Distributed Knowledge and Intelligence in the Extended Enterprise
–
A Network Analysis of the Petrochemicals Industry in Western Europe

A paper by
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0. Abstract

This paper examines the role of networks in establishing and sustaining industrial sectors and clusters, the consequent behaviours of those clusters and their participants, and ultimately the implications of the extended enterprise for participants, regulators and researchers.

In the first section I reflect on the nature of network driven dynamics and explore the tools and techniques that might be used to test for them. I then investigate the testability of various theories of network-enabled sustainability and network-driven growth, innovation and information exchange. Finally I examine the implications for both research and practice.

Throughout the paper a variety of tools and techniques are illustrated with reference to a specific study of the petrochemicals industry in Western Europe. The results demonstrate that, despite being characterised as mature, the petrochemicals industry continues to evolve and its constituent companies and locations are still actively co-evolving within it. I establish the interplay between the roles of local and long-range networks for the diffusion of knowledge and innovation within the industry. The clear implication is that companies need to be well connected into the industry's network and that this is best achieved through a diverse and disparate geographical presence.

This study demonstrates the generic applicability of network and co-evolutionary theories to an examination of industrial sectors, and tests the viability of various social network analysis tools and techniques that might be used to illustrate the associated structures and dynamics.

1. Introduction

Traditionally, most thinking about regional economic geography has fallen into three broad bodies of literature (MacKinnon et al 2002, Storper 1997).

The *institutional* school of regional economic geography began with Marshall's (1919) introduction of the idea of geographical specialisation generating, and generated by, a local "industrial atmosphere" which institutionalised custom, tradition and practice in a unique set of social and cultural norms. Piore & Sabel (1984) produced a contemporary interpretation of the idea with flexible specialisation based on the allocation of capabilities and resources forged in local historical, institutional and social structures. The American school attempted to address the problem of spontaneous development with a model that combined a strong academic centre with a political coalition that proactively encouraged entrepreneurship in science-based clusters. An alternative European school developed the concept of the milieu which is represented through a network metaphor, but is intangible in most of the literature.

Rational-economic thinking is epitomised by the California school's postulation that disintegration and specialisation is the natural response to risk in dynamic markets (Storper 1997:9, MacKinnon et al 2002:295), and that regional agglomeration is the resultant effect of a minimisation of transaction costs. These dynamics are amplified for mature industries where attention is focussed on the incremental improvement of products and the minimisation of costs.

Since the 1990s *innovation and evolution* have been highlighted by the identification of increasing returns available from "untraded interdependencies" (Storper 1997:5) which "are seen as key sources of learning which enable certain regions to respond and adapt effectively to changes in the external market environment" (MacKinnon et al 2002:301).

1.1 The Relevance of the Petrochemicals Industry

The petrochemicals industry in Western Europe is characterised by a large degree of fragmentation, but without a correspondingly high degree of specialisation. It follows that, despite its typical characterisation as a mature, or even declining industry, transaction cost minimisation cannot be the dominant dynamic in the geographical concentration of the industry.

All petrochemicals are produced from a common family of feedstocks, forming a number of inter-connected production chains (figure 1.1). While many operators in the European industry produce products at most points along these production chains, they surprisingly rarely operate complete chains at a single location. Instead, their facilities are integrated into production chains that include other operators, and are spread across a number of locations. The geographical analogue is that complete, integrated production chains can often be found at discrete operating locations, but these are rarely operated by a single owner.

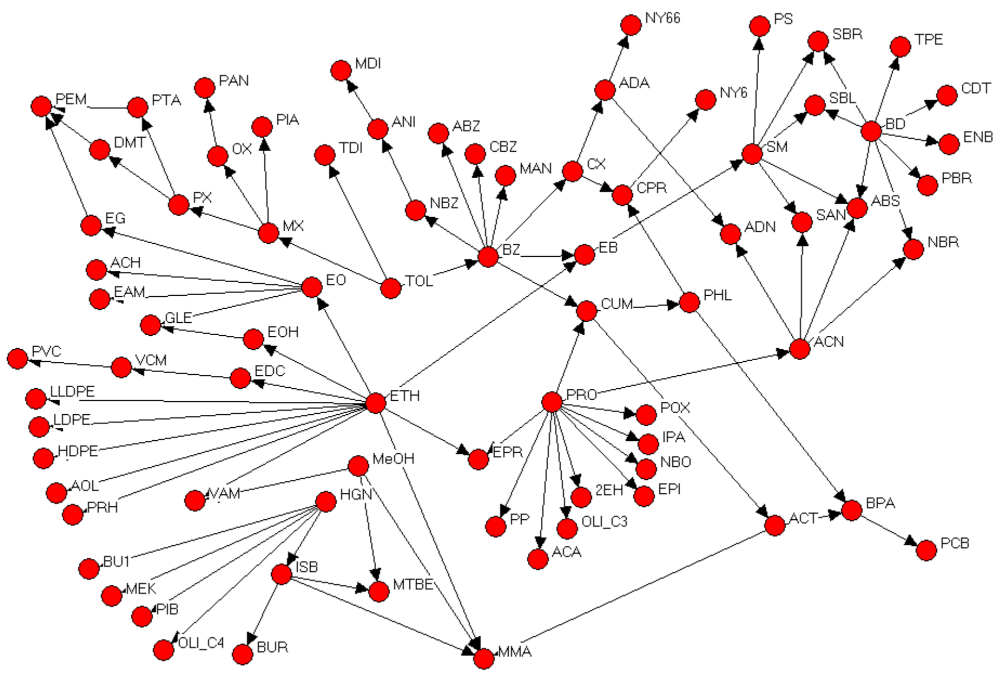


Figure 1.1 – Generic Production Map for the Western European Petrochemicals Industry

1.1.1 Analysis of the Industry

The ownership structure, generic production chain definition and product stream location information were analysed using UCInet (Borgatti et al 2002). This generated networks representing the individual production chains for each of the 140 companies and 167 locations. For example, figure 1.2 shows the production chain for Dow. The circles represent specific products, and the arrows link feedstocks to the products that they produce.

