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7 The Demography of Clusters—Findings from the Cluster Meta-Study

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Industry clusters have become the focus of public debate, economic policy, and academic research. This is a relatively recent phenomenon. A quick search using the Lexis/Nexis news retrieval service shows that just a decade ago, in 1990, when the "Competitive Advantage of Nations"[1] which stresses the importance of industry clusters first appeared, the major newspapers in the English-speaking world ran only four articles in which the term "industry cluster" occurred. By 1993, this figure had increased to 27, followed by 105 in 1996, 280 in 1999, and 409 articles in 2001. Some of these articles make only cursory mention of industry clusters while others may contain only anecdotal cluster information. Many others, however, contain detailed information on specific clusters.

Parallel to this development in the popular press, a similar increase in interest can be observed in the economic development literature. Industry clusters have increasingly become an important focus of economic development policy. With cluster initiatives having taken place or taking place in at least 39 countries, as well as at least 22 states of the United States, there now exists a large body of cluster studies with a wealth of information on individual clusters all over the world.

A third thrust has been academic research into clusters. A body of theoretical literature has emerged, much of it only in recent years. It includes research on growth poles, linkages, agglomeration economies, economic geography, urban and regional economics, national innovation systems, regional science, industrial districts, and social networks.[2] While theoretical in focus, many of these studies contain also detailed information on individual clusters.

Many quantitative studies involving industry clusters have been published. They are usually restricted to individual clusters or countries, or, if cross-sectional, are narrow in focus. Thus, for example, there are studies investigating networks in packaging machinery clusters or technical discontinuities in watch-making clusters and there are studies researching R&D spillovers in clusters, inter-firm cooperation and clusters, or innovation in clusters.

To our knowledge, however, there have been no attempts at pooling the information from these studies, similar to what is done in meta-analyses in medical research or the social sciences, which systematically search and quantitatively

[1] Porter, Michael E. The Competitive Advantage of Nations. New York, 1990.

[2] For a review of the theoretical cluster literature see Porter, Michael E. Clusters and Competition, p. 207; in: Porter, Michael E. On Competition. Boston, 1998.

combine the results of studies that address a similar research question and then isolate moderator variables and verify their overall impact on the relationship being studied.

There are perhaps good reasons why we don't see any meta-analyses in cluster-related research. For one, meta-analysis has its known shortcomings even in the medical or social sciences. Publication bias is a major one of these shortcomings. It results when only certain outcomes, such as significant treatment effects, are reported while other outcomes are ignored, because they are negative or may not be deemed worthy of publication. Publication bias is a serious limitation, but can be reduced by making extra attempts at including all types of studies, even unpublished ones. To some extent the effects of publication bias may also offset one another, thus alleviating the problem somewhat. Thus, successful clusters may get more press in general, but this bias may be offset by the cluster development literature which often focuses and reports on less competitive clusters.

Nonetheless, there are even more serious reasons for the absence of meta-analyses in cluster research. First, in medical studies the dependent variable is usually well-defined. In studying the influence of a particular medical treatment on a certain type of cancer, it is clear that the incidence of healing or the ensuing rate of death will be the dependent variable. Cluster research, on the other hand, is interested in a variety of outcomes, such as the rate of innovation, job creation, wealth creation, market share, labor wages, or company survival. A second reason is that cluster research, and cluster studies in particular, tend to be much more qualitative than quantitative in nature, making it more difficult to pool data from different studies. A third and somewhat related reason behind the absence of meta-analyses in cluster research is that unlike the case in the medical or social sciences there is no standardized methodology for analyzing clusters. In fact, there is not even agreement on a common definition for competitiveness, let alone on how to measure it in a uniform way. Nor is there a common definition for a cluster. Inadequate and non-conforming designs of the underlying studies may well be the biggest problem that confronts the researcher who seeks to combine information from cluster studies.

With these obstacles in mind we set out not to conduct a formalized cluster meta-analysis, but what for lack of a better term we now call a cluster meta-study (see Table 7.1). Our meta-study pools information from a large number of original sources, but unlike the case with meta-analysis, these are non-experimental case studies with large amounts of non-standardized, qualitative data.

Table 7.1 Meta-Analysis vs. Meta-Study

Meta-Analysis	Meta-Study
Based on experimental studies	Based on non-experimental information
Primarily quantitative data	Codifies primarily qualitative data
Underlying studies are quite uniform	Underlying studies are not uniform
Focus on reporting studies	Clusters as the unit of analysis
Tests the impact of one or several variables on a dependent variable	Captures the universe of available studies
Seeks to prove a causal relationship	Descriptive statistics and associations

Our project has three objectives:

1) to systematically collect as much literature as possible on clusters,
2) to create a uniform template to gather a large variety of quantitative and qualitative data about clusters from this literature, and
3) to quantitatively analyze this data with respect to cluster evolution, cluster structure, cluster competitiveness and the reasons behind it.

7.1 Bibliography of Studies

Compiling as many studies and reports on clusters was the first step in this project. While collecting cluster literature and adding to our cluster bibliography remains an ongoing part of this project, we think we have already assembled a substantial and representative portion of the relevant literature. Currently our bibliography consists of more than 370 entries, including 185 research or fact-oriented documents, and 129 cluster initiative and cluster development oriented books and articles. The remaining studies are theory-oriented with only cursory cluster information or have not yet been evaluated.

We strove to collect as broad a range of cluster literature as possible, with the extremes ranging from detailed one-hundred-page studies of single clusters to cursory mentions of a cluster in newspaper articles. As of this writing, some 210 entries in our library contain detailed data on clusters, while 75 contain only cursory or anecdotal information. The remaining entries have not yet been referenced.

To minimize publication bias we have been actively searching for unpublished studies. Our bibliography currently contains 80 unpublished documents. In addition, we have begun to augment the published information with our own data, coding it as such in these cases. In doing so, we hope to not only reduce the type of publication bias described above, but also to correct data which may be biased or limited by the original researcher's knowledge or belief systems. This may be the case, for instance, in cases where rivalry is considered harmful and thus not further researched as a possible reason behind the cluster's competitiveness or when factor conditions are deemed most important and get overemphasized without further analysis.

Our library currently contains information on 833 clusters in 49 nations of which 25 are developed nations and 24 are developing nations. Clusters from developing countries represent 20.3% of the total, which possibly reflects more the current state of reporting on clusters than the actual distribution of clusters in developing and developed countries.

7.2 Cluster Template

Following the compilation of our library, we created a detailed cluster template to facilitate data entry and analysis in a standardized form. It consists of 120

variables which allow us to collect information ranging from basic descriptive statistics such as a cluster's name, location, or employment to more difficult to acquire statistics such as its competitiveness as measured by its world export share, growth, or ability to innovate, to complex qualitative statistics concerning the reasons behind its competitiveness, its initial rise or its decline. Clearly, there are even more variables which we would like to include in the template. Besides making it more unwieldy, however, and after having looked at dozens of studies, we feel that we have included the relevant variables which capture most of the richness of a cluster.

