TECHNOLOGICAL SPECIALIZATION IN INDUSTRIAL COUNTRIES

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Abstract

This paper employs distribution dynamics and patent data to study the empirical dynamics of technological specialization in industrial countries. Large countries spread innovation activities across a wider range of technologies and their specialization level in a field displays lower probability to move around its initial level (*country size effects*). *Mobility is high* and *asymmetric*: it is difficult to improve specialization in very disadvantaged technologies, while high comparative advantages revert towards lower specialization levels. These findings undermine the theory of technological accumulation and path-dependence, its implication of persistence in trade specialization patterns and the effectiveness of targeted industrial and technology policies.

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I INTRODUCTION

In the past years, technological change has attracted the attention of many economists working within different fields. Industrial economists modeled R&D investment decisions by private enterprises to understand how technical change influences the dynamics of competition and how the resulting market or industry structure in turn affects technical change. Recent developments in macroeconomic growth theory use this interpretation to explain sustained growth of per-capita productivity, comparative advantage and trade of countries. There is now a large literature suggesting that the link between technology, competitiveness and growth is an important one, but its implications require additional assumptions on the cross border mobility of R&D output, which is in turn determined by the characteristics of knowledge.

On the one side, knowledge is often considered as a *public* good with the economic property of *non-rivalry* in use (Romer 1990): this should favor the diffusion of knowledge within and across national borders. On the other side, the literature on innovation (Nelson and Winter, 1982; Dosi, 1988;

Malerba 1992) has emphasized how knowledge may be *specific* to the agent who has produced it or/and to the environment where it has been produced (because, for example, it is complementary to specific knowledge and skills available only in the firm or country that has done the R&D). This would go in favor of limited international mobility of R&D output[1] and would imply the existence of reinforcing effects: the more a country innovates today, the higher the probability it can innovate in the future.

In endogenous growth theory models the creation of knowledge through private R&D yields positive external effects: part of the new knowledge adds to a public stock, accessible to all firms doing R&D themselves, thus reducing every firm's costs of future R&D. Over time, the public stock of knowledge grows, allowing more differentiated or higher quality products to be introduced without a continual increase in the amount of resources spent in R&D activities[2]. This is referred to as *knowledge spillovers*, so called because the benefit of innovation accrues not only to the innovator, but "spills over" to other firms by raising the level of knowledge upon which new innovations can be based. Thus, knowledge spillovers serve as endogenous engine of economic growth.

The distribution of countries' output per capita and their comparative advantages are then determined by the process of technical progress in one country being independent from that in the others. Perfect technology diffusion (i.e. new ideas flowing as quickly to other countries as they flow within countries) favors the convergence of per capita output levels and leaves factor endowments as the sole determinants of trade patterns. However, if there are impediments to technology diffusion across national borders and the rate of knowledge spillover is much stronger within nations than across them[3], differences in levels of per capita output across countries will be persistent and the patterns of trade can exhibit path-dependence and lock-in (as a consequence of reinforcing effects characterizing a country's technological change). Small initial inter-country differences lead then to divergence in

[1] It would also, at least partially, explain why an increasing share of international technology transfer takes place within multinational corporations.
[2] See, for example, Grossman and Helpman (1991).
[3] Jaffe (1989), Jaffe et al. (1993), Bottazzi and Peri (1999) suggest this, among others. Keller (2000) finds evidence pointing to the relevance of geographical proximity, but also shows that the detrimental effect of geographical distance on international technology diffusion has fallen by about 20 percent over the period 1970-1995.

specialization patterns and growth[4].

Recent empirical studies on trade dynamics[5] have found persistence in the trade patterns of industrial countries, a fact whose origin may lie in the nature of technological progress or in the relatively stable position of advanced countries in the international economy. In the first case, stability in trade patterns arises as a consequence of technological progress being path-dependent and subject to localized knowledge spillovers, whereas in the second case knowledge spillovers are pervasive and persistence is generated by stability in relative factor endowments. Understanding which of the two explanations applies is of primary importance, not least because they have different theoretical and normative implications.

If the actual specialization profile of a country is determined by its past strengths and weaknesses, industrial and technology policies targeted at selected industries and technologies in order to change the sectoral distribution of the country's comparative advantages would have lasting effects. Under the assumption that the government can identify the more promising technological trajectories, it can then pursue the deepening of specialization along those technologies, by shifting resources towards them. Empirically, if the explanation of the stability in trade specialization were based on the nature of technology, then persistence should be particularly pronounced in technological specialization, where the positive external effects in the form of knowledge spillovers from R&D have their most direct and strongest impact[6].

In order to find evidence in favor or against the persistence of a country's technological specialization profile, this study applies the dynamic tools offered by distribution dynamics modeling to the analysis of the evolution of the technological specialization profile of industrial countries in the last two decades. As the empirical findings will make clear, there is no evidence of strong tendency towards persistence, with the exception of situations of initial complete or high de-specialization. The relative stability in the degree of specialization of most countries hides significant intra-distribution

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[4] If a country acquires a temporary advantage in an R&D intensive sector, it can innovate in that sector at a faster rate than other countries. This is because the knowledge base on which domestic firms build their innovations grows faster than anywhere else, given that it cannot quickly spread to foreign competitors. Hence the country can build on an initial advantage, eventually developing a position of enduring comparative advantage.

[5] See Proudman and Redding (1998, 2000) and Brasili et al. (2000).

mobility. In particular, high specialization levels are not persistent in time; rather, they revert towards lower levels, the reversion being faster and more pronounced for smaller countries (i.e. countries with higher overall degree of specialization). This is not at all in line with a theory of technological accumulation and is consistent with the findings in Stolpe (1995), which cast doubt on the often alleged causality from hysteresis in technology to hysteresis in trade specialization.

The paper is organized as follows. Section II defines the technological specialization profile of a country and explains how it can be measured. Section III studies the evolution of the overall degree of technological specialization through an inequality index and the non-parametric estimation of the density functions representing the specialization patterns of ten OECD countries. Section IV then studies intra-distribution movements (i.e. changes in time of a country's specialization in a particular technology field) through the estimation of Markov stochastic kernels and transition probability matrices. Section V concludes.

II TECHNOLOGICAL SPECIALISATION PROFILE: MEASUREMENT AND EVOLUTION

To evaluate the extent of *mobility* and *persistence* in patterns of international technological specialization I employ the CESPRI patent database, which covers all the patent applications filed at the European Patent Office (EPO hereafter) between 1978 and 1996.

The main reason to use patents to measure a country's specialization profile is that they are the only available indirect evidence of technological activity offering a detailed break down by sector for a large number of countries and for long time series[7]. Hence, they will be taken here as an indicator of countries' sectoral distribution of research output: their distribution across technological sectors will summarize the technological frontier of a country and its pattern of technological specialization[8] at a specific point in time.

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[6] See also Stolpe (1995).

[7] A detailed discussion on the advantages and the problems related to the use of patent data can be found in Griliches (1990).

It is usually claimed that international patents are characterized by higher average quality than national patents[9]. Using patenting at the EPO to explore a country specialization profile has an additional advantage: all the firms patenting at the EPO are patenting abroad[10], so that, in principle, the analysis on this data is not greatly affected by "domestic market bias"[11]. This is likely to have adversely affected the analyses on the specialization pattern of the United States, because of the widespread use of US patent data for studies on the technological specialization profile of advanced countries. For this reason, the specialization profile of the United States emerging from previous studies does not appear as an accurate description of the areas of technological strength and weakness of the US in international markets[12]. Finally, in the Cespri database all individual applicants have been eliminated: this avoids distortions in the representation of a country's specialization profile due to individual inventors bursting specialization with low average quality applications in those sectors where they are particularly active.

To characterize the extent of specialization in a technological field, previous studies[13] have employed the so called Technological Revealed Comparative Advantage (TRCA) index, computed in the same way as Balassa's (1965) index of Revealed Comparative Advantage (RCA) used in trade theory. The TRCA index is defined as a country's share of all EPO patenting in a technological field, relative to its share of all EPO patenting in all fields,

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[8] See Jaffe (1986) for a similar use of patent data.