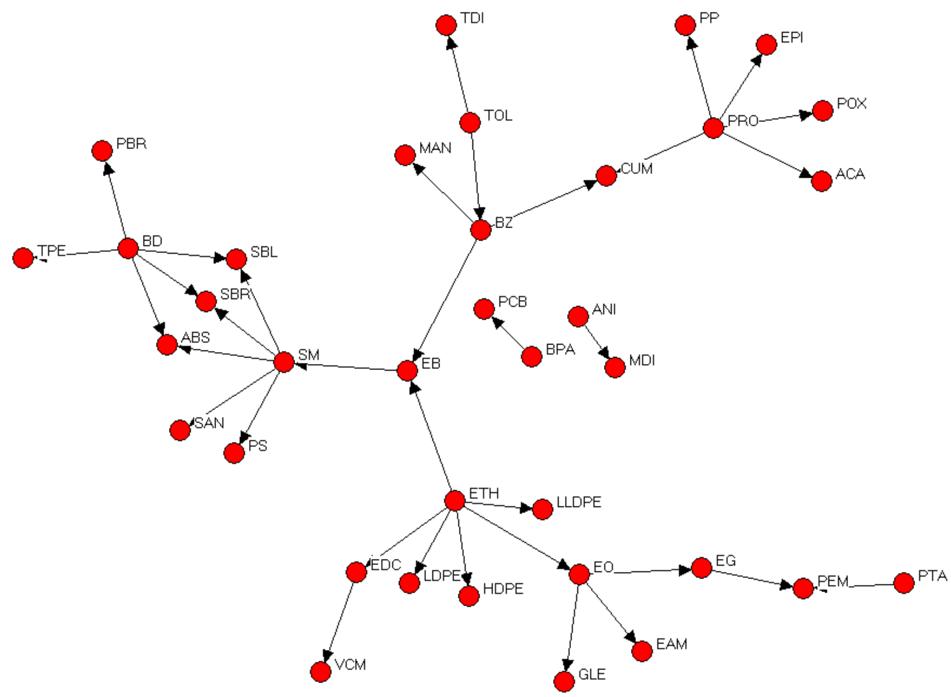


Figure 1.2 – Production Chain Map for Dow

I then divided these production chains according to their location to identify the fully integrated (i.e. by ownership and location) production fragments. The largest of these fragments was measured to give an indication of the size of the largest fully integrated complex for each company. Figure 1.3 shows the production fragment map for Dow. The circles are individual product streams (i.e. it identifies products from specific production plants), and it is clear that there are 7 geographically distinct production chain fragments (represented by different colours in the diagram).

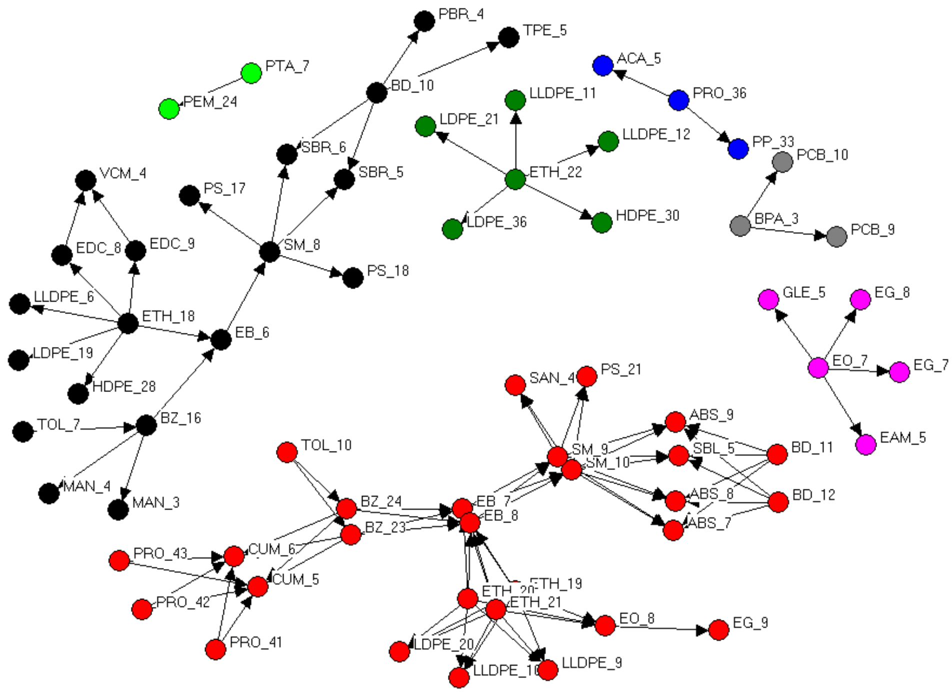


Figure 1.3 – Production Fragment Map for Dow

1.1.1.1 Production Chain Integration

Figure 1.4 shows the size of the largest production component against the total number of product streams for each company (fig. 1.4) and for each location (fig. 1.5). It is clear that for virtually all companies and location, irrespective of size, the vast majority of the products that they produce can be integrated into a single production chain (i.e. the trend line has a gradient close to 1).

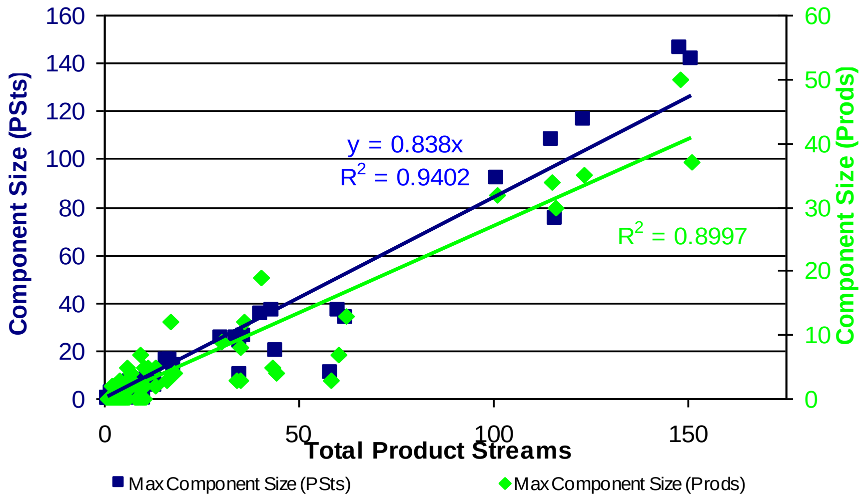


Figure 1.4 – Largest Component Size by Total Product Streams (Companies)