The template is divided into five sections (see Table 7.2). The first section contains biographical information for the underlying cluster studies, basic statistics showing the number of qualitative and quantitative observations for the cluster in question, and descriptive statistics about the cluster, including which generic cluster it belongs to (Materials, Forest/Paper, Petroleum and Petrochemicals, Semiconductors, Multipurpose, Transport, Power Generation and Distribution, Office Materials, Telecommunication, Defense, Food, Textiles, Housing, Health, Personal, and Leisure), which generic vertical stage it is primarily associated with (Primary Goods, Primary Services, Production Machinery, Inputs, Support Services, Multiple Stages), the number of companies in the cluster, as well as employment data.

Table 7.2 Cluster template

CLUSTER
Biographical information
LOCATION
Geographic boundaries
Regional economic development
STATE OF COMPETITIVENESS
Indicators of competitiveness
DIAMOND
Factors conditions
Demand conditions
Related & supporting industries
Firm strategy & rivalry
EVOLUTION
Cluster birth
Cluster decline

The second section consists of locational variables, including information about the nation, region, and city the cluster is located in, it's geographic bounds (from geographically concentrated to more dispersed), the size of the cluster's country, and the size of the area the cluster is located in. This section also contains data about the economic development of the cluster's region, including GDP, regional per capita income, and whether the cluster's nation is an OECD member country or not.

A third section contains an assessment of the cluster's current competitiveness. Some of the variables in this section are fairly straightforward, such as the

cluster's world export share, annual growth, and annual export growth. Others are more difficult to obtain or quantify. These include assessments of the cluster's competitiveness relative to other competing clusters worldwide, its change in competitive position, and its national and local economic importance. They also include appraisals of the cluster's international marketing capabilities, branding and diversification strategies, innovativeness, adoption of generic strategies, and foreign direct investment behavior, both inward and outward.

The fourth and largest section concerns the reasons behind the cluster's current competitiveness. Following the structure of the diamond model set forth in Porter's "Competitive Advantage of Nations", most variables are assessments of individual aspects of the diamond, from general and specialized factor conditions, local demand conditions, and related and supporting industries, to the context for strategy and rivalry. Two other factors, the role of chance and government, are also thoroughly assessed in this section. With many variables the scale ranges from "strong advantage" to "neutral" to "strong disadvantage" to the cluster's competitiveness. We are trying to aggregate narrowly defined variables into broader ones and these into even more broadly defined variables in this section. For instance, variables regarding the timing of local demand and local demand sophistication are "rolled up" into a broader variable about local demand qualities, which in turn, is rolled up into a variable about local demand size to determine an overall demand conditions variable. Ideally, the individual rankings of the lower-level variables should numerically be computed into the ranking of the next higher-level variable. We have found this to be impracticable, because lower-level data is often missing. In addition, the same variable often has a very different impact on different clusters, making the use of a uniform algorithm for calculating higher-level variables impossible.

The fifth and last section is concerned with the cluster's evolution over time and the reasons behind it. Following an initial variable about the cluster's current stage of development, there are variables about the cluster's date of establishment and the reasons behind its rise as well as variables about the beginnings of the cluster's demise, and, once again, the reasons behind that. We have been able to collect a considerable amount of information about the reasons behind cluster establishment. Finding data about the fall of clusters is not as easy and will remain a focus of subsequent work of our study.

In the template most every variable is separated in fields, the first being a numeric field containing a ranking from –3 to +3 on a seven point Lickert scale, the other being a text field to be used for additional explanations and descriptions. Developing a taxonomy for each variable has been a challenge. They have to be uniform in scale and unambiguous with minimum room for interpretation. The wide variety of underlying data makes this difficult and sometimes impossible. We are still revising the scales from time to time. Every revision forces us to go back and verify all rankings for the existing data in our database—a procedure that is greatly facilitated by the existence of the descriptive fields mentioned above.

The homepage of the Institute for Strategy and Competitiveness contains a section about the cluster meta-study under the address http://www.isc.hbs.edu/econ-clustermetastudy.htm. Among others, it shows the template for three representative clusters: The watch cluster in Hong Kong, the tufted carpets cluster in

south-west Flanders in Belgium, and the oil and gas cluster in Houston. This may demonstrate the template better than any description.

Besides its initial purpose as a data-collection and -analysis tool for the cluster meta-study, we have found the cluster template to be a useful instrument for profiling clusters and assessing their competitiveness in a standardized way. It also facilitates a quick and uniform display of information about individual clusters.

7.3 Basic Data Description

The following represents a first analysis of our data based on a total of 773 clusters that can be quantitatively evaluated. These clusters represent a total of 26,035 observations of which 14,069 are quantitative observations to the wide variety of our information sources, all clusters in our database suffer to differing degrees from missing data. Some clusters have up to 140 observations of which up to 85 can be quantitatively evaluated (the rest being supplementary descriptive observations), while the least developed cases have less than ten observations of which only 5 can be quantitatively evaluated. The 773 clusters currently have on average 32 observations of which 18 can be statistically evaluated. Right now, of the 120 quantitative variables in our template, 59 have more than 50 observations and another 20 more than 30 observations, permitting us to conduct some first and preliminary analysis.

This is work in progress and we will continue to add to the database in the future. We do not claim that our sample is precisely representative of the world's clusters. We believe, however, that it is the largest and most representative one that has ever been assembled. It is time to begin to analyze and learn from it. Even if we can only provide some first statistics and some results may be imperfect, a beginning had to be made. There is a need to finally go beyond single case studies. Facts and results are required. Hopefully these will then serve as a roadmap for future research.

7.3.1 Location

The sample that we evaluated currently contains clusters from 49 countries, including 612 from 25 developed nations with per capita GDPs higher than $15,000 and 161 clusters from 24 developing nations. With 144 clusters or 18.6% of the total sample, the United Kingdom accounts for the largest number of clusters, followed by the United States, India, France, Italy, Denmark, and Germany with 141, 106, 82, 72, 34, and 29 clusters, respectively (see Table 7.3). These numbers are unlikely to be representative of the true population of clusters in these countries and may reflect to some extent differences in public and academic interest in clusters in the respective countries. Nonetheless, we do think that the number of clusters in our database is already sufficiently high to allow some first careful analysis.

Table 7.3 Location of clusters in the database

25 Developed Nations				23 Developing Nations			
2	Andorra	72	Italy	3	Brazil	5	Morocco
4	Australia	4	Japan	1	Chile	1	Nepal
7	Austria	6	Netherlands	1	Colombia	1	Pakistan
1	Belgium	10	New Zealand	2	Costa Rica	8	Palestinian Auth.
1	Bermuda	1	Norway	3	Ecuador	1	Poland
13	Canada	4	Portugal	1	Estonia	2	South Africa
34	Denmark	3	Singapore	1	Ghana	1	Taiwan
11	Finland	6	Spain	106	India	1	Thailand
82	France	5	Sweden	4	Jordan	1	Turkey
29	Germany	13	Switzerland	4	Kenya	2	Venezuela
11	Hong Kong	144	United Kingdom	3	Lebanon		
2	Ireland	141	United States	1	Malaysia		
6	Israel			8	Mexico		
612	**Clusters from Developed Nations**			**161**	**Clusters from Developing Nations**		

Note: Developed nations = 2000 GDP per capita greater than $15,000. Only clusters which were evaluated in subsequent analysis are included.

