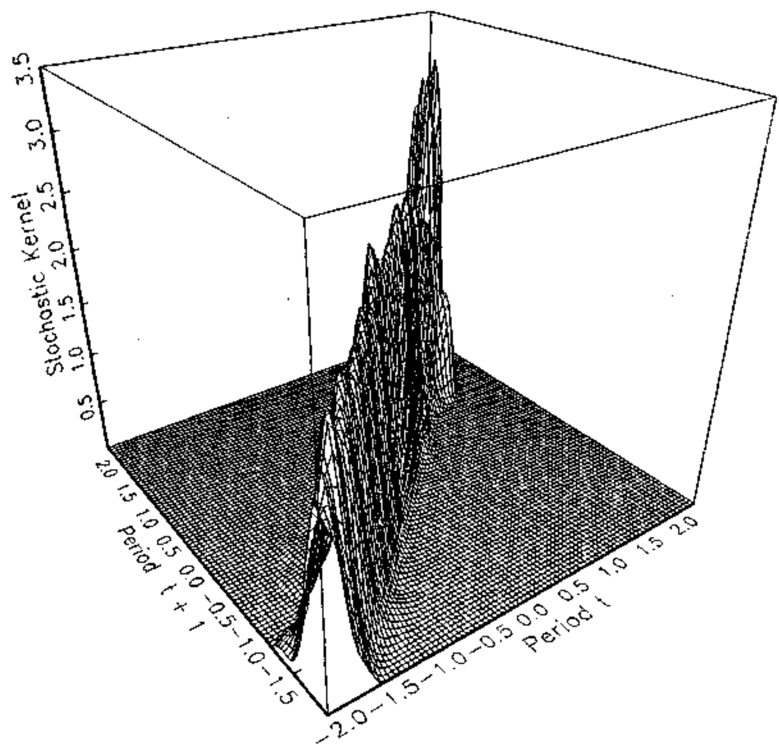

Figure 2

Stochastic kernel estimate for industry specialization transitions after five years

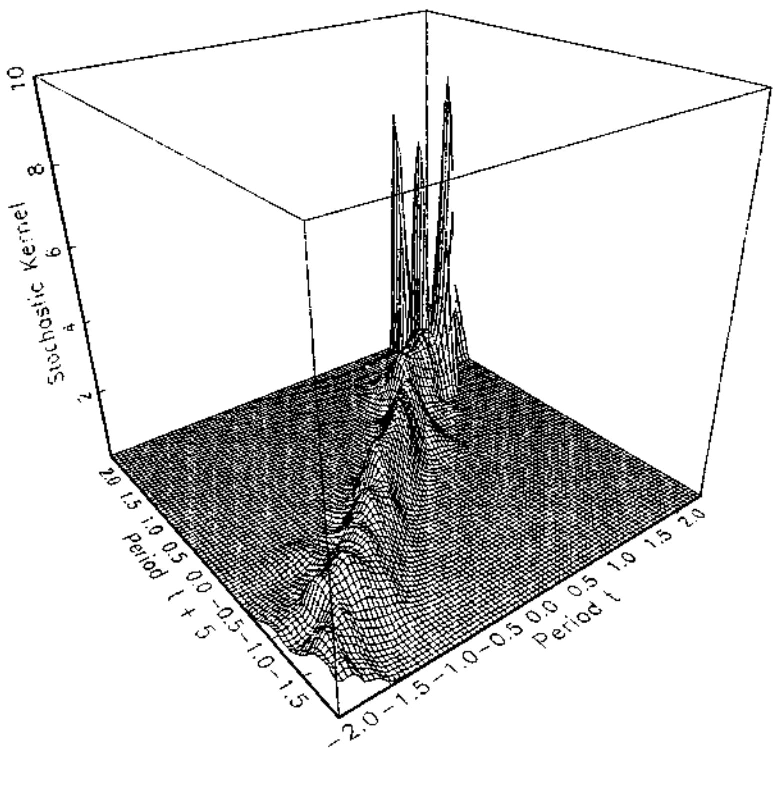

Figure 3

Stochastic kernel estimate for technology specialization transitions after one year

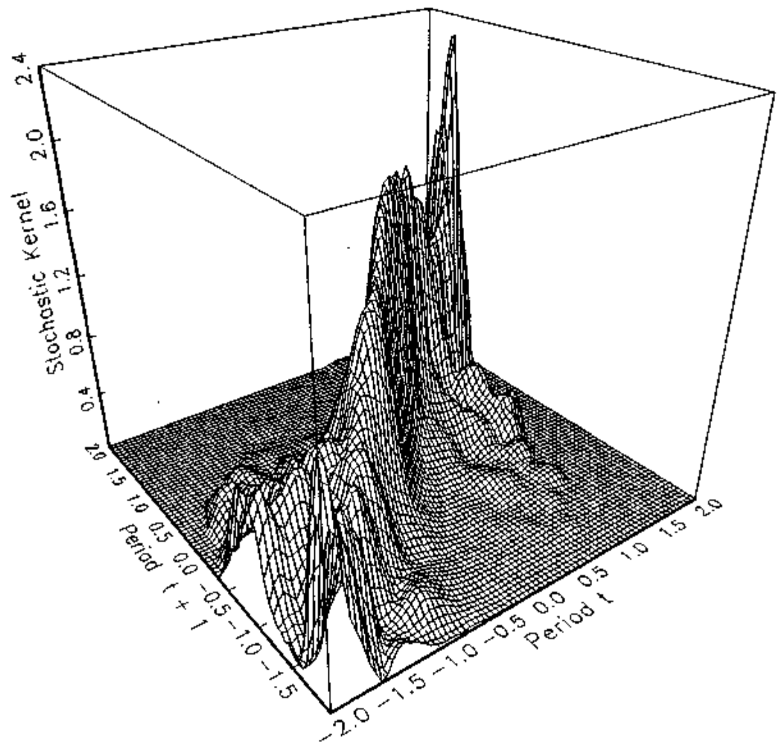

Figure 4

Stochastic kernel estimate for technology specialization transitions after five years