[9] Eaton et al. (1999) mention a study by Putnam that uses micro-level data on a set of countries to estimate a model of patent filing decision. He estimates that over 95 percent of the total value of patent rights world-wide is contained in inventions that are filed in at least one country outside their home country.

[10] The EPO was founded on the basis of an agreement among 13 European countries: Austria, Belgium, France, West Germany, Greece, Italy, Liechtenstein, Luxembourg, the Netherlands, Spain, Sweden, Switzerland and the United Kingdom. Seven more states have become members later (Cyprus, Denmark, Finland, Ireland, Monaco, Portugal and Turkey). A single application at the EPO can potentially be extended to all the member countries, and on average, the number of contracting states designated for protection is about 8 per patent.

[11] Since the EPO is located in Germany, German firms show a higher propensity to apply for a patent there in the first years. However, as it will be specified later on, the first years of operation of the EPO will not be used in the analysis.

[12] The specific sectoral strengths and weaknesses of the US differ substantially in domestic and in external patenting, with no correlation emerging between data from the US patent office on the one hand and from the EPO, France and Germany patent offices on the other. The specialization profiles emerging from different foreign markets are consistent, however, with correlation coefficients always higher than 0.7 (Archibugi and Pianta 1992b: 52).

[13] See, for example, Soete (1981) and Patel and Pavitt (1991).

$$TRCA_{ij} = \frac{P_{ij} / \sum_i P_{ij}}{\sum_j P_{ij} / \sum_{ij} P_{ij}} \tag{1}$$

where P_{ij} denotes the number of EPO patents of country i in the technological sector j.

The TRCA yields information about the pattern of international technological specialization insofar as it evaluates a country's patenting share in an individual sector, relative to some benchmark: the country's share of total patenting. A value of $TRCA_{ij}$ above unity indicates that country i is comparatively advantaged or specialized in technological sector j.

Proudman and Redding (1998 and 2000), have recently adopted a modified version of that index, according to which an economy's share of patenting in a given technological field is evaluated relative to a different benchmark, which is its *average* patenting share in all fields:

$$RTA_{ij} = \frac{P_{ij} / \sum_i P_{ij}}{\frac{1}{N} \sum_j (P_{ij} / \sum_i P_{ij})} \tag{2}$$

where N is the total number of technological fields.

By construction, for each country the mean value of RTA across sectors is constant and equal to one[14]. Again, a value of RTA_{ij} above unity indicates that the country i's share of patenting in field j exceeds its average share in all fields: that is, country i specializes in field j. Note that the index ranges between 0 and N[15], hence it is asymmetric as the TRCA index, with which it is perfectly correlated.

The pattern of international technological specialization at any one point in time can be

[14] It can be easily shown that:

$$RTA_{ij} = TRCA_{ij} / \frac{1}{N} \sum_j TRCA_{ij} \tag{3}$$

The TRCA measure is normalized by its cross-sectional mean in order to abstract from the changes in the average extent of specialization that it is subject to. In this way, it is always possible to follow movements of a country's specialization in a field with respect to its average specialization level.

characterized by the distribution of RTA across sectors. Hence, evaluating the dynamics of patterns of international technological specialization over time requires an analysis of the evolution of the entire cross-section distribution of RTA. This involves two different, but related issues. On one hand, there is the issue of the changes in the overall degree of international technological specialization, which may be evaluated by analyzing the evolution of the *external shape* of the RTA distribution. Do we observe an increasing specialization in a limited subset of technology fields (a polarization of the RTA distribution towards extreme values), or has the degree of specialization remained broadly unchanged?

On the other hand, there is the issue of persistence versus mobility in international technological activities. This addresses questions of *intra-distribution dynamics*, such as: what is the probability that a technological sector moves from one quartile of the RTA distribution to another? Are all the sectors in which $RTA_{ij} > (<) 1$ at time t, still specialized (de-specialized) at time $t+k$ ($k \geq 1$)? If not, at what level of specialization is the greatest degree of mobility observed, and how far are those sectors moving towards low (high) values of RTA?

The present study mostly differs from previous empirical studies on technological specialization in that it directly addresses these two fundamental issues[16].

The evolution of RTA distribution over time is here modelled adopting a distribution dynamics approach, a technique recently developed by Quah (1993a, 1996a, 1996b, 1996c) to analyze income convergence in the cross-country growth literature. This empirical methodology is more informative than the ones adopted in previous empirical studies because it exploits both the cross-sectional and the time series variability in the data.

The analysis presented in the following pages will address the first issue above (*changes in the external shape of the distribution*) by estimating the distribution of RTA across technology fields for

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[15] Note that the maximum value *TRCAij* can take varies both in time and across countries. *TRCAij* is highest when country *i* only applies for patents in sector *j* and no other country does. In this particular case, *TRCAij* reduces to $(\sum_{ij} P_{ij}) / P_{ij}$, which differs among countries, while *RTAij* is equal to N.

[16] Cantwell (1989), Amendola, Guerrieri and Padoan (1998) and Laursen (2000) employ the Galtonian regression model, which may suffer of the well-known Galton's fallacy (Hotelling 1932; Friedman 1992; and Quah 1993b). In Archibugi and Pianta (1992a, 1992b, and 1994) changes over time of the profile and degree of specialization are analyzed by looking, respectively, at the correlation coefficients of the TRCA vectors at different time periods and at the evolution of the chi-square index over time. Only Stolpe (1995) uses the same

each country. It will then shed light on the *persistence vs. mobility* issue, where persistence will be interpreted as a measure of the probability of remaining in the state in which a country initially is. Namely, if a country is specialized in a sector, we are interested in knowing what is the probability that it remains specialized as time passes by. All the probability density functions, Markov stochastic kernels and transition probability matrices, presented in the following sections, have been estimated from EPO data on 118 3-digit technology classes, classified according to the International Patent Classification (IPC) system, using Danny Quah's econometric shell TSRF.

III CHANGES IN THE DEGREE OF TECHNOLOGICAL SPECIALISATION

In what follows we shall restrict the analysis to the period 1982-1996, thus dropping the very first years of activity of the EPO, which were characterized by a relatively low number of applications. The countries analyzed here include the first ten countries for number of applications at the EPO: Austria, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, United States.

The number of patent applications filed each year at the EPO varies widely across countries. On average, each year US firms apply for 13629 patents, a number well above the average number of applications coming from each of the other countries. The other countries with a relatively high level of patenting activity are: Germany (9094 applications each year, on average), Japan (8724), France (3600), the UK (2719), Switzerland (1684), Netherlands (1554), Italy (1467), Sweden (765) and Austria (397). These numbers imply a share of about 30 percent of all the applications at the EPO for the US throughout the whole period. Germany and Japan have a share fluctuating around 20%; France has a constant 8% share, while the UK has a share declining from 8% in 1982 to 4% in 1996. All the remaining countries have a share lower than 5 percent.

A measure of specialization that can be borrowed from the inequality literature is the widely

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methodology employed here to assess the evolution of patterns of technological specialization in OECD used Gini coefficient. To derive the country specialization Gini, first rewrite the TRCA index in country *i* and technological sector *j* as the ratio of sector *j*'s patenting share in country *i* over sector *j*'s share of total patenting[17]. Then construct the Lorenz curve as follows: rank the TRCA index in ascending order, then plot the cumulative of the numerator on the vertical axis against the cumulative of the denominator on the horizontal axis[18]. The Gini is equal to twice the area between the 45-degree line and the Lorenz curve. If the technological structure of country *i* matches the world technological structure, the Lorenz curve will coincide with the 45-degree line and the Gini coefficient will be zero. The higher the Gini the more specialized is a country.

The evolution of the Gini coefficient for the analyzed countries is reported in Figure 1. The G5 countries have a lower degree of specialization (the Gini coefficient is always below 0.3 except, but only occasionally, for Japan) compared to that of the other countries, which is also characterized by wider fluctuations[19].

Note, that the analysis on patent applications at the EPO shows a tendency towards a declining degree of technological specialization in OECD countries, contrary to previous findings based on US patent data (e.g. Cantwell 1989). This tendency appearing stronger for countries with higher initial degree of specialization. Indeed, a simple cross-section linear regression of the change in the Gini coefficient during the sample period on its initial value reveals a strong and significant negative effect (see regression (3) in Table 3). This result is confirmed when the sample size is extended to include other countries with fewer patent applications at the EPO than the countries analyzed here. Hence, small countries, might be highly specialized in the development of new knowledge and products, but their degree of specialization is declining over time.