An important question for which we are trying to find answers is how geographically concentrated clusters are. Our data suggests that clusters tend to be highly concentrated. Of the total of 705 clusters for which we had data, 41.8% were located within the boundaries of a city, followed by 18.9% within a metropolitan area, 19.9% within part of a state, and much lower percentages of clusters in a state or nation or across state or national borders. (Note that to some extent this is a tautological question: All clusters are geographically concentrated, otherwise, by definition, they wouldn't be clusters. Thus, it is the degree of geographic concentration we are interested in, not if they are concentrated per se.)

7.3.2 Size

The clusters display a wide variation with respect to their size, although, with a median number of 150 companies per cluster, it is clear that small clusters tend to be the rule. Of 382 clusters for which we have data, 41.6% consisted of less than 100 firms, compared to 13.9% with between 100 and 200 and 9.4% with between 200 and 300 firms. Among the largest clusters, all with more than 9,000 firms, were the textiles clusters in Prato, Italy and in Ludhiana in the Indian province of Punjab, as well as the Dutch flower cluster. Among the smallest clusters in our sample were the Swiss hearing aids cluster and the ion implanting equipment cluster close to Boston in Massachusetts, both with three companies at their core. The latter cluster, which produces a special type of semiconductor manufacturing machinery, is also a good example of how world-leading clusters can get by unnoticed by official statistics: Despite the presence of three companies with a combined world market share of almost 90%, hundreds of skilled employees, world leading research, specialized suppliers and cut-throat rivalry, only industry insiders are aware of this cluster (see Fig. 7.1.).

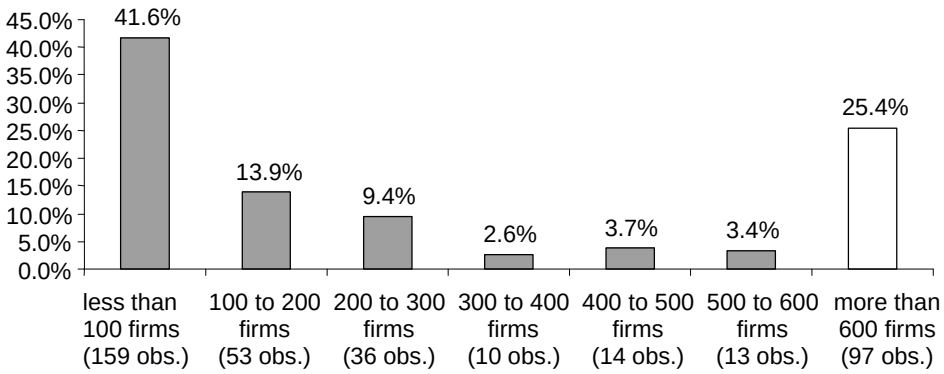

Fig. 7.1 Number of companies in cluster or core industry

Similar to the number of companies, the employment per cluster figures also show that rather small clusters with less than 15,000 employees tend to be the rule. Of 457 clusters with available data, 38.1% had less than 5,000 workers, followed by 12.3% with between 5,000 and 10,000 workers and 8.8% that had between 10,000 and 15,000 workers. Slightly more than a quarter of the clusters in our sample had a workforce of more than 30,000 people. The median employment size was 10,000. Among the largest clusters in terms of employment were the computers and communications cluster in Silicon Valley with an estimated workforce of one million and the automotive cluster in Detroit with a workforce of a quarter million people, while the smallest cluster was the musical instruments cluster in the French village of Mirecourt in the Lorraine, where 8 companies employed 50 people (see Fig. 7.2.).

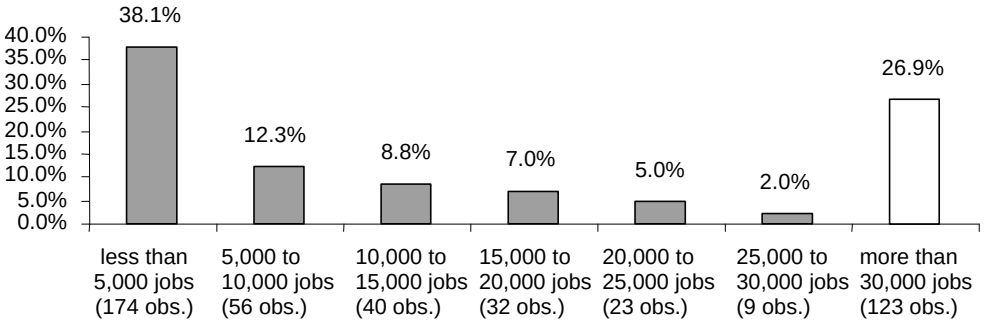

Fig. 7.2 Size of workforce in cluster or core industry

The clusters displayed marked differences in size depending on which country they were located in. Taking median employment per cluster as a measure of cluster size (not averages to prevent results distortion from outliers), we were astonished to see that Canadian, American and British clusters had a median employment of 26,000, 23,831, and 21,000, respectively, compared to Italian, Danish, German, French and Indian clusters with median employment figures of only 5576, 5,000, 5000, 2300, and 5000, respectively. Thus, clusters from the first three countries appear to be four to five times as large as clusters from the latter

five nations (see Fig. 7.3). We cannot explain the reasons for this difference. One might speculate that Anglo-Saxon clusters are larger than other ones, but this would not explain the figure for Canada where most clusters in our sample were from French-speaking Quebec.