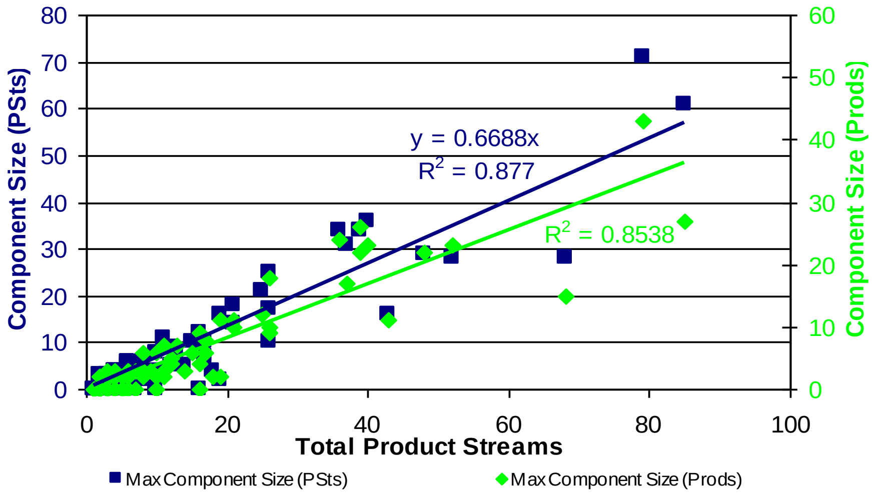


Figure 1.5 – Largest Component Size by Total Product Streams (Locations)

The linear increase in the number of products with the number of product streams indicates that the size of the larger companies and locations is a consequence of diversification rather than specialisation.

1.1.1.2. Fragmentation

Figure 1.6 shows the impact of location on company production chains, and figure 1.7 the analogous impact of ownership on production sites. The apparently contiguous production chains are distributed geographically in such a way that their contiguity is broken. In both cases, no component is larger than 30 product streams, and relatively small companies operate with components of this size[1]. The number of products within a fragment also has an upper limit of around 20.

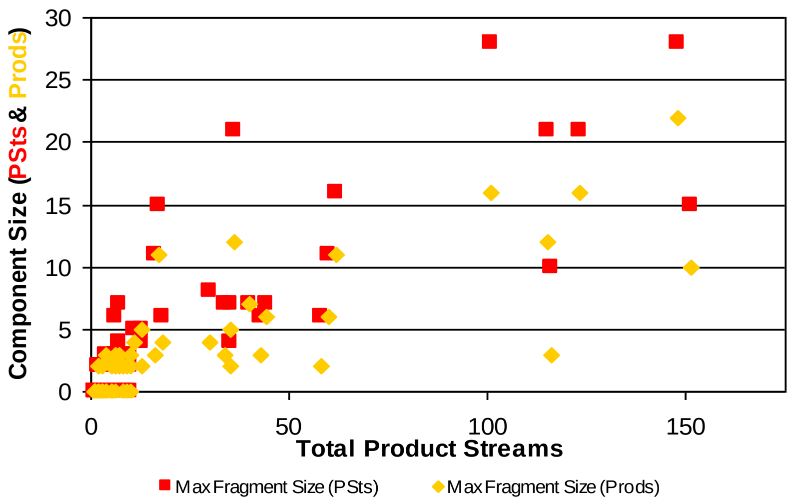


Figure 1.6 – Largest Fragment Size by Total Product Streams (Companies)

[1] An effort to fit a trend line gives R^2=0.75, but is influenced by the high number of very small companies, and it is clear to the naked eye that any correlation breaks down for the larger companies.

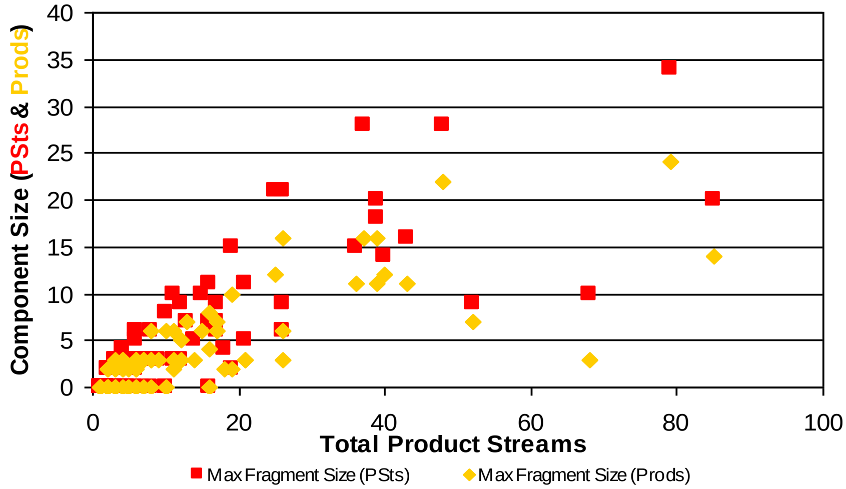


Figure 1.7 – Largest Fragment Size by Total Product Streams (Locations)

1.1.1.3. Degrees of Integration and Fragmentation

I created two metrics that describe the extent of the fragmentation observed in the data. The *Product Integration Factor* is simply the proportion of all of the product streams for each company (or location) that are part of a production chain component, irrespective of location. The *Fragmentation Factor* is the proportion of the product streams that are part of a fully integrated ownership (or location) fragment. The higher the value of each of these factors, the greater is the level of integration[2].

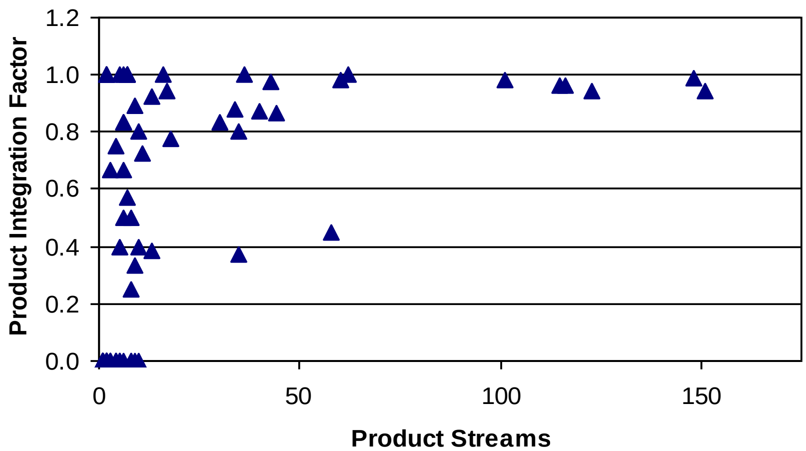


Figure 1.8 – Product Integration Factor by Total Product Streams (Companies)

[2] In Dow's case the Product Integration Factor is 0.98, because all but 2 of its 101 product streams are integrated into one of the production components that are shown in figure 1.2. Dow's Fragmentation Factor is 0.66, because when location is considered, only 67 of the total 101 product streams are integrated into the production fragments illustrated in figure 1.3. The remaining 34 product streams are isolated by geography from the production components that they were members of.