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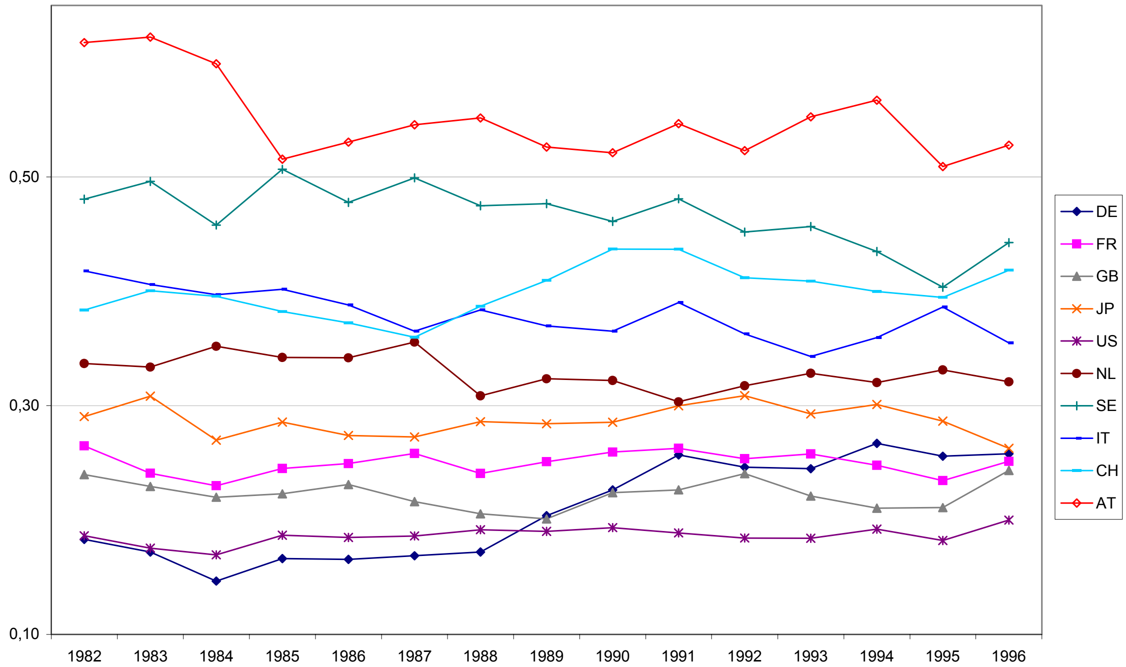
countries, albeit with an emphasis on the distinct dynamics within individual industries.

[17] Hence:

$$TRCA_{ij} = \frac{P_{ij} / \sum_j P_{ij}}{\sum_i P_{ij} / \sum_{ij} P_{ij}} \qquad (4)$$

[18] Note that by constructing the Lorenz curve in this way we are comparing the distribution of country *i*'s patenting across technological sectors to the distribution of the total patenting across sectors and not to the uniform distribution, as it is usually the case (see Amiti, 1999).

Figure 1. *The evolution of the Gini coefficient for country specialization*



However interesting, the analysis on the Gini coefficient can give us a first insight into the degree of specialization of the different countries and its evolution in time, but it is not fully satisfactory. Suppose that there is a transfer in terms of shares from one technological field to another, how does this affect the inequality measures obtained above? The Gini coefficient places a rather curious relative value on changes that may occur in different parts of the distribution. Hence, a transfer from a more specialized class to a less specialized one has a much greater effect if the two classes are near the middle rather than at either end of the spectrum[20]. In both cases, the main problem relates to the difficulties in identifying and evaluating intra-distribution movements, which might also generate changes in the shape of the overall distribution.

To take care of this problem, recall that the pattern of technological specialization can be represented by the distribution of the RTA index across technological fields; hence we can estimate from the data this cross sectional distribution for each country at different time periods. This has been done for all the countries by pooling the observations into three sub-periods: 1982-1986, 1987-1991,

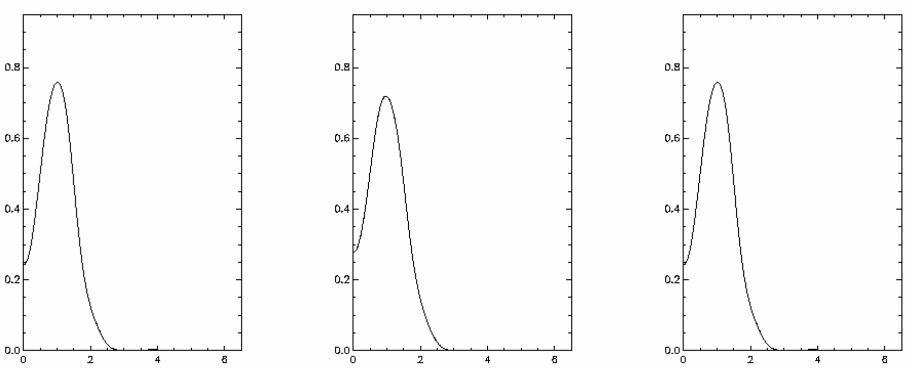
[19] Note, however, the significant change in the Gini coefficient for Germany between 1989 and 1991, as a consequence of the unification with East Germany.
[20] The origin and destination class must be the same distance apart. For further details, see Cowell (1995).

1992-1996 (Figure 2). All the densities are estimated by Gaussian kernel smoothing, taking non-negativity into account and following the procedure and automatic bandwidth choice from Silverman (1986: 2.10 and 3.4.2).

The *US*, *Germany*, *France* and the *UK*, as expected, show a low degree of specialization: they are characterized by a cross sectional distribution centered around 1. For all the countries belonging to this group, the distribution function shows a quite remarkable stability over the three periods[21].

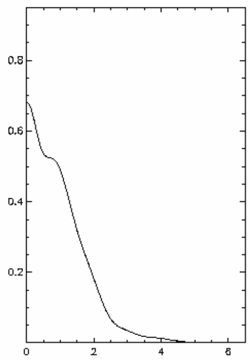
Japan is somewhat different in that it shows a much higher weight of very de-specialized sectors and a consequently higher weight of sectors with high specialization. In other words, Japan shows a greater degree of specialization than that of the above countries (as in Cantwell 1989). This tendency appears less pronounced in the last period, when Japan experiences a widening degree of technological specialization: the evolution of the cross sectional distribution being characterized by a decreasing weight of the very de-specialized sectors and a slight movement towards the right.

Figure 2. *Estimated cross-sectional distributions*

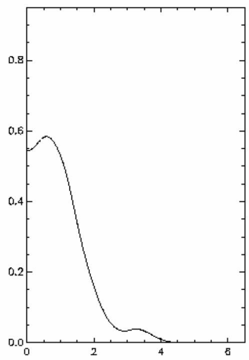


US 1982-1986 US 1987-1991 US 1992-1996

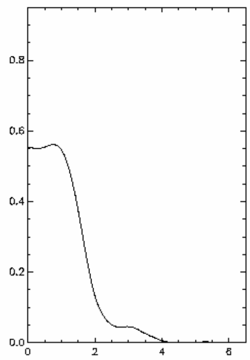
[21] To save space, in Figure 2 the evolving pattern of the cross sectional RTA distribution is reported only for the most representative countries. Density estimation results for the remaining countries can be obtained from the author upon request.