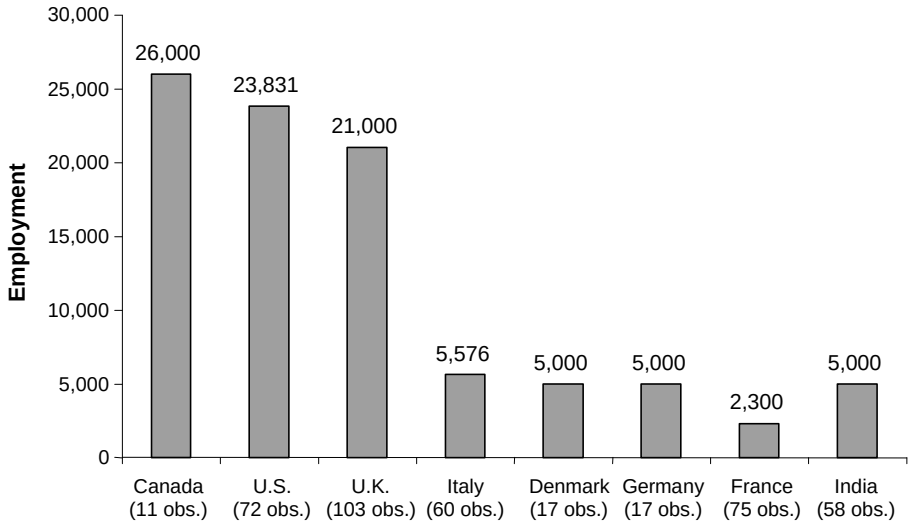

Fig. 7.3 Median cluster size by country

Note that these differences were clearly apparent only with respect to the median of cluster employment, but not with respect to cluster employment averages that may be the result of distortion from outliers. Furthermore, these national differences applied only to cluster employment and were not visible with respect to the median number of firms per cluster. The median for the number of firms in Canadian clusters was 500, compared to 228 in the U.S., 173 in the U.K., 400 in Italy, 94 in Denmark, 76 in Germany, 51 in France, and 200 in India. Again, we cannot explain these wide differences and will have to wait until we have more complete data. Whatever the true reason, it appears to be clear that employment size of clusters in North America and the United Kingdom is much larger than in Continental Europe or India.

7.3.3 Competitiveness

We rated cluster competitiveness using data such as world export share, world production share, or world market share. In cases of less competitive clusters where these shares were too small to be measurable and reported upon, we often had to revert to estimates such as “internationally significant” or “nationally significant”. Of the 429 clusters for which we were able to assess their competitiveness, 11.0% could be considered the world’s strongest cluster in their industry, followed by another 9.3% and 11.4% which were among the world’s 3 and 10 most competitive clusters, respectively. Nineteen, or 4.4%, of the clusters were considered uncompetitive, while 18.4% were weak (see Fig. 7.4).

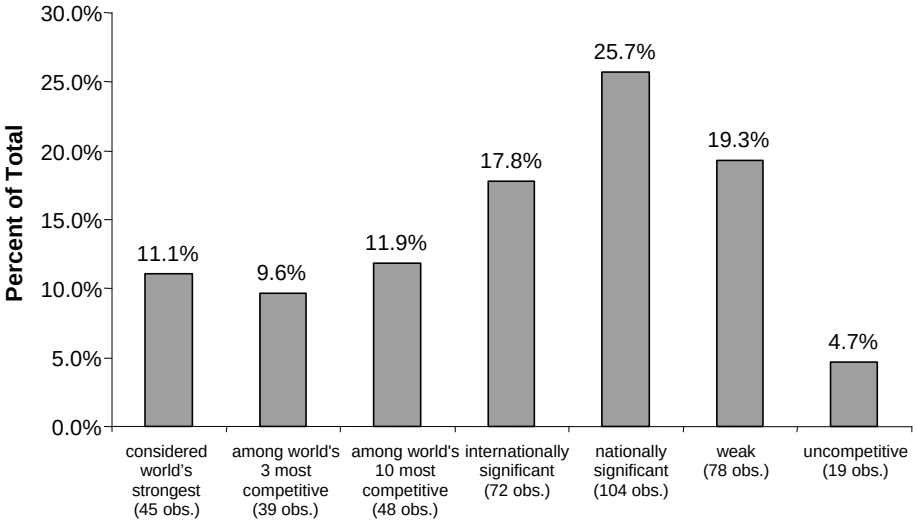

Fig. 7.4 Cluster competitiveness compared to competing clusters

The Swiss clusters in our sample were most competitive, followed by those from Italy, Germany, the U.S., India, Canada, France and the United Kingdom. Some of these differences were statistically significant. Nonetheless, we should refrain from drawing any conclusions from this ranking as to the respective countries' general competitiveness. For most countries the sample size is simply too small and data from some countries may be affected by publication bias (e.g. successful clusters being reported on, others not).

Many clusters are very old and we were surprised at their high average age. For the 205 clusters whose early history we could ascertain with reasonable certainty, the average year of establishment (first company founded, first mention of industry, etc.) was 1861 with a median of 1940. Clusters that had been established before the year 1800 represented 19.5%, compared to 21.5% in the nineteenth century and 59.1% in the twentieth century. A further breakdown of those clusters that were established in the twentieth century shows 8.3% of them to have been established between 1900 and 1925, 28.1% between 1925 and 1950, 37.2% between 1950 and 1975, and the remaining 26.4% in the period between 1975 and 2000 (see Fig. 7.5).

Depending on which country a cluster is based in, there are large and significant differences in the mean and median years of cluster establishment. Clusters in Europe are much older than their counterparts in the United States, New Zealand, or India. The median year of establishment in Europe varies between 1800 and 1823, compared to 1949 to 1955 in the U.S., New Zealand, or India. We may safely assume that these differences are primarily a reflection of the differing economic histories of the respective nations.

The youngest cluster in our sample is the nascent electronics-manufacturing cluster in the Central Valley of Costa Rica that was established only in 1996 and four years later consisted of a few companies engaging in electronics assembly surrounded by another 150 software producers. The oldest cluster is the plastics

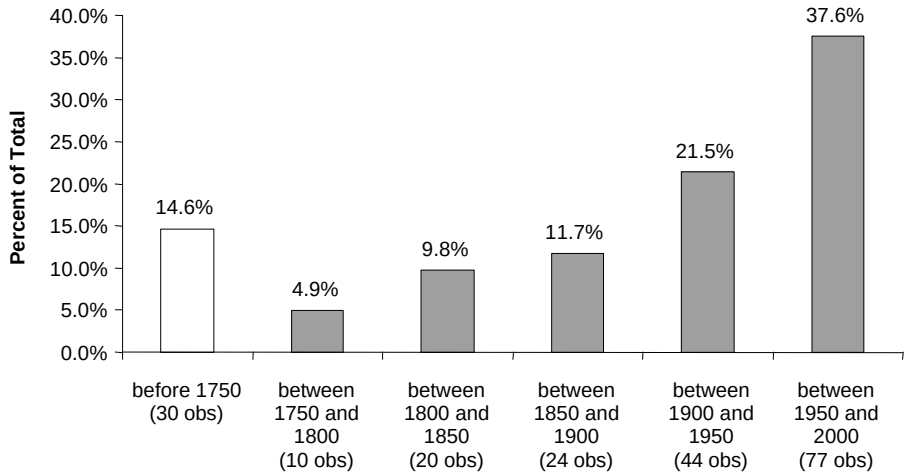

Fig. 7.5 Year of cluster establishment

injection-molding cluster in the small French town of Oyannax. This cluster of 600 firms can trace its history back to the year 630 when the village was given a monopoly to make combs. Wooden combs were followed by celluloid combs in the 19th century which made Oyannax famous. When combs fell out of fashion in the 1920s and 1930s, the unemployed craftsmen reacted and turned to the production of plastic toys, glasses, eyewear, etc. A further innovation was the adoption of injection molding in 1936, which firmly established Oyannax as a French center of plastics manufacturing. By 1998 600 firms with a total workforce of 12,700 produced Euro 1.8 billion worth of plastic toys, eyewear, hair accessories and fashion goods annually.