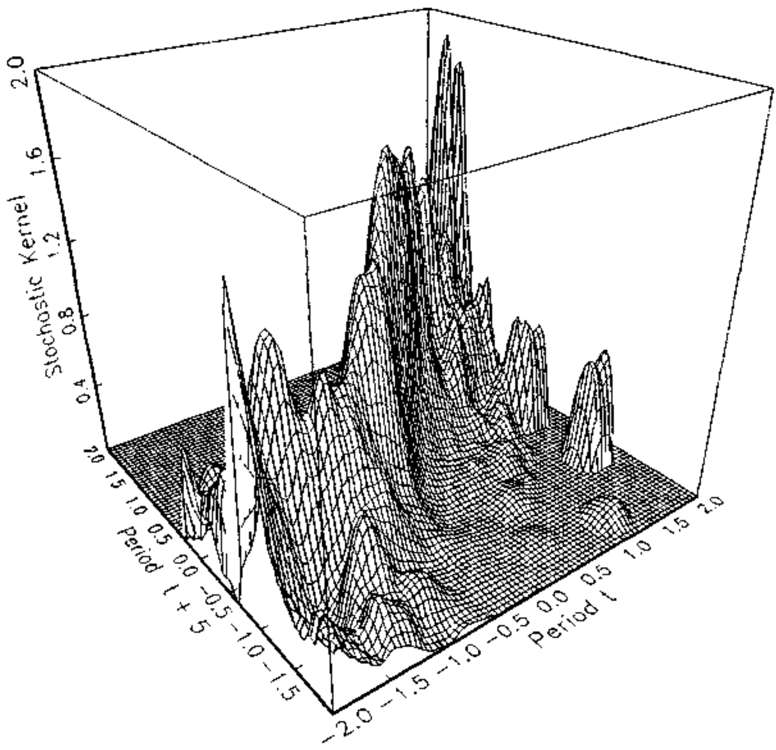

Figure 5

Non-parametric density estimates for the industry specialization indicator for the years 1970 (above) and 1988 (below)

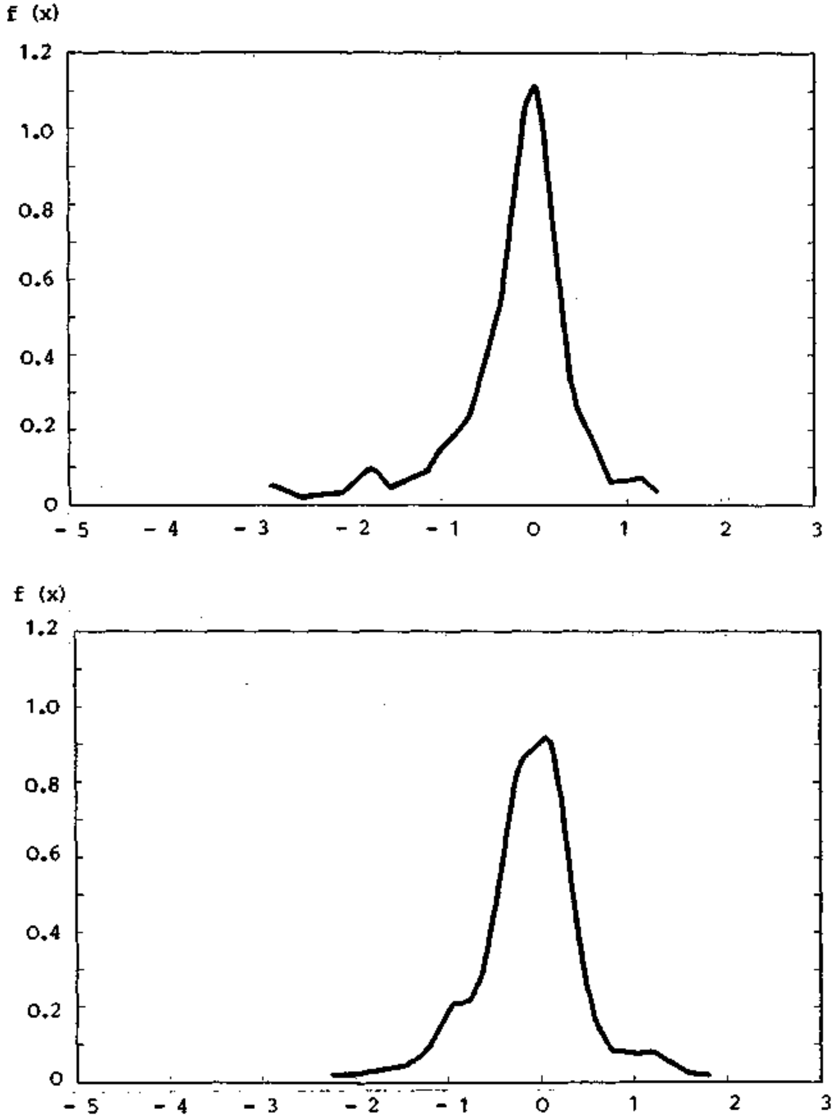

Figure 6

Non-parametric density estimates for the technology specialization indicator for the years 1972 (above) and 1989 (below)