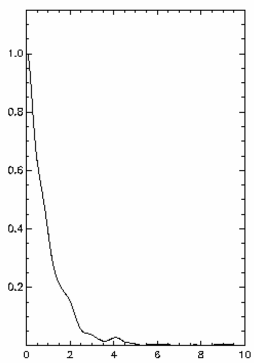
JP 1982-1986



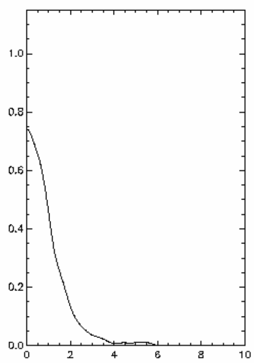
JP 1987-1991



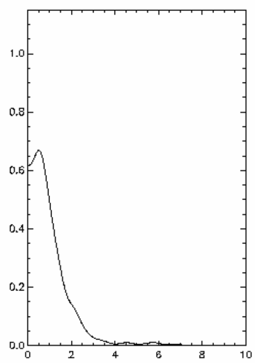
JP 1992-1996



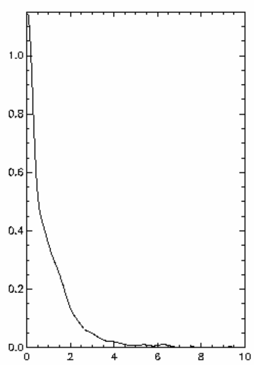
IT 1982-1986



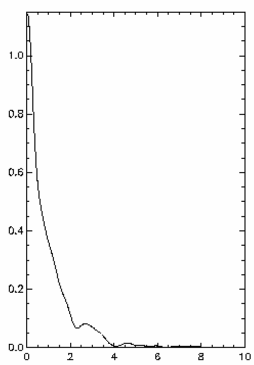
IT 1987-1991



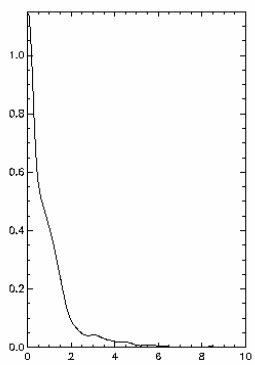
IT 1992-1996



SE 1982-1986



SE 1987-1991



SE 1992-1996

The remaining countries are definitely more specialized than the G5: the cross-sectional distribution of the specialization index has a declining pattern. These countries have a large number of de-specialized sectors, but also values around and above 1 appear to have significant weight.

All these countries, except Italy, appear quite stable with regard to the shape of the cross-sectional density function. *Italy*, however, seems to evolve differently: the weight of highly de-specialized sectors becomes progressively lower and the distribution moves to the right, showing a peak at 0.5 in the last period. This confirms what has happened in the past decades, during which *Italy has moved from a specialization pattern similar to that of small countries towards one more similar to that of the large countries*[22].

Large countries could, however, display a low degree of specialization simply because they themselves make a considerable part of the total world patenting. Since this is especially true for the US, I checked whether the US is really characterized by a low degree of specialization or this property results from the US having an extremely large share of patent applications at the EPO. I calculated the revealed comparative advantage index, excluding US patents from the world technology fields and grand totals, and then estimated again the cross-sectional densities. The resulting cross-sectional distributions, although with heavier tails, were still centered on one, the mean value of the index, thus signaling a low overall degree of technological specialization[23].

IV INTRA-DISTRIBUTION DYNAMICS

Intra-distribution dynamics include information on switches in ranks and on the distance traversed when such switches happen. A way to quantify this phenomenon in a sequence of distributions is to obtain Markov stochastic kernels, which give the conditional distribution of a continuous variable at time t, given its value at time $t+k$. More precisely, assume that the process

[22] A finding that contrasts with the apparent stability of the pattern of Italy emerging from the analysis of Laursen (2000).

[23] Again, the estimated cross sectional densities can be obtained from the author upon request.

governing the evolution of the specialization level of a country in a technology field (i.e. $RTA^{t}_{ij} = X_t$) is a *General Markov Chain*:

$$\{X_t\} : \Pr(X_{t+1} \in A_{t+1} | X_t = x, X_{t-1} \in A_{t-1}, \ldots) = \Pr(X_{t+1} \in A_{t+1} | X_t = x) \quad (5)$$

The law of motion of the sequence of measures $\{\phi_t : t \geq 0\}$ can then be described by a first order time-invariant autoregressive process:

$$\phi_{t+1} = T^*(\phi_t) \quad (6)$$

*T** is a Stochastic Kernel and can be estimated non-parametrically from the data.

For each country, two Markov stochastic kernels have been estimated to represent the conditional probability distributions of the RTA index for one-year and ten-year transition periods. For each cross-sectional unit (i.e. each 3-digit IPC class) a time series from 1982 to 1996 is available. The stochastic kernels here presented were estimated considering every time series as an independent realization of the same process and by pooling all the observations on the transitions between period *t* and period *t+k* (where k is equal to 1 and 10).

The estimation procedure adopted is the following. First, an Epanechnikov kernel is used to non-parametrically estimate the joint density of the comparative advantage of a given country in field *j* at dates *t* and *t+k*, choosing window width optimally, as suggested in Silverman (1986: 4.3.2). This estimated joint density implies a current period marginal density, which is calculated by numerical integration. Dividing the joint density by the estimated marginal gives the conditional density of the specialization index at time *t+k*, given the value it has at time *t*, i.e. the stochastic kernel graphed in Figure 3.

For presentation, the kernels in Figure 3 have been drawn such that the grid lines become more finely spaced where more data were available for estimation. The graphs are obtained for ranges including the 95% of the distribution of observations (i.e. cutting off the right tail), so to avoid the problem of over-smoothing and spikes for very disperse and isolated observations. Contour plots are obtained by projecting vertically onto the floor the stochastic kernels: the contour levels have been chosen to be informative of some of the fine structure in those kernels.

Under assumptions giving consistency for the joint density estimator, the implied marginal is also consistently estimated. Provided then that the true marginal is bounded away from zero, the stochastic kernel is consistently estimated as well[24].

Figure 3 shows the stochastic kernels for 1-year and 10-year transitions in the RTA data between 1982 and 1996[25]. Imagine cutting the one year transition stochastic kernel perpendicularly to the (*Period t*, *Period t+k*) plane, starting from any point on the axis marked *Period t* and extending parallel to the axis marked *Period t+k*. Saying that the stochastic kernel is a conditional probability density function means precisely that the projection traced out is non-negative and integrates to unity. That projection is the equivalent of a row of the transition probability matrix, with non-negative entries summing to 1. This probability density describes transitions over *k* year(s) from a given RTA value in period *t* and the whole graph shows how the cross-sectional distribution at time t evolves into that at time *t+k*.

If most of the graph were concentrated along the 45-degree diagonal, then the elements of the distribution tend to remain around the values where they started. Of course, the greater the dispersion around the diagonal, the heavier the tails of the conditional distribution, and the farther an observation can move away from its initial value (ceteris paribus). If, on the contrary, most of the mass in the graph were rotated 90 degrees counter-clockwise from that 45-degree diagonal, then substantial overtaking occurs (specialized sectors tend to become de-specialized and vice-versa). If most of the graph were concentrated around the 1-value of the *Period t+k* axis -extending parallel to the *Period t* axis- then the cross-section distribution converges towards equality to the world specialization pattern over a *k*-year horizon. More generally, if the conditional distributions appear to be the same regardless of the starting (*Period t*) value, then the stochastic kernel is one where a *k*-year transition takes any

[24] The literature on large-sample properties for density estimation is quite vast: the best reference is Silverman (1986: 3.7) and the references given there.
[25] The same remark reported in footnote 21 applies here.

initial distribution to the same long- run cross-sectional distribution.

For the *United States*, 95% of all the observations in the panel lie between 0 and 1.889, hence the range is quite narrow. Looking at the one-year transition stochastic kernel, innovation production activities in the US appear significantly and quite equally persistent through the whole range, as most of the mass of the stochastic kernel is concentrated around the 45-degree line[26]. On the contrary, but as expected, a greater dispersion signals persistence is less strong over a 10-year horizon.

The range that contains the lower 95% of the RTA values for *Germany* is (0, 1.859), hence very similar to that of the US. Also the 1-year transition kernel is quite similar to the US one, suggesting a significant tendency to persistence for Germany as well. The two countries differ as for the 10-year transition kernel: for Germany, it is characterized by regression towards the mean for values of the specialization index above 1, an interesting feature that characterizes other countries.

France and the UK show similar features. The ranges including the lower 95% of the observations are (0, 2.31) and (0, 2.259), respectively, hence larger than for the US and Germany. This is also true for the dispersion, as confirmed by the height of both the estimated kernels, which are flatter for the UK. Still, as the US and Germany, France and the UK are characterized by persistence, especially for values around the mean of the index (slightly below for the UK). There is, again, a tendency to regression towards the mean for high specialization values, more pronounced over a 10-year horizon.