The surprising longevity of many of the clusters in our sample and their ability to transform and upgrade themselves often over several centuries may partly be the result of the publication bias discussed above: Very old clusters tend to get more press than young and unknown ones. Nonetheless, it is clear that clusters can get very old and stay competitive. We will discuss cluster competitiveness versus cluster age further below.

7.4 Relationship Analysis

7.4.1 Cluster Competitiveness

There appears to be a positive and statistically significant relationship between cluster size in terms of employment and cluster competitiveness. Clusters with employment figures of less than 15,000 were slightly less competitive than those employing more than 15,000 (see Table 7.4). However, no simple relationship, such as that clusters get more competitive as they increase in size, was discernible. In fact, the least competitive clusters in our sample were those employing between 10,000 and 15,000, while those employing less were actually slightly more

competitive. Clusters with more than 30,000 employees were the most competitive in our sample, although compared to other size-categories this difference in competitiveness was statistically significant only in a few cases.

Table 7.4 Cluster size vs. cluster competitiveness

Employment	**<=15,000**	**>15,000**
Median	–1,0	0,0
Mean	–0,5	0,0
Std. Deviation	1,4	1,6
No. Observations	123	144
Z-Statistics:		
<=15,000	0,00	**3,58**
>15,000	**–4,43**	0,00

Note:
3 = world's strongest cluster
2 = among world's top 3
1 = among world's top 10
0 = internationally significant
–1 = nationally significant
–2 = weak
–3 = uncompetitive

Z-statistics < –1.97 or > 1.97 denote a significant difference between the mean years of establishment in the two respective countries.

It is tempting to speculate about the reasons that could have led to this relationship between size and competitiveness. One explanation might be that clusters need a certain size in terms of producers and suppliers in order to fully function and be internationally competitive. With more data we might be able to test this.

We investigated if there was a relationship between a cluster's age and its competitiveness. It is sometimes speculated that clusters may go through a typical lifecycle where they reach their maximum competitiveness after a certain period of gestation, only to then retrograde again and ultimately fail. We cannot identify any such lifecycle patterns in our sample (see Fig. 7.6). Fifty-one percent of the clusters in our sample which had been established between 1950 and 2000 were considered to be among the world's ten most competitive clusters in their respective industries. This compares to 70.8% for clusters established between 1900 and 1950, 68.8% between 1850 and 1900, 87.5% between 1800 and 1850, 30.0% between 1750 and 1800, 50.0% for clusters established before 1750, and 58.9% for the entire sample. It is difficult to discern any patterns from these numbers. This may be due to too small a sample size and we will have to wait until we have even more data and can conclusively answer this question. For the time being we may assume, though, that clusters do not have a typical lifecycle.

The oldest world-leading cluster in our sample is the cutlery industry in the German town of Solingen, which was mentioned first in 1348. Among the youngest world-leading clusters is the multimedia cluster in San Francisco, which was

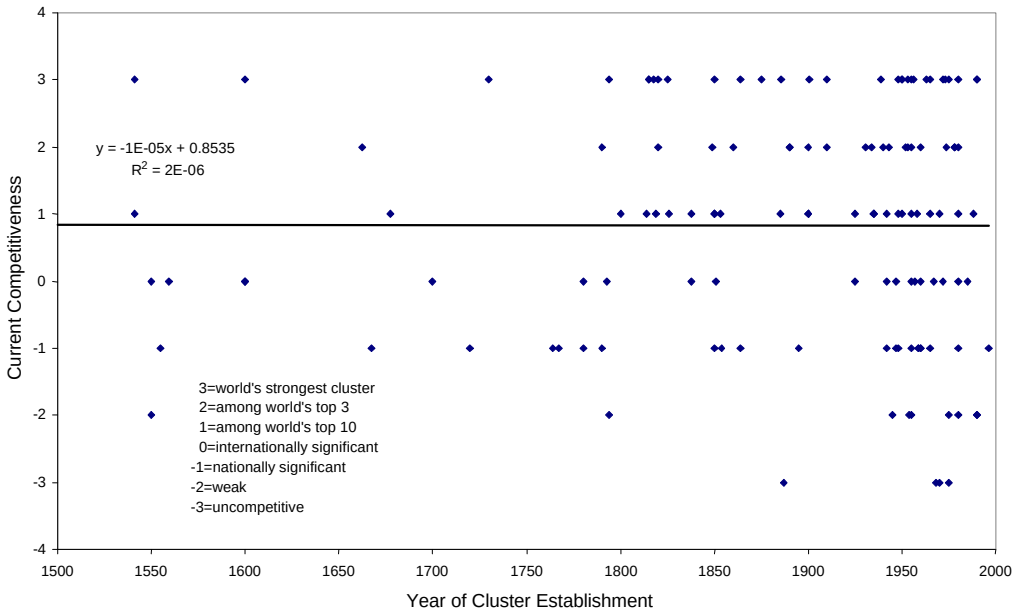

Fig. 7.6 Competitiveness vs. cluster age

established only around 1990. Our data shows that a century-old cluster is just as likely to be world leading as a cluster that was established only a decade or two ago.

Nonetheless, the simple fact that the number of clusters in our sample does diminish as they get older, indicates that clusters have a limited lifespan, although this is measured in centuries rather than decades. Such a limited lifespan would seem to be only natural. As clusters get older, the probability of a major technology shift or other exogenous shock increases. Few clusters can manage to survive major transformations such as the shift from wooden combs to plastic toys or silk to carbon fiber. As time passes, the likelihood of a major technology shift increases and so does the probability that the cluster becomes unable to adapt to it, fails to be competitive, and ultimately ceases to exist.

7.4.2 Determinants of Competitiveness

One of the most important questions we are interested in concerns the drivers of cluster competitiveness. In 158 cases we were able to assess the most prominent reason behind a cluster's competitiveness. For our analysis we relied on the diamond model of competitiveness which was first introduced in "The Competitive Advantage of Nations" in 1991 (see Fig. 7.7). Factor conditions were the most important determinant in 43.0% of these cases. They were followed by demand conditions with 24.7%, related and supporting industries (13.3%), the context for strategy and rivalry (13.3%), and other reasons, including chance, isolated individual entrepreneurs, and early mover advantages, with 5.7% (see Fig. 7.8). Note that these results did not change materially when we controlled for industries that

depend on the extraction of natural resources. An inclusion of too many of these industries would skew the percentages towards factor conditions on which they rely almost by default for their success. However, the sample included only 15 "natural resource extractive" industries, which, when omitted from the analysis, still left factor conditions as the most prominent determinant (37.1% of all cases), followed by demand conditions (27.3%), related and supporting industries (14.7%), the context for strategy and rivalry (14.7%), and "other" reasons (6.3%).