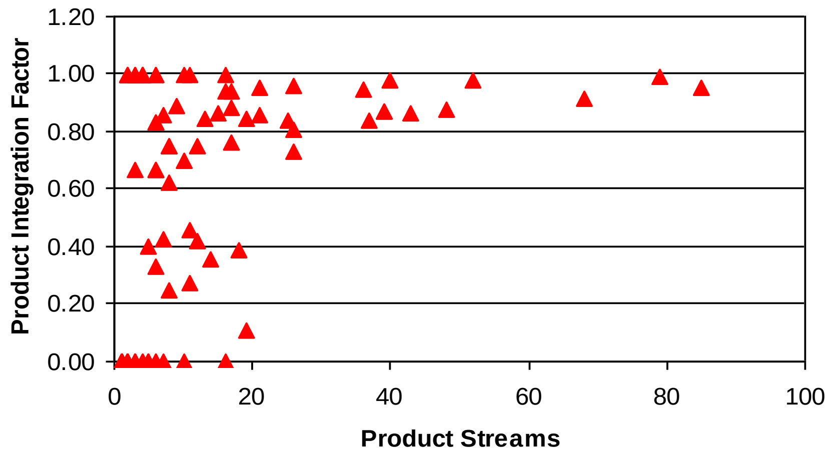


Figure 1.9 –Product Integration Factor by Total Product Streams (Locations)

There is a wide diversity in the *Product Integration Factors* (figs 1.8 and 1.9) and *Fragmentation Factors* (figs 1.10 and 1.11) amongst the smaller companies and locations, but as they grow and become more diverse they converge to a surprisingly consistent level of integration. Virtually every product stream that any company or location produces is connected to every other through their production chains (the *Product Integration Factor* tends towards 1). But, far fewer are locally integrated – the companies appear to converge to a common level of local integration at about 70% of all of their product streams, and locations to a common level of local integration at about 80% of all of their product streams. So, locations seem to be slightly more integrated than companies.

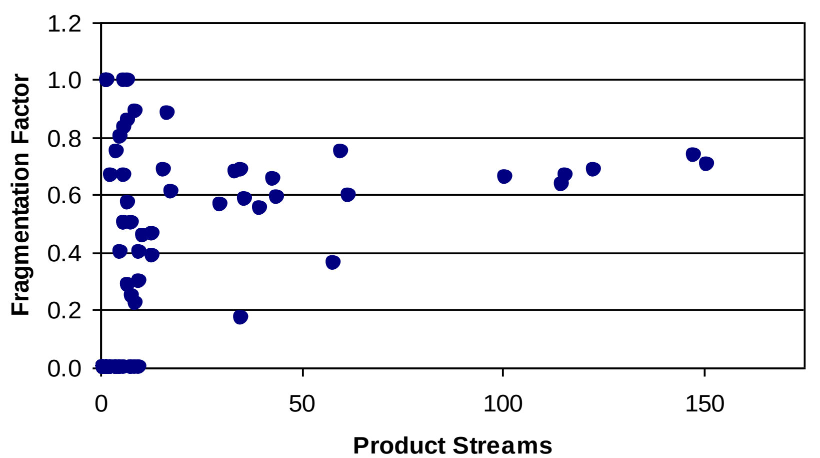


Figure 1.10 – Fragmentation Factor by Total Product Streams (Companies)

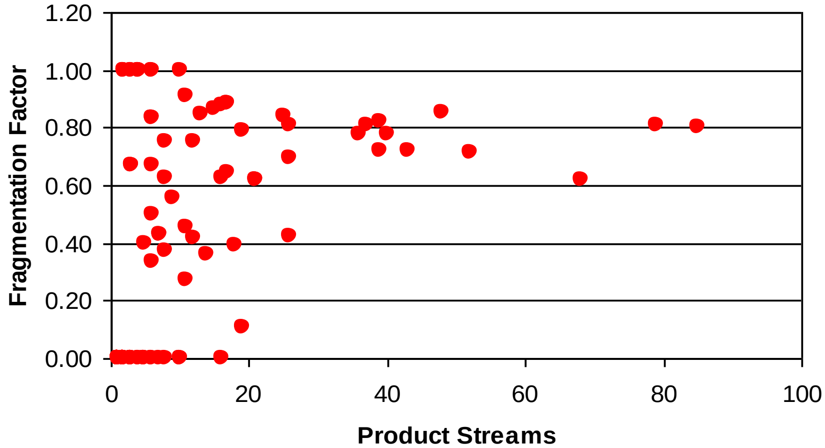


Figure 1.11 – Location Fragmentation Factor by Total Product Streams

1.1.2 Implications

There is a large degree of fragmentation (i.e. low values for the maximum fragment size and fragmentation index), but without a correspondingly high degree of specialisation (the number of products increases linearly with the number of production streams), within the petrochemicals industry. As such, it seems likely that an investigation of the operation of networks as adaptive systems for the promotion of innovation and learning will be insightful in helping to rationalise the industry's structural form. This in turn should enlighten a more generic consideration of these concepts, not least because of the clear integration benefits and the contained and discrete nature of the petrochemicals sector.

2. Network Driven Dynamics

"What the science of networks can do, even now, is give us a different way to think about the world, and in so doing help us to shed new light on old problems" (Watts 2003:16).

"Immanuel Kant, writing more than two centuries ago, saw organisms as wholes. The whole existed by means of the parts; the parts existed both because of and in order to sustain the whole" (Kauffman 1995:69). Kauffman explains that while the rules of evolution drive the development of a network's structure, random, exogenous events also play a part. In a similar fashion Kogut (2000) makes the distinction between "emergence and intentionality" in determining network structure. The network has no authority relationship that allows it to impose its structure on its participants. Its structure is "an emergent outcome generated by rules that guide the cooperative decisions of firms in specific competitive markets. The observed differences in the patterns of cooperation between industries are not happenstance. They reflect rather the implicit operation of these cooperative rules and the competing visions that come to shape a network……..structure is emergent in the initial conditions of a specific industry" (Kogut 2000:405).

It is not only the network that evolves. The firms within the network are also engaged in a co-evolutionary journey within their regional and/or market environments: "the dialectic between specific markets and individual firm competence drives a co-evolution that enjoys a reflection in the structure of the network" (Kogut 2000:412). Hence there is no single normative, unique path, because decisions and developments at a micro-level impact on the macro-structure and vice versa. One example might be that the network 'learns' how to supply inputs at a lower cost than any individual firm can achieve (ibid.). This capability, combined with the on-going development and enhancement of trust between the participants (Staber 2001), significantly reduces the benefits and incentives associated with vertical integration.