The lower 95% percent of observations for *Japan* lies below 2.649, hence the range is of the same order of magnitude as that of UK and France, but the dispersion is somewhat lower for the 1-year transition kernel. Persistence is significant throughout the whole range, even if this time the mass is concentrated just above the diagonal. The 10-year transition kernel is, again, characterized by relatively strong persistence and regression towards the mean for values above 1.5.

[26] Note how the conclusions about the US emerging from the cross-sectional distribution and the stochastic kernels analyses do not agree with those of Cantwell (1989), Laursen (2000) and Amendola et al. (1998). This study does not show any tendency of the US towards increasing specialization; rather this country appears as the most remarkable example of stability. Most likely, the reason of the different result lies in the different data sets employed rather than in the different estimation techniques used. As mentioned at the beginning, the home country bias problem may adversely affect the results for the United States if US patent data are employed. This

For the remaining countries, the upper limit of the lower 95% range lies between 2.908 (Switzerland) and 4.169 (Austria); hence, the ranges are wider than those of the first group. The 1-year and 10-year transition kernels of four countries (*Switzerland, the Netherlands, Italy, and Sweden*) have common characteristics. The 1-year kernel's pick follows the 45-degree line, remaining right above it, except for very low values. In other words, over one year, the specialization index shows some sign of persistence around (maybe slightly below) its initial value, when this is not too low. When it is, there is, instead, a tendency to move a little to the right (i.e. to increase), but not very far. This tendency is confirmed in the 10-year transition kernels, while medium and high values are characterized by regression towards the mean. This phenomenon appears stronger for Sweden and Switzerland than for Italy and the Netherlands[27]. Note that for Italy, over ten years, there's a higher probability of very disadvantaged sectors to improve specialization: at very low values the kernel is much more centered around 0.5 on the *Period t+10* axis. Note also that Italy is the only country of the group showing in the 10-year transition kernel a dispersion similar to (and not higher than) that in the 1-year transition. Both these findings are consistent with the different evolution of Italy's cross-sectional distribution, shown in the previous section.

Once again, the stochastic kernels for the US have been estimated excluding US patents from the totals to check for the robustness of the lower mobility (higher persistence) result for large countries. As expected, the estimated stochastic kernels are characterized by higher dispersion. Nevertheless, the one-year transition stochastic kernel is still centered around the main diagonal and so is the ten-year transition one for the range of values of the RTA index above 0.5 and below 1.5, that is in the range where most of the values are observed. Outside this range, the shape of the estimated stochastic kernel is consistent with the asymmetry result[28].

However informative, the estimation of Markov stochastic kernels leaves us with the fundamental problem of evaluating the extent of mobility within a country and comparing it to that of

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would go in favor of a greater reliability of the results obtained here in comparison with those of the earlier studies.

[27] *Austria* is somewhat particular in that the 1-year transition kernel is similar to the 10-year transition one; i.e. it already shows strong regression towards the mean from above.

[28] Also these estimated stochastic kernels and contour plots are available from the author upon request.

the other countries. A way towards quantifying mobility and checking for similarities in the dynamics of different countries is to discretize the state space of specialization index values. The discrete cells obtained span the space of all possible realizations (the interval [0,N] in our case) and can be used to estimate a transition probability matrix by Maximum Likelihood. This is simply done by counting the observed transitions out of each discrete cell into itself or the other cells, and then normalizing this count by the total number of observations starting from that particular cell (Basawa and Prakasa Rao 1980)[29].

Table 2 presents estimates of the probability of transiting between different grid cells of a country's distribution of RTA. This is done for both one-year and ten-year's transition period. In each case, boundaries between the cells have been chosen such that class-year observations are divided roughly equally between the grid cells.

Each panel in the table has to be interpreted as follows. The numbers in the first column are the total numbers of class-year observations beginning in a particular cell, while the first row of numbers denotes the upper point of the corresponding grid cell[30]. Row j includes the estimated probability of remaining in state j (i.e. the element (j,j) of the matrix) and of moving from state j to state s. The final row of each panel gives the implied ergodic distribution.

Estimated values of transition probabilities close to one along the diagonal are indicative of persistence in a country's pattern of RTA, while large off-diagonal terms imply greater mobility. The results of Table 2 for the one-year transition period suggest a significantly high degree of mobility in patterns of international technological specialization in all the countries. This finding is consistent with the visual evidence presented earlier: the stochastic kernels were indeed all characterized by quite a high spread.

The table does not reveal any particular striking difference between the two different groups

[29] It should be mentioned that, when underlying observations are, as in this case, continuous variables, such a discretization could distort dynamics in possibly important ways. The most extreme consequence of this would be a failure of the fundamental Markov property that the state occupied by the system in period t depends only on the state the system occupied in period $t-1$ and not on the previous ones (see Bulli 2001). However, this potential problem is not considered to have a dramatic effect on the estimation results, as the widespread use of transition probability matrices testifies.

of countries identified before. Even for the US all the intermediate grid cells along the main diagonal have values below 0.5, and this is almost always true for all the other countries[31]. Mobility is somewhat lower at the bottom of the distribution: it is more difficult for a country to improve its level of specialization in those technological fields where it is very de-specialized[32].

The difficulty to move out of a situation of strong relative disadvantage signals the importance of own research for the ability of a country to innovate. A country that today does not have enough experience (i.e. accumulated knowledge) and capabilities in a technology area to be an innovator will find it increasingly difficult to innovate in the future. Even if R&D output can be transferred intentionally (through international patents and licenses) or unintentionally (through spillovers), it is not necessarily adopted and further improved in a country unless it has developed itself some previous knowledge in the field, i.e. unless the country has reached some *threshold* level of knowledge[33].

The ergodic distribution of RTA implied by the estimated one-year transition probability matrix was obtained and reported in the last row of each country's panel. Recall the ergodic distribution provides the asymptotic unconditional probability of being in one state, that is the probability of being in one state regardless of the initial state. In each case the ergodic distribution is close to a uniform distribution as a consequence of the discretization criterion adopted (i.e. because the estimated matrices are approximately a fractile)[34].

The second half of Table 2 shows that, as expected, the degree of mobility is even higher over a ten-year transition period. Still, the same tendencies that characterize the one-year dynamics appear

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[30] Note how for Austria the first cell is not an interval, but a single point at zero. This happens because of the great number of zero observations, a clear sign of high degree of specialization

[31] Such a generally high level of mobility should not come as a surprise. Innovation is an activity whose outcome is subject to randomness: jumps in the percentage number of patents applied for by a country in a given sector are to be expected.

[32] Mobility appears lower also at the top, even if to a lesser extent compared to what happens at the bottom of the distribution. Note, however, that the grid cell at the top is defined by a very wide range, whereas the others are not. Given the results of the stochastic kernel analysis, it should be it clear that this could hide possibly relevant dynamics. For this reason, it is preferable not to draw conclusions from the apparently high persistence rate in the top state.

[33] Cohen and Levinthal (1990) first recognized the ability to exploit external knowledge as a critical component of innovative ability and named it "absorptive capacity".

[34] Note that for the stability of the transition probability matrix and the existence of the ergodic distribution the highest eigenvalue has to be equal to 1 and all the others need to be smaller than 1 in absolute value. This happens for all the countries, the first eigenvalue being equal to 1 within a two-digit approximation.

also here[35]. The results for Italy are peculiar in that they show a probability of transition out of the bottom grid cell much higher than that of the other countries. This is consistent with the findings about the changing shape of the cross-sectional distribution in section 3[36].