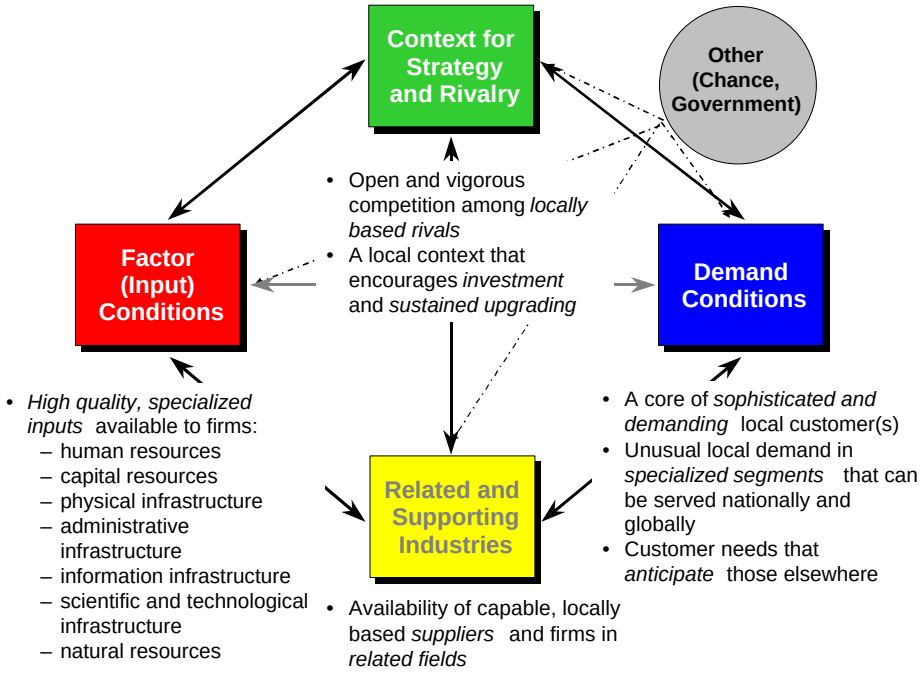

Fig. 7.7 Determinants of cluster competitiveness: The Diamond

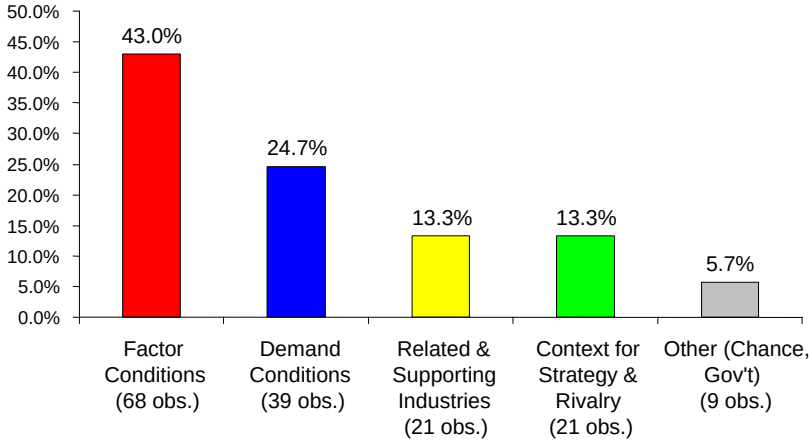

Fig. 7.8 Dominant determinant of current cluster competitiveness

We would like to know if competitive clusters base their success on a different or broader set of determinants than uncompetitive clusters. Once again, our analysis suffers from a lack of observations, as there were only 23 uncompetitive clusters with both competitiveness and determinants of competitiveness data. Nonetheless, it appears as if uncompetitive clusters rely primarily on just two determinants, factor and demand conditions (with related and supporting industries being a distant third), while competitive clusters often rely on all determinants of the diamond. Clearly, rivalry is an important determinant in competitive clusters, while it does not play a role in uncompetitive clusters. Random events or government influence, on the other hand, are the least important determinants in competitive clusters, while they play a much more important role in uncompetitive clusters (see Fig. 7.9).

To further shed light on this question we looked at cluster competitiveness as a function of the most important reason for competitiveness. This analysis clearly suggests a hierarchy of the determinants of competitiveness. Clusters that based their competitiveness primarily on factor or demand conditions were significantly less competitive than clusters that based their competitiveness on related and supporting industries or the context for strategy and rivalry. Clusters whose success rested primarily with "other reasons" such as chance advantages were the least

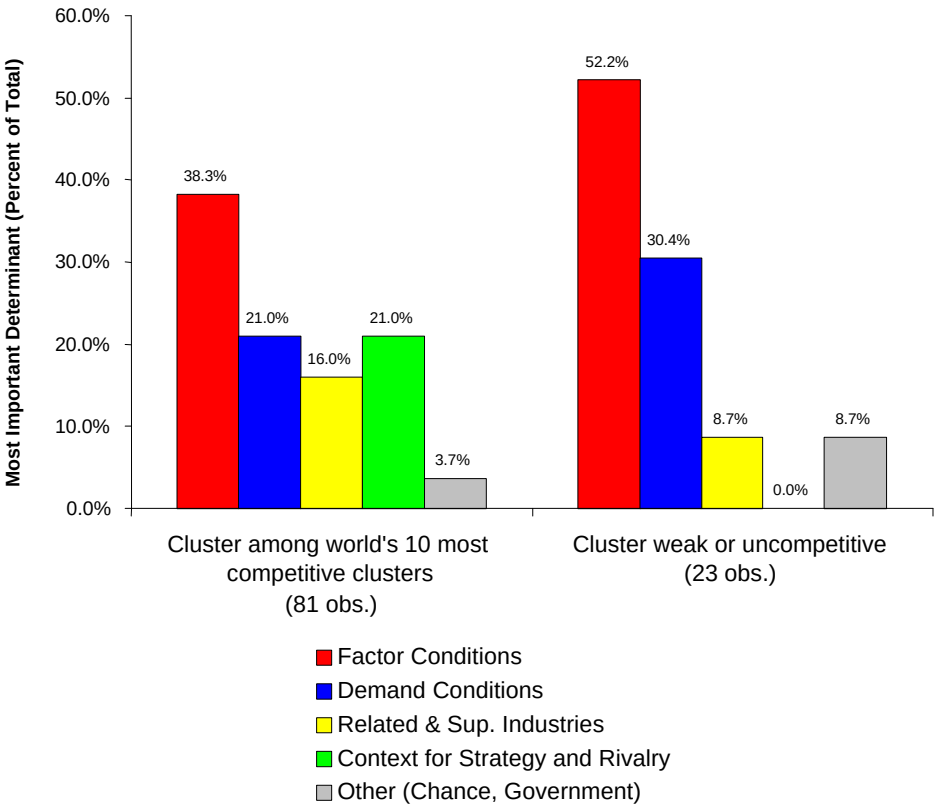

Fig. 7.9 Dominant determinant of current cluster competitiveness in competitive and uncompetitive clusters

competitive, although this difference was significant only with respect to the context for strategy and rivalry and not with the other determinants of competitiveness (see Fig. 7.10).