2.1 Consideration of Diversity

An evolutionary theory of industrial development (e.g. Kauffman 1995, Kogut 2000) would predict a correlation between diversity and success. Larger companies and locations should exhibit higher levels of diversity, in marked contrast to the specialisation that gives rise to economies of experience and scale.

Stirling (2004) offers an unusually rich characterisation of diversity:

> *Variety* indicates the number of categories into which the property under consideration can be segmented.
> *Balance* measures the relative apportionment of that property between these categories.
> *Disparity* assesses the extent to which the categories themselves are distinct.

I developed metrics that quantified each of these dimensions as exhibited by the companies and locations (table 2.1). The diversity of companies was considered in terms of their geographical spread, and of locations in terms of their ownership. In both cases I also looked at their production portfolio diversity. These were tested for their correlation with co-evolutionary success as indicated by growth and scale[3].

	Companies	Locations
Geographical Diversity		
- Variety	No. operating locations	N/A
- Balance	$\left(\frac{Size\ of\ largest\ location}{Average\ location\ size}\right)-1$	N/A
- Disparity	Bespoke disparity index[4]	N/A
Ownership Diversity		
- Variety	N/A	No. of ownership fragments
- Balance	N/A	$\left(\frac{Size\ of\ largest\ fragment}{Average\ fragment\ size}\right)-1$
- Disparity	N/A	Bespoke disparity index[5]
Production Portfolio Diversity		
- Variety	No. of product types	
- Balance[6]	$\left(\frac{Frequency\ of\ most\ common\ product}{Average\ product\ frequency}\right)-1$	
- Disparity[7]	$\frac{No.\ product\ types-1}{No.\ product\ streams-1}$	

Table 2.1 – Diversity Measures

[3] In all cases both the number of individual product streams and the total production tonnage were considered as indicators of scale, but there was no discernable difference in the results, so for convenience only those results relating to production tonnage are presented in this paper.

[4] The geographical disparity of a company indicates how (dis)similar each of its operating locations are – identical locations produce exactly the same product portfolio and completely dissimilar locations have no products in common. I developed the following metric which measures the extent to which each product is produced at every location. An analogous measure looks at the ownership disparity of operating locations and is generated simply by replacing the locations with companies in the formula.

$$Disparity\ Measure\ (companies) = \frac{(No.\ products \times No.\ locations) - Prod.Count\ by\ Location}{No.locations}$$

The theoretical maximum number of occurrences of each product is given by the total number of products multiplied by the number of locations. If every product that a company produces is produced at every location, then every location would appear to be the same, and there would be no disparity. In this circumstance, the product count by locations would equal the maximum number of occurrences, and the numerator would equal zero. Division by the total number of locations stops the disparity measure from increasing exponentially as the number of locations gets smaller.

[5] See above

[6] When looking at production chain diversity, the balance metric is a measure of the degree to which each product is equally significant in the overall portfolio.

[7] Disparate production chains will show little duplication of products, whereas similar ones will produce the same products many times. So the ratio of the number of products to the number of product streams is used as the disparity metric for production chains.

2.1.1 Diversity between Companies

There is a clear correlation between all three of the diversity dimensions and increasing company size (figure 2.1). This correlation is strongest for the disparity index, and is reasonable for the variety index, implying that larger companies tend to produce different products at their various operating locations (they have a high disparity index), and that they operate in many locations (they have a high variety index). The balance index suggests that there is a greater variety in the extent of larger companies' operations across their operating locations.

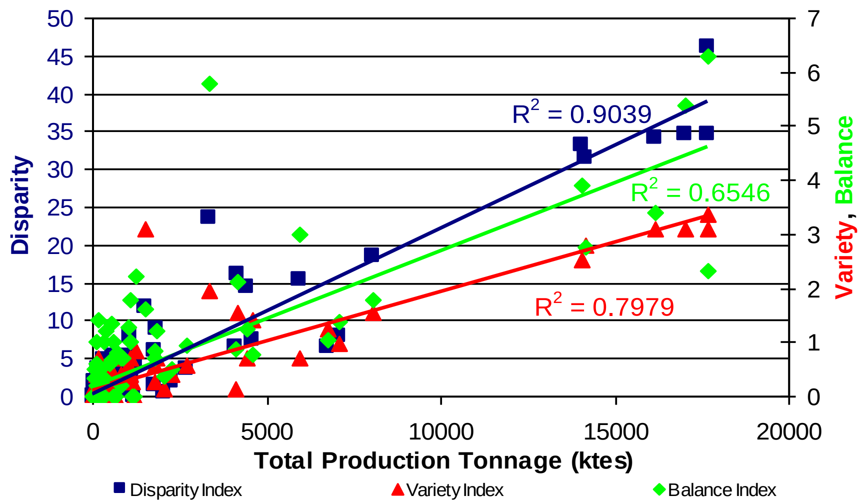


Figure 2.1 – Geographical Diversity of Petrochemical Companies

Figure 2.2 shifts the emphasis to the diversity of the companies' production portfolios. There is a strong correlation between the number of products produced (variety) and company size. It would seem that the number of plants producing each of these products becomes increasingly unbalanced as company size increases.

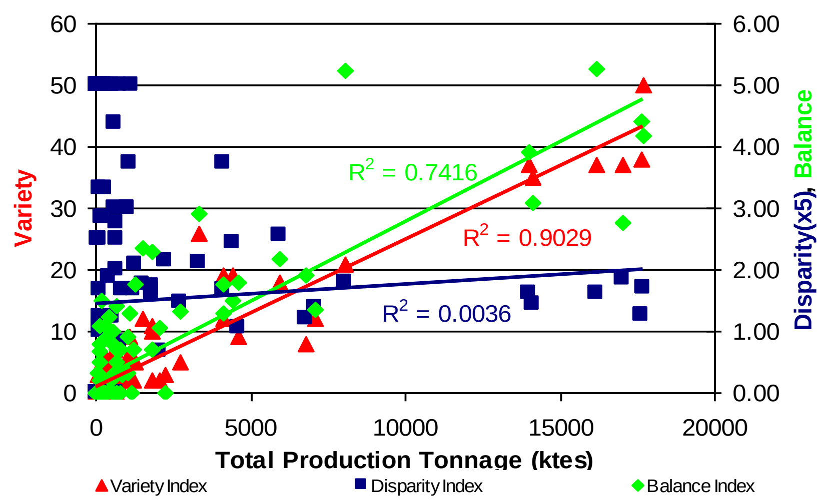


Figure 2.2 – Production Diversity of Petrochemical Companies

There is no meaningful correlation between company size and production disparity, which converges to a value of about 0.3 as company size increases. This implies that large companies have an average of about 3 production streams for each product, though we must bear in mind that the number of production streams per product becomes increasingly unbalanced with size.

2.1.2 Diversity between Locations

Again there are good correlations between all three diversity dimensions and increasing location size (Figure 2.3), the strongest of which is with ownership disparity. The largest locations have the greatest number of operating companies, and critically these companies tend to produce different things. We also see that the variety in size of companies' operations at any location tends to increase with larger location size.

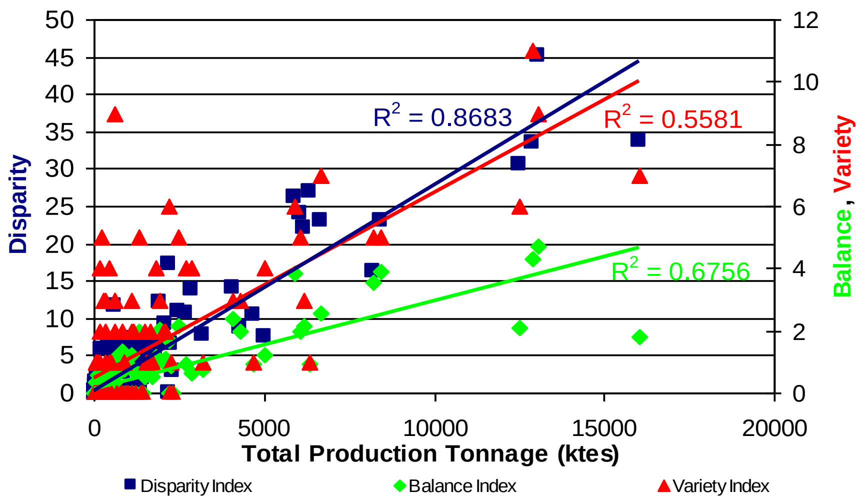


Figure 2.3 – Ownership Diversity of Petrochemical Production Locations

Figure 2.4 focuses on production portfolio diversity for the same locations. Variety is unsurprisingly correlated with increasing size but, as was the case for companies, production disparity (duplication of product types) is invariant with scale. So it seems that locations grow through product diversification and not through specialisation. Again, location disparity tends towards an "optimum" value, of about 0.6, as location size increases. So, sites tend towards an average of two production streams per product, though the imbalance between the most and least common products also increases with size.

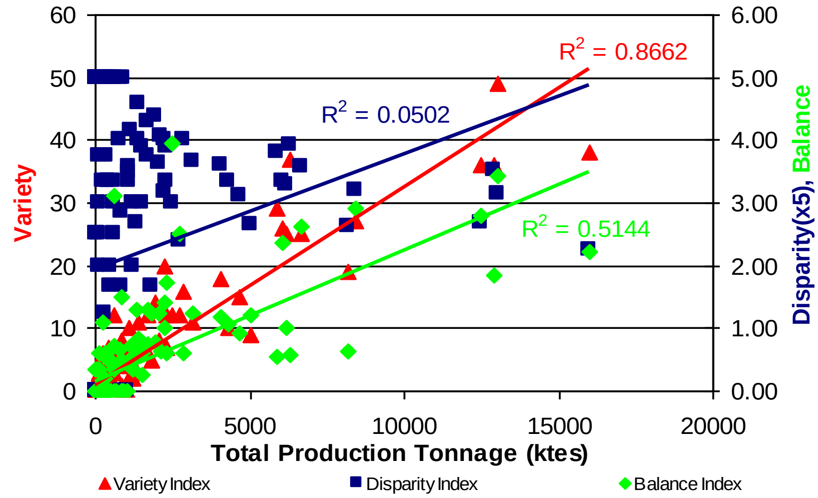


Figure 2.4 – Production Diversity of Petrochemicals Production Locations

2.1.3 Conclusions & Implications

The results suggest that the largest companies are characterised as operating with the highest levels of geographical diversity. They operate at a large number of locations, and critically produce different products at each location. They also have the widest product portfolio, and the greatest degree of imbalance in the scale of their geographical operations and their product portfolios. The same sets of characteristics are seen in the largest operating locations. This clearly does not support any suggestion that specialisation, leading to economies of scale and experience, is a common competitive strategy, but supports the case for further examination of the industry from a co-evolutionary perspective.

2.2 Growth & Attractors

Power-laws are taken to indicate the presence of a growth dynamic in which the larger or better connected actors attract a disproportionate or preferential opportunity for further growth or connectivity (Barabasi & Albert 1999). By contrast, a Gaussian distribution is generated by a system or network in which there is a typical or optimum size and any growth is distributed without bias. As such, the actual distribution of a real system can be used to infer the underlying dynamics that describe that system's behaviour (Amaral et al 2000).

Following the procedure established by Amaral et al (2000), the cumulative frequency and rank-order distributions of scale and of network connectivity can be plotted using linear and log scales. A straight line in a linear plot of cumulative distribution against a log plot of scale indicates an exponential decay curve, which is typical of an underlying Gaussian distribution. This indicates that a typical scale or degree of connectivity exists, about which the real observations are distributed. Alternatively a straight line in a log–log plot indicates a power law distribution in which there is no typical scale.

This methodology was applied to the petrochemicals industry data. Scale was investigated using the number of product streams and total production tonnage. Network connectivity of both companies and locations was examined through the number of links to locations and owners respectively, the number of interlocks between companies and locations, and also the number of product types that they produce. The results are summarised in table 2.2 and then illustrated in the subsequent figures.

	Companies	**Locations**	**Production Webs**
Product Stream Distribution	Power-Law (Truncated)	Ambiguous	Power-Law
Production Tonnage Distribution	Power-Law (Truncated)	Ambiguous	Predominantly Power-Law
Product Type Distribution	Power-Law (Truncated)	Predominantly Gaussian	Power-Law
Company Link Distribution	N/A	Gaussian	Power-Law
Location Link Distribution	Power-Law (Truncated)	N/A	N/A
Production Web Link Distribution	Power-Law (Truncated)	N/A	N/A
Interlock Distribution	Gaussian	Predominantly Gaussian	Gaussian

Table 2.2 – Observed Distributions in the Power-Law Study

2.2.1 Scale and Connectivity of Companies

Scale Metrics

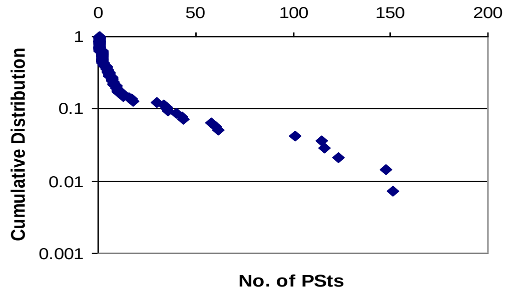


Figure 2.5 – Company Cumulative Distribution of Product Streams (log-normal)

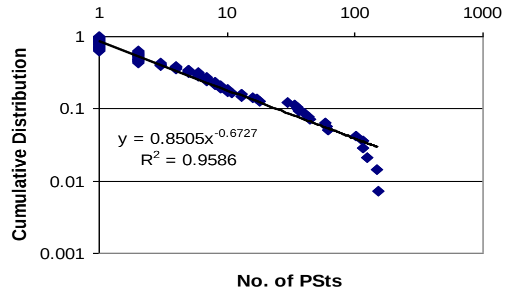


Figure 2.6 – Company Cumulative Distribution of Product Streams (log-log)

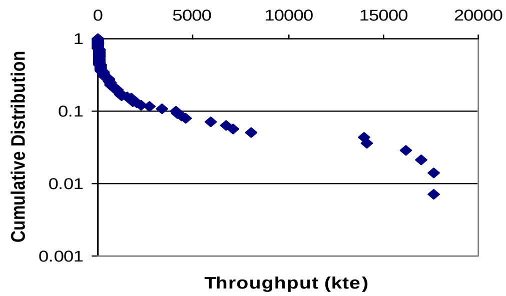


Figure 2.7 – Company Cumulative Distribution of Production Tonnage (log-normal)

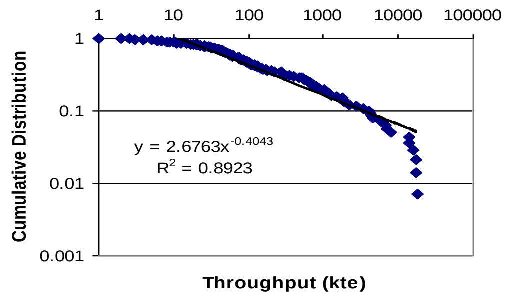


Figure 2.8 – Company Cumulative Distribution of Production Tonnage (log-log)

Connectivity Metrics

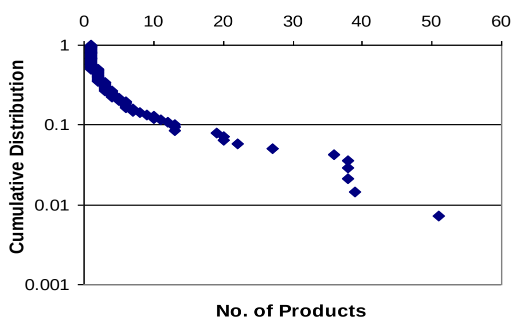


Figure 2.9 – Company Cumulative Distribution of Product Types (log-normal)

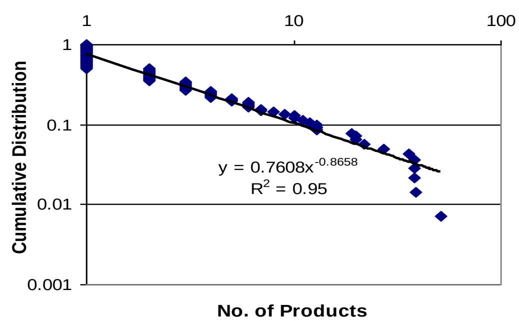


Figure 2.10– Company Cumulative Distribution of Product Types (log-log)

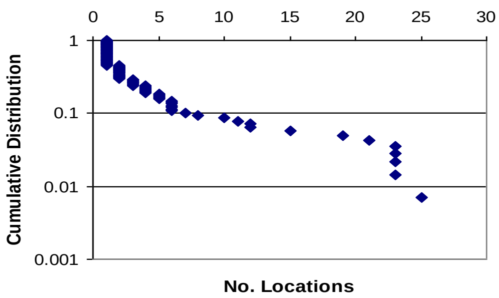


Figure 2.11 – Company Cumulative Distribution of No. of Locations (log-normal)

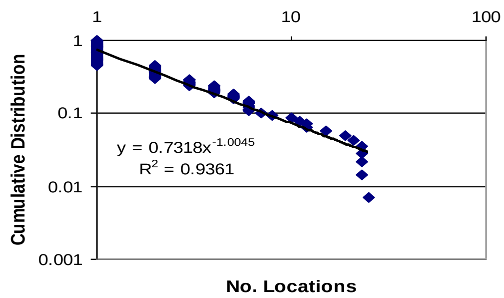


Figure 2.12 – Company Cumulative Distribution of No. of Locations (log-log)

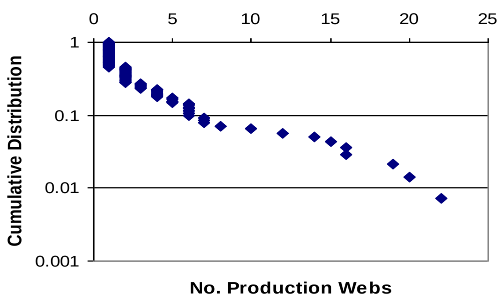


Figure 2.13 – Company Cumulative Distribution of No. of Production Webs (log-normal)

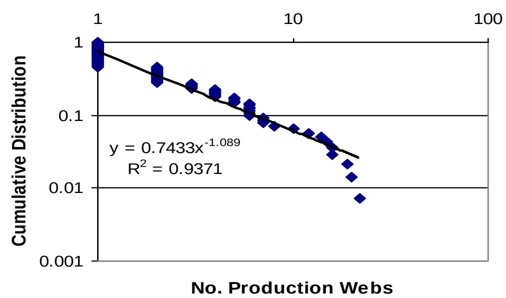


Figure 2.14 – Company Cumulative Distribution of No. of Production Webs (log-log)

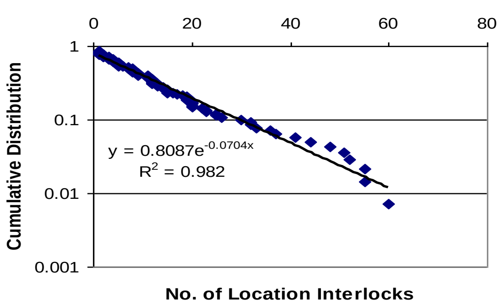


Figure 2.15 – Cumulative Distribution of No. of Company Interlocks (log-normal)

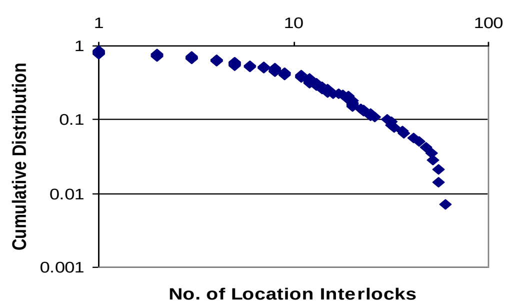


Figure 2.16 – Cumulative Distribution of No. of Company Interlocks (log-log)

The company scale and connectivity distributions show very clear truncated power-law distributions, the only exception being the interlock distribution which is Gaussian.

2.2.2 Scale and Connectivity of Locations

Scale Metrics

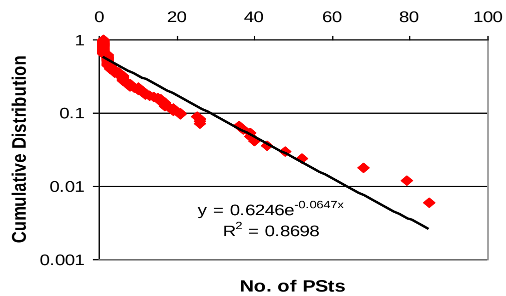


Figure 2.17 – Location Cumulative Distribution of Product Streams (log-normal)

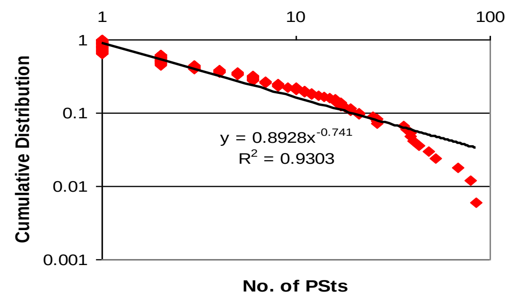


Figure 2.18 – Location Cumulative Distribution of Product Streams (log-log)

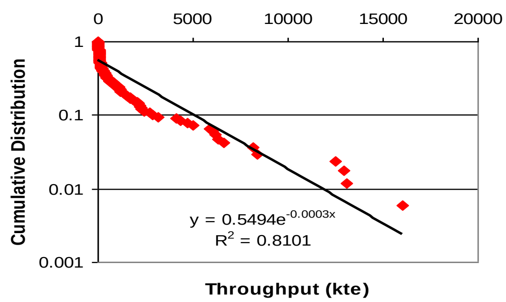


Figure 2.19 – Location Cumulative Distribution of Production Tonnage (log-normal)

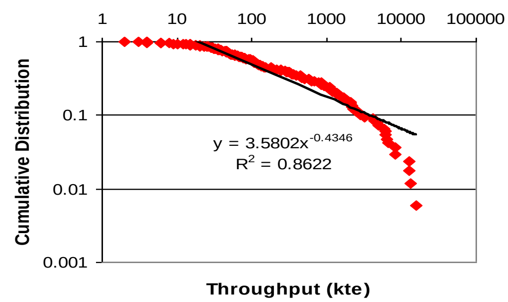


Figure 2.20 – Location Cumulative Distribution of Production Tonnage (log-log)

Connectivity Metrics

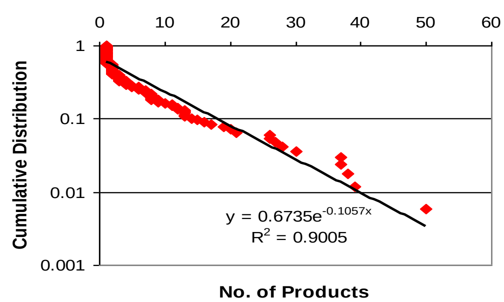


Figure 2.21 – Location Cumulative Distribution of Product Types (log-normal)

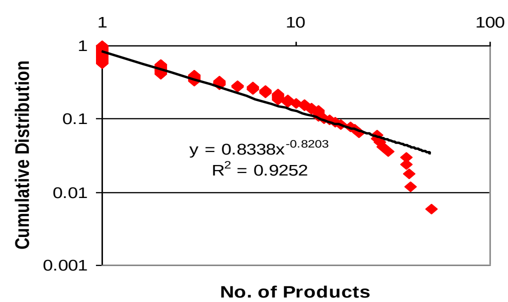


Figure 2.22 – Location Cumulative Distribution of Product Types (log-log)

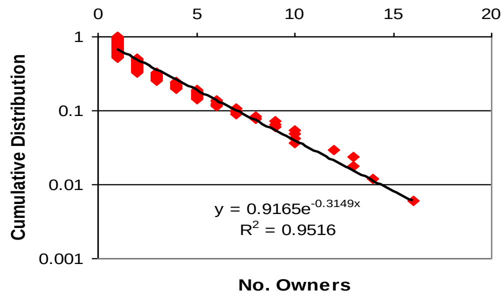


Figure 2.23 – Location Cumulative Distribution of No. of Companies (log-normal)

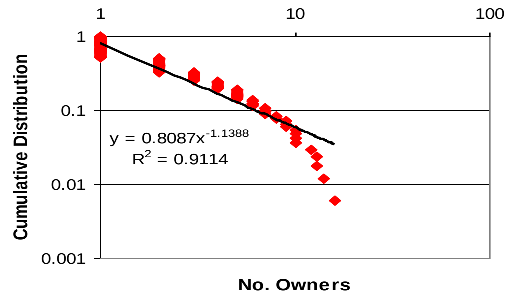


Figure 2.24 – Location Cumulative Distribution of No. of Companies (log-log)

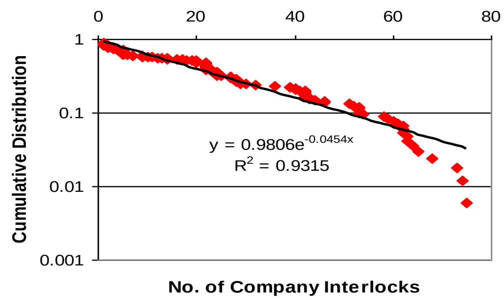


Figure 2.25 – Cumulative Distribution of No. of Location Interlocks (log-normal)

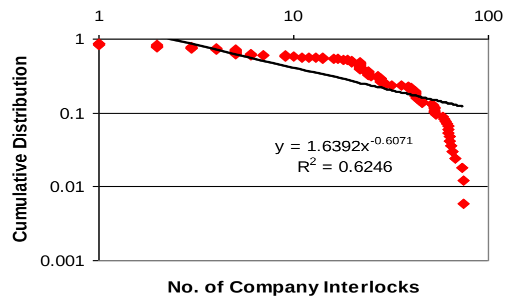


Figure 2.26 – Cumulative Distribution of No. of Location Interlocks (log-log)

The scale distributions of locations are ambiguous, neither fitting a Gaussian or power