Table 1. *Some mobility indices.*

	$M_1 = \frac{n - tr(P)}{n-1}$	$M_2 = \sum_k \pi_k \sum_l p_{kl} \lvert k-l \rvert$	$M_3 = \frac{n - \sum_m \lvert \lambda_m \rvert}{n-1}$	$M_4 = 1 - \lvert \det(P) \rvert$	$M_5 = 1 - \lvert \lambda_2 \rvert$
US	0.598	0.665	0.598	0.987	0.292
Germany	0.645	0.740	0.645	0.994	0.321
France	0.710	0.906	0.710	0.998	0.474
UK	0.770	1.012	0.770	0.999	0.556
Japan	0.545	0.574	0.545	0.974	0.232
Italy	0.700	0.869	0.700	0.997	0.431
Switzerland	0.665	0.824	0.665	0.993	0.416
Netherlands	0.645	0.808	0.645	0.992	0.393
Sweden	0.648	0.867	0.648	0.996	0.410
Austria	0.668	0.930	0.667	1.000	0.403

Table 1 calculates a variety of mobility indices (following Shorrocks 1978; Geweke et al. 1986; Quah 1996b) for each of the countries. Each of these indices attempts to reduce information about mobility from the matrix of stationary one-year transition probabilities P to a single statistic. Thus, M_1 evaluates the trace of the matrix (*tr(P)*), M_4 analyses the determinant (*det(P)*), and M_3 and M_5 are based on the eigenvalues λ_j of the matrix. Finally, M_2 presents information on the average number of class boundaries crossed by an observation originally in state k, weighted by the corresponding proportion π_k of the ergodic distribution.

The results in Table 1 confirm that the overall degree of mobility is quite high. Among the countries in the sample, Japan has the lowest value of all the indices: its specialization pattern appears as the least subject to shifts from one year to the next, as measured by the cross boundaries transitions under the stationarity assumption. The US comes right after and seems to be somewhat equally distant from Japan and Germany, which follows. Moving towards higher values of the mobility indices, we

[35] Note that the probabilities estimated over ten-year transition periods differ from the one-year transition probabilities iterated ten times, suggesting that the evolution of the vector of RTA is not fully characterized by a first-order, time homogeneous model, as the one employed here. However, again, explicitly adopting a higher order auto-regression is not considered to influence the estimation results dramatically.

then find a group of three countries very close to each other (the Netherlands, Sweden and Switzerland), followed by Italy and then, surprisingly, by France and the UK. The evidence on Austria is rather mixed.

The asymptotic properties of first-order Markov chains derived in Anderson and Goodman (1957) can be used to test for the statistical significance of the similarities between the dynamics of different countries[37]. The test has been implemented for each pair of countries in both directions (i.e. using alternatively the transition probability matrix of each of the country in the pair as the null). The null is almost invariantly rejected[38], that is idiosyncratic elements are quite strong and do affect the dynamics of countries' specialization patterns. This result is somewhat more striking since it emerges from the comparison of the most advanced countries, hence of those countries we would think as being more similar because of their industrialization level and the intense relations they have with each other. As the literature on national systems of innovation[39] claims, those specificities could originate from the institutions and mechanisms supporting technological innovation, which might greatly differ among countries.

V CONCLUDING REMARKS

The results emerging from the econometric analysis clearly emphasize the existence of two strong *country size effects*: one static and one dynamic. The first one is well known and has been accounted for in previous analyses[40]: *economically "large" countries are less specialized and spread their innovation activities across a wider range of technological fields*. The analysis on the shape of the specialization index distribution has shown that this is fairly symmetric around one for the most

[36] Cefis and Orsenigo (2001) had already found that Italy appears to be less persistent than the G5 countries; this analysis has further shown that this country has been characterized by a probability of moving out of the de-specialization state higher than the other countries and increasing with time.
[37] See Proudman and Redding (1998 and 2000) for an analogous application of the Anderson and Goodman test.
[38] The only exception is the Italy-Switzerland pair, for which the two hypotheses specified above cannot be rejected at the 95% confidence level.
[39] See Nelson (1993).

industrialized countries, with the partial exception of Japan whose distribution is more skewed to the right, but less and less so in time. This static size effect is also confirmed by a simple cross-country linear regression of the degree of specialization, as measured by the Gini coefficient, on the manufacturing output, a proxy for size (Table 3)[41].

Table 3. *Some simple cross-sectional regressions*

	(1)	(2)	(3)
Variable	Gini1982	M2	Gini1996/Gini1982
C	0.411** (7.403)	0.916** (19.22)	1.255** (10.409)
Isic300_82_US	-0.28* (-2.035)	-0.328** (-2.77)	
Gini1982			-0.745* (-2.25)

Note:

(1) Regression for the static size effect. The Gini coefficient is regressed on a constant and each country's manufacturing output (ISIC 300) measured in dollars and relative to US.

(2) Regression for the dynamic size effect. The M2 mobility index (the one also measuring mobility outside the main diagonal) is regressed on a constant and each country's manufacturing output (ISIC 300) measured in dollars and relative to US.

(3) Regression of the change in the Gini coefficient over the sample period on a constant and its initial value.

* Significant at the 10 percent level. ** Significant at the 5 percent level.

Data on manufacturing output and the exchange rate are taken from the OECD STAN database (note that manufacturing output is not available for Switzerland, which had to be excluded from the sample when that variable was involved).

There is then a second size effect, which could not emerge from previous studies. Because the approaches adopted in those studies are fundamentally static in nature and are averaging across observations in various ways, they have difficulties in capturing the genuine dynamic forces characterizing the evolution of countries' technological specialization patterns. The distribution dynamics analysis performed in this study has shown that *economically "large" countries are also characterized by a higher degree of persistence (i.e. lower degree of mobility)*, this result being less

[40] See, for example, Archibugi and Pianta (1992b).

[41] The regressions reported in Table 3 are performed on a relatively small sample size. However, the results are confirmed and even reinforced when the sample size is extended to include other countries with fewer patent applications at the EPO than the countries analyzed here. Regressions (1) and (2) are also relative to the initial year of the sample: the same results are obtained when the regressions are performed, for example on the cross-section of countries in any other year of the sample period.

strong for France and the UK[42]. This means that the specialization level of large countries in individual technology fields displays lower probability of moving around and far from its initial level. Again, this result is confirmed by a simple linear regression of a mobility index on the size of a country (see Table 3, column (2)).

Regardless of the distinction between "large" and "small" countries, the tendency towards *persistence is never pronounced*: technological specialization in advanced countries displays fluctuations around and far from its initial level with a probability almost always higher than 0.5 or more[43]. Furthermore, mobility in technology appears higher than that emerging from trade analyses[44], thus weakening the case for causality from hysteresis in technological development to hysteresis in trade specialization patterns[45].

In other words, this result seems to undermine the theory of technological accumulation, and more specifically the proposition that *international patterns of technological advantage, having been established, will remain relatively stable over periods of ten or even twenty years, under the assumption that only the emergence of new technological paradigms and industries can, in the long term, generate important changes in the specialization trajectories of both firms and countries* (Cantwell 1989).

Mobility is also *asymmetric*: it seems to be mostly difficult for a country to improve the specialization level of very de-specialized technology fields, while highly specialized fields show a fairly general tendency to revert towards lower specialization levels. From both the estimated stochastic kernels and transition probability matrices it emerges a tendency of observations to revert towards the mean, but only from one side of the distribution. Furthermore, *on average, but with the exception of Italy, the probability of remaining a highly specialized country declines more than that of remaining an occasional innovator as time passes by*. This clearly explains the decline in persistence

[42] Recall the results on the mobility indices for France and the UK, which rank them as the most mobile countries among the ten analyzed in detail.
[43] Mobility is also invariantly higher over ten than over one year transition period (Italy being the only exception among the countries here examined), a result consistent with those of Cefis and Orsenigo (2001), who find that persistence in firms' patenting activity declines significantly as the transition period lengthens.
[44] See, again, Proudman and Redding (1998 and 2000) and Brasili et al. (2000).
[45] Recall that localized spillovers should have their most direct effect on technological specialization.

(i.e. the increased mobility) as the transition period lengthens.

Asymmetry in technology dynamics suggests that even if R&D spillovers were international in scope, countries need to have some prior level of knowledge, R&D investment, or complementary assets in the relevant field to be able to understand and employ knowledge produced elsewhere. In the absence of a sufficiently high *absorptive capacity* (Cohen and Levinthal 1990), originated from previous experience in a technology field, countries are not likely to overcome their weaknesses. Since the speed of reversion to the mean from above is inversely related to country size, this result, again, does not support the existence of self-enforcing mechanisms deepening initial specialization patterns, or even locking them in. If that were the case, not only a country should retain its initial comparative advantage in a field and possibly reinforce it, but also this persistence effect should be stronger the more the country's initial specialization pattern is skewed.