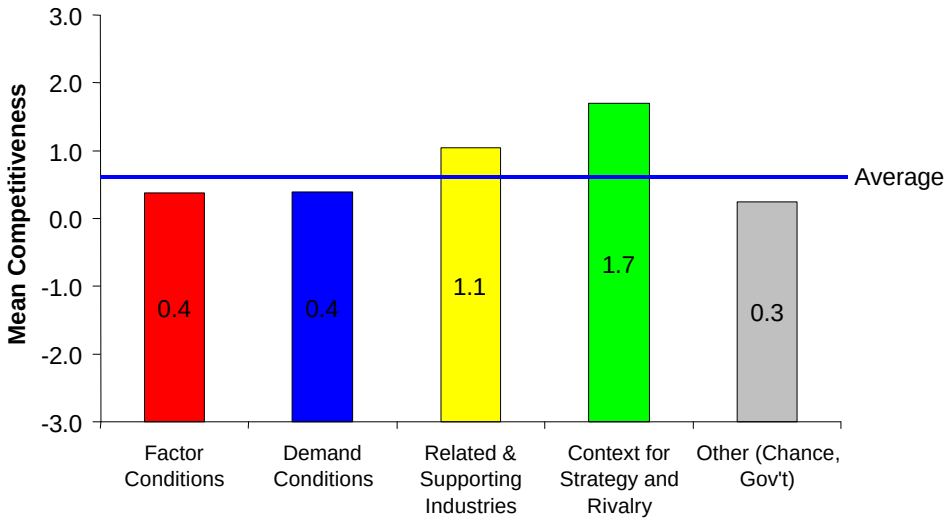

Fig. 7.10 Dominant determinant versus cluster competitiveness

We also analyzed if clusters in developed nations rely on different determinants than clusters in developing nations. Clusters in developing nations rely much more on factor conditions as the primary reason behind their competitiveness than clusters in developed nations. For 66.7% of the clusters in developing nations factor conditions were the most prominent determinant, compared to only 35.3% of clusters based in developed nations. Also, clusters in developed nations often based their competitiveness not solely on factor conditions and demand conditions, as was the case in the developing nations, but on the entire set of determinants in the diamond (see Fig. 7.11). These results appear to be similar to those of the above comparison of the determinants of competitive and uncompetitive clusters. A first thought leads one to suspect that this may be because clusters in developing nations are not competitive, resulting in the two samples being too similar. However, this is not the case as 11 of the 23 uncompetitive clusters in the above analysis were located in developed nations. Nonetheless, the low number of observations once again forces us to treat these findings with caution.

7.4.3 Cluster Evolution

Some major questions for cluster practitioners and economic development agencies concern the reasons behind the initial establishment of clusters. Why do clusters get established in the first place? Is it usually due to favorable local factor conditions, special demand conditions, or the presence of other related or supporting industries close by? Or can public action trigger the establishment of a cluster?

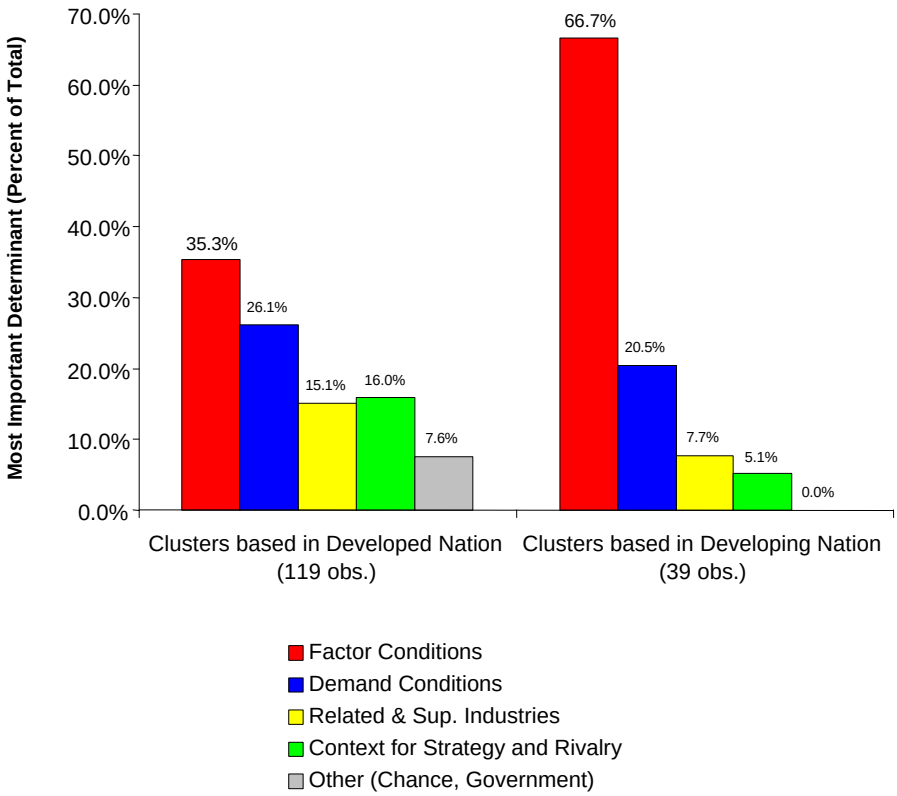

Fig. 7.11 Dominant determinant of current cluster competitiveness in developed and developing nations

Ordinarily, clusters do not get established due to the context for strategy and rivalry, simply because the requisite group of firms does not exist in the cluster's initial phase of establishment. The reason for cluster establishment will usually be one of the other three determinants of competitiveness or chance or a combination of these (see Fig. 7.12).

In our sample factor conditions are by far the most common cause of cluster establishment. They provided the initial impetus for the cluster to get established in 39.8% of the 186 clusters with available data. While it is difficult to provide precise data due to a lack of observations, it appears as if simple factor conditions such as the presence of certain raw materials (e.g. for porcelain in Limoges, France), cheap labor (e.g. watch making in Hong Kong), or special growing conditions (e.g. for shrimp in Ecuador), were initially more important than specialized factors such as a well-trained labor force or a specialized knowledge base in close-by universities.