In sum, none of the empirical dynamics of technological specialization emerging from the analysis of industrial countries seems to support the idea that there are cumulative and reinforcing mechanisms at work, which could then generate path-dependence in the original technology and trade specialization patterns. These results are complementary to the conclusions drawn in Stolpe (1995), who found that countries' patenting activity in individual industries is less persistent than indicators of trade related specialization in industrial production, thus casting doubt on the often alleged causality from hysteresis in technology to hysteresis in trade specialization.

If then there is, as it seems, persistence in the trade patterns of industrial countries, this must then be the consequence of these countries occupying a relatively stable position in the international economy in terms of factor endowments. Furthermore, the immediate normative implication of this result is that targeted industrial and technology policies might not be effective, because an initial comparative advantage can be eroded by the knowledge on which it is based flowing to foreign competitors. There is, however, one notable exception: policies aimed at building competitive ability in very disadvantaged sectors may take a country out of an otherwise enduring weak position in the international arena.

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Table 2. *Five states transition probability matrices*

One year transition

US	*Upper endpoint*				
Number	0.59	0.87	1.11	1.38	118
332	0.65	0.24	0.06	0.02	0.03
344	0.21	0.44	0.22	0.09	0.04
320	0.06	0.25	0.41	0.21	0.08
333	0.04	0.08	0.20	0.48	0.20
323	0.04	0.03	0.08	0.22	0.63
Ergodic	0.199	0.212	0.193	0.206	0.190

Ten years transition

US	*Upper endpoint*				
Number	0.59	0.87	1.11	1.38	118
123	0.53	0.22	0.08	0.11	0.06
115	0.23	0.39	0.20	0.10	0.08
118	0.10	0.29	0.36	0.19	0.06
112	0.05	0.12	0.23	0.43	0.17
122	0.04	0.06	0.11	0.32	0.47

Germany	*Upper endpoint*				
Number	0.62	0.88	1.085	1.32	118
330	0.66	0.22	0.04	0.03	0.04
338	0.22	0.39	0.23	0.10	0.06
322	0.06	0.24	0.38	0.21	0.11
341	0.03	0.09	0.20	0.45	0.24
321	0.05	0.06	0.10	0.25	0.54
Ergodic	0.206	0.199	0.186	0.210	0.199

Germany	*Upper endpoint*				
Number	0.62	0.88	1.085	1.32	118
104	0.56	0.17	0.12	0.04	0.11
141	0.27	0.30	0.20	0.15	0.08
135	0.09	0.18	0.30	0.27	0.16
106	0.04	0.15	0.19	0.31	0.31
104	0.12	0.05	0.15	0.24	0.43

France	*Upper endpoint*				
Number	0.51	0.75	1.02	1.38	118
324	0.54	0.20	0.08	0.09	0.08
333	0.20	0.37	0.24	0.16	0.04
335	0.07	0.25	0.38	0.22	0.07
337	0.11	0.13	0.23	0.32	0.22
323	0.09	0.05	0.09	0.22	0.55
Ergodic	0.203	0.202	0.206	0.202	0.188

France	*Upper endpoint*				
Number	0.51	0.75	1.02	1.38	118
115	0.55	0.21	0.06	0.08	0.10
114	0.20	0.29	0.27	0.16	0.08
111	0.10	0.25	0.32	0.22	0.11
130	0.11	0.18	0.26	0.22	0.22
120	0.12	0.09	0.13	0.25	0.40

UK	*Upper endpoint*				
Number	0.52	0.8	1.07	1.4	118
332	0.48	0.22	0.10	0.09	0.11
329	0.20	0.35	0.24	0.13	0.07
342	0.11	0.23	0.32	0.23	0.11
320	0.10	0.13	0.24	0.30	0.22
329	0.11	0.07	0.10	0.25	0.47
Ergodic	0.202	0.204	0.201	0.200	0.194

UK	*Upper endpoint*				
Number	0.52	0.8	1.07	1.4	118
124	0.40	0.20	0.06	0.19	0.14
111	0.15	0.34	0.19	0.21	0.11
131	0.17	0.21	0.21	0.27	0.15
92	0.18	0.18	0.17	0.27	0.18
132	0.09	0.13	0.17	0.27	0.33

Japan	*Upper endpoint*				
Number	0.34	0.71	1.06	1.52	118
335	0.63	0.24	0.07	0.04	0.01
335	0.21	0.51	0.21	0.06	0.02
333	0.08	0.21	0.45	0.21	0.05
319	0.03	0.05	0.22	0.51	0.19
330	0.02	0.02	0.06	0.18	0.72
Ergodic	0.185	0.207	0.206	0.203	0.200

Japan	*Upper endpoint*				
Number	0.34	0.71	1.06	1.52	118
141	0.52	0.30	0.11	0.04	0.04
99	0.19	0.35	0.25	0.17	0.03
116	0.09	0.24	0.33	0.26	0.08
104	0.03	0.09	0.18	0.46	0.24
130	0.03	0.05	0.15	0.26	0.51

Table 3 (cont.)

One year transition (cont.)

Italy	*Upper endpoint*				
Number	0.27	0.56	0.89	1.49	118
338	0.47	0.22	0.12	0.09	0.09
330	0.21	0.42	0.25	0.08	0.03
328	0.12	0.21	0.34	0.23	0.09
320	0.08	0.13	0.23	0.38	0.18
336	0.09	0.02	0.07	0.23	0.59
Ergodic	0.187	0.201	0.207	0.206	0.199

Switzerland	*Upper endpoint*				
Number	0.24	0.55	0.85	1.47	118
332	0.51	0.20	0.11	0.09	0.08
333	0.23	0.45	0.20	0.06	0.05
329	0.12	0.21	0.38	0.21	0.08
329	0.07	0.08	0.24	0.41	0.19
329	0.07	0.05	0.07	0.22	0.59
Ergodic	0.203	0.203	0.202	0.196	0.196

Netherlands	*Upper endpoint*				
Number	0.15	0.57	0.95	1.53	118
335	0.56	0.19	0.09	0.09	0.07
328	0.19	0.46	0.23	0.09	0.03
340	0.09	0.24	0.38	0.21	0.08
324	0.10	0.07	0.22	0.40	0.21
325	0.07	0.03	0.11	0.18	0.62
Ergodic	0.198	0.197	0.205	0.196	0.205

Sweden	*Upper endpoint*				
Number	0.03	0.45	0.9	1.55	118
326	0.61	0.08	0.09	0.11	0.11
335	0.08	0.61	0.21	0.06	0.03
335	0.07	0.21	0.37	0.25	0.10
320	0.11	0.09	0.24	0.32	0.24
336	0.12	0.03	0.11	0.24	0.50
Ergodic	0.199	0.204	0.205	0.195	0.197

Austria	Upper endpoint				
Number	0	0.26	0.69	1.57	118
517	0.66	0.04	0.08	0.11	0.12
145	0.18	0.31	0.42	0.08	0.01
330	0.11	0.22	0.41	0.22	0.05
330	0.15	0.02	0.27	0.38	0.18
330	0.19	0.00	0.04	0.20	0.57
Ergodic	0.307	0.089	0.208	0.202	0.194

Ten years transition (cont.)