With 26.3% of all cases, the second most important reason for cluster establishment was what we simply termed "other reasons", i.e. usually random events such as the establishment of a company that proceeded to spawn other companies which formed the nucleus of a cluster (e.g. Boeckler Instruments spawning the optics cluster in Tucson, Arizona), the random presence of an unusually entrepre-

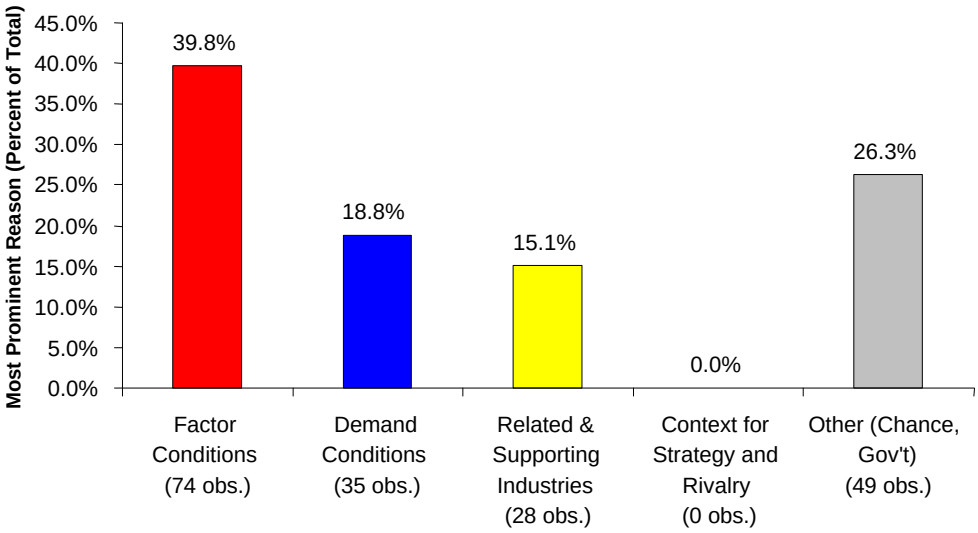

Fig. 7.12 Most important reasons for cluster establishment

neurial individual whose success was followed by others engaging in similar businesses (e.g. Johann Müller beginning to produce mother of pearl buttons which led to the buttons cluster in Bärnau, Germany), or simply a prolonged strike which prompted customers to look elsewhere for purchases (e.g. the Bombay textile mill strike allowing the establishment of the textile cluster in Bhiwandi, India). Such random events constituted the vast majority (73.5%) of "other reasons" which prompted the establishment of clusters. In this context it is interesting to note that a surprising number of clusters can trace their origin to an outsider or even foreigner who provided the initial impetus for its establishment. Might it be possible that fresh and innovative ideas are more difficult to achieve by insiders or locals who are comfortably settled and are less prone to be forced to try something new?

The remaining 26.5% of "other reasons" were represented by government actions. However, these government actions also include the surprisingly high number of clusters that were established following a war or some other political turmoil in another nation. Examples include the Swiss watch and banking clusters which were founded in Geneva by protestant Huguenots fleeing persecution in France, Italy, and Flanders, and by French entrepreneurs fleeing the French revolution, respectively. They also include the German musical instrument cluster in Markneukirchen, Saxony, which was established by violin makers fleeing Bohemia during the Thirty Years War from 1618 to 1648, or the black beads cluster in Varanasi, India which began to develop after a bead making school had been opened there by a gentleman called Handrick who had fled Czechoslovakia during World War II. It appears as if it was more common for governments to drive away clusters to other countries, than to consciously get them established in their own countries.

In our sample we are aware of only one competitive cluster that was established primarily due to a conscious government action to attract it. The electronics goods cluster in the Hsinchu Science Park, Taiwan was established after the Taiwanese

government decided to foster electronics production following a visit in Silicon Valley in the 1970s.

The third most important condition leading to cluster establishment were demand conditions, with 18.8% of all cases. It is quite common that local demand, which could not be satisfied through imports due to closed borders or because it was too specialized to be satisfied from abroad, lead to the establishment of companies. The communications equipment cluster in Jylland, Northern Denmark, for instance, was established following the increased demand for specialized communications equipment by the Danish fisheries and maritime shipping industries. Likewise, the world leading dredging cluster in Sliedrecht, the Netherlands has its origins in the stringent domestic demand for dredging services and equipment by a country that is constantly battling the water because it needs to protect itself against the sea and rivers.

Related and supporting industries, finally, were the primary reason for cluster establishment in 15.1% of all cases. The French medical supplies cluster in Saint-Etienne in the Loire region, for example, has its origins in the presence of a strong local cluster of textile ribbon makers which subsequently diversified into medical textiles. In Dalton, Georgia, the carpet cluster has its origins in the presence of numerous local producers of bedspreads. Such cases are common.

7.5 Conclusion

This research represents work in progress and its findings are preliminary results. While we have assembled a large sample of clusters, many variables still have an insufficient number of observations, preventing more sophisticated analyses and forcing us to treat results with caution.

The aim of this cluster meta-study is to systematically aggregate data from existing cluster publications to learn more about the locational, economic and competitive characteristics of industry clusters, the reasons behind their competitiveness or uncompetitiveness, and their patterns of evolution over time as well as the reasons behind these patterns. To do so it was first necessary to assemble hundreds of articles and publications about industry clusters worldwide. We then created a data template to collect information about clusters from a wide variety of different data sources in a uniform and consistent way. The content of our library was coded with the help of this data template.

A preliminary analysis of the sample yielded the following main conclusions:

- North American and British clusters tend to be substantially larger in terms of employment than clusters from Continental Europe while clusters in India are of similar size as their Continental European counterparts. No such clear differences exist with respect to the number of firms per cluster.
- Smaller clusters (with employment less than 15,000) were slightly less competitive than larger clusters.
- Clusters can be very old and often trace their origin back hundreds of years. Cluster evolution appears to be a matter of decades and centuries, rather than mere years.

- There are large differences in age, depending on a cluster's location. On average, European clusters are at least 100 to 150 years older than clusters in the United States, New Zealand, or India.
- There appear to be no typical cluster lifecycles nor typical evolutionary patterns. A cluster that is several centuries old may be just as competitive as one that was established only some decades ago.
- Factor conditions were most often the primary reason behind cluster competitiveness, followed by demand conditions, related and supporting industries, and local rivalry.
- Uncompetitive clusters tended to rely on a narrower set of determinants of competitiveness as competitive clusters, where often the entire diamond was at play. Rivalry, in particular, appeared to be often absent in uncompetitive clusters, whereas it played a prominent role in competitive clusters. Random events or government influences, on the other hand, played an important role in uncompetitive clusters, but were the least important determinants in competitive clusters.
- The analysis suggests a hierarchy of the determinants of competitiveness. Clusters that based their competitiveness primarily on factor or demand conditions were significantly less competitive than clusters that based their competitiveness on related and supporting industries or the context for strategy and rivalry.

To further substantiate these results we plan to increase the amount of data they are based on in the next phase of the project by including even more case studies and by augmenting published data with our own observations. There is still a large body of literature to be processed and coded into the database. We will seek more unpublished information in order to alleviate the publication bias inherent in our methodology. We also plan to augment the data from the cluster literature with observations based on our own knowledge about the clusters in question. Taken together, these steps will hopefully allow us to place our conclusions on firmer ground by moving away from the simple descriptive statistics we are currently using towards a more sophisticated statistical analysis.