Italy	*Upper endpoint*				
Number	0.27	0.56	0.89	1.49	118
154	0.26	0.30	0.17	0.18	0.09
107	0.16	0.36	0.29	0.17	0.02
107	0.10	0.21	0.29	0.31	0.09
98	0.09	0.11	0.29	0.26	0.26
124	0.07	0.06	0.14	0.26	0.47

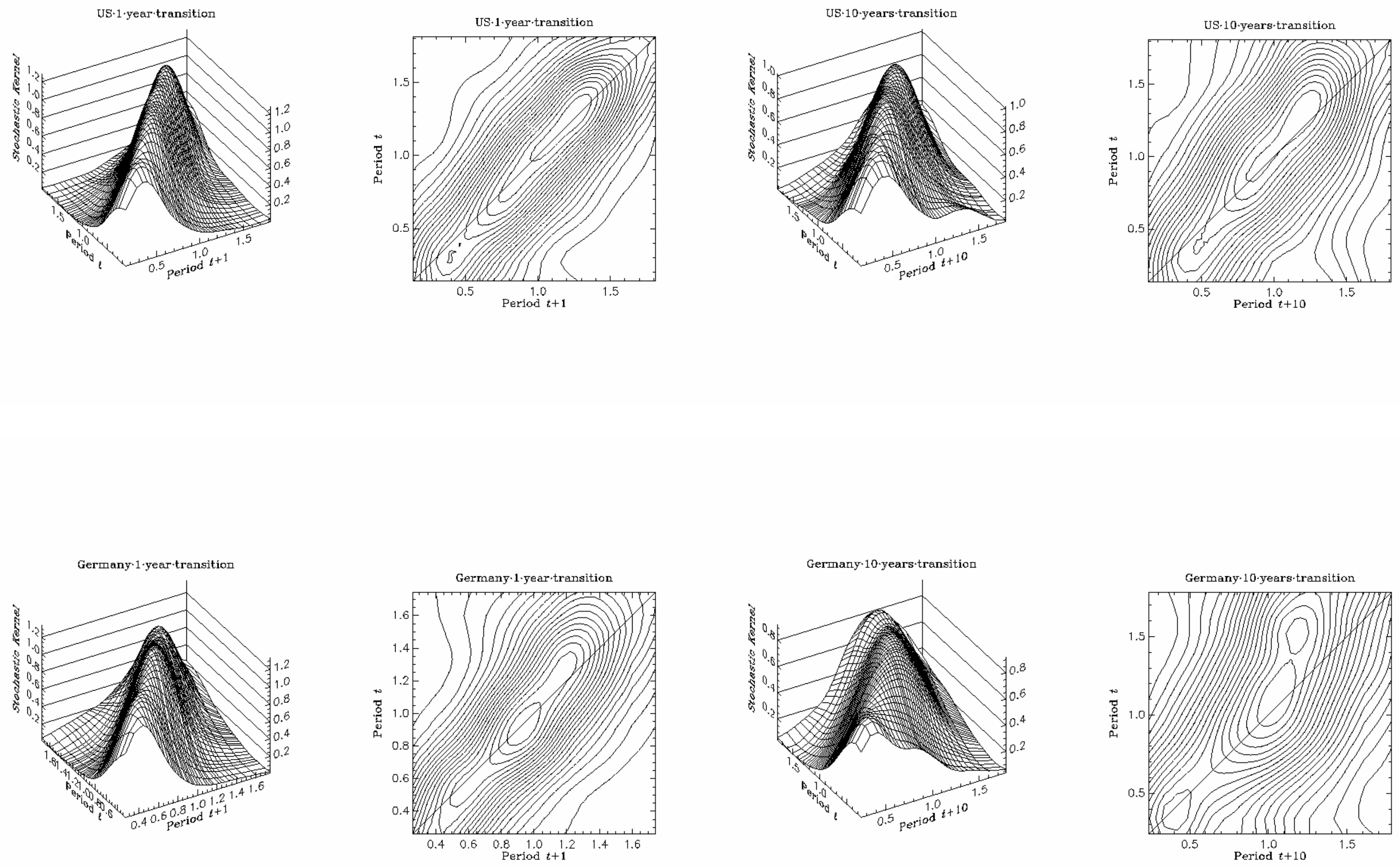
Switzerland	*Upper endpoint*				
Number	0.24	0.55	0.85	1.47	118
118	0.52	0.14	0.09	0.17	0.08
115	0.17	0.41	0.23	0.11	0.09
120	0.17	0.27	0.27	0.20	0.10
110	0.09	0.13	0.26	0.26	0.25
127	0.10	0.07	0.14	0.29	0.39

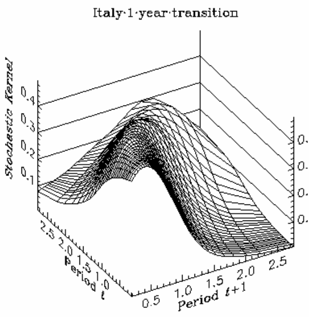
Netherlands	*Upper endpoint*				
Number	0.15	0.57	0.95	1.53	118
136	0.53	0.18	0.10	0.09	0.10
115	0.19	0.43	0.23	0.11	0.04
123	0.06	0.17	0.31	0.28	0.18
107	0.09	0.12	0.18	0.28	0.33
109	0.08	0.08	0.10	0.21	0.52

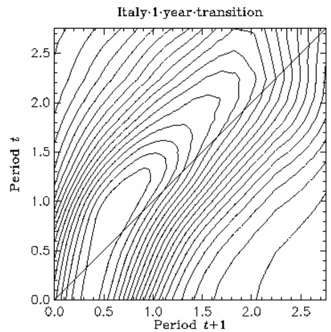
Sweden	*Upper endpoint*				
Number	0.03	0.45	0.9	1.55	118
120	0.58	0.10	0.10	0.10	0.12
118	0.04	0.50	0.24	0.18	0.04
111	0.11	0.22	0.35	0.23	0.10
113	0.14	0.11	0.25	0.27	0.24
128	0.16	0.05	0.14	0.30	0.36

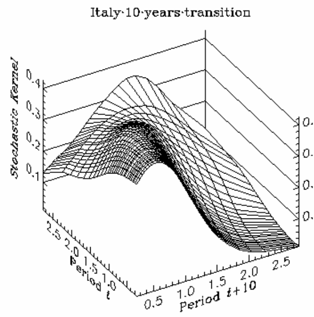
Austria	*Upper endpoint*				
Number	0	0.26	0.69	1.57	118
213	0.55	0.04	0.09	0.16	0.16
47	0.13	0.32	0.49	0.06	0.00
101	0.14	0.18	0.41	0.22	0.06
105	0.21	0.07	0.24	0.30	0.18
124	0.20	0.00	0.11	0.31	0.38

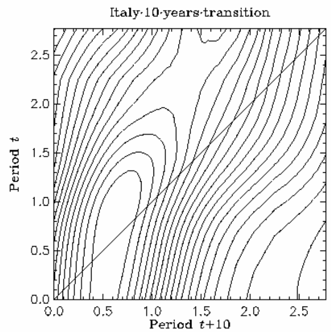
Figure 3. *Estimated stochastic kernels*

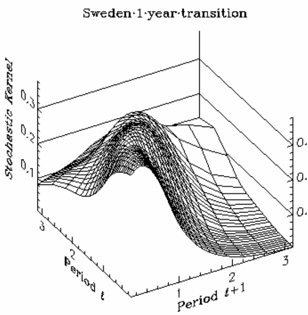


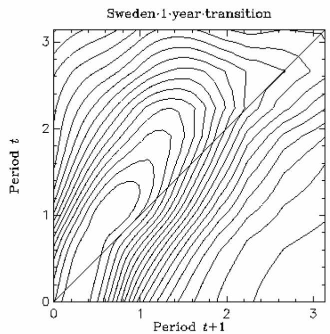

Italy 1 year transition
Stochastic Kernel
Period t
Period t+1

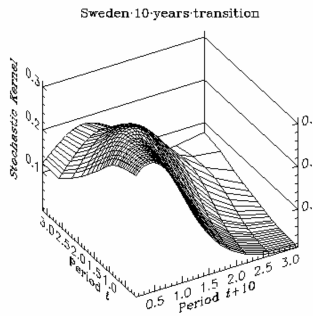

Italy 1 year transition
Period t
Period t+1

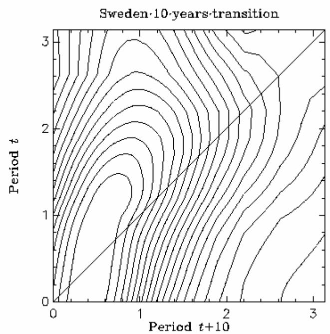

Italy 10 years transition
Stochastic Kernel
Period t
Period t+10


Italy 10 years transition
Period t
Period t+10


Sweden 1 year transition
Stochastic Kernel
Period t
Period t+1


Sweden 1 year transition
Period t
Period t+1


Sweden 10 years transition
Stochastic Kernel
Period t
Period t+10


Sweden 10 years transition
Period t
Period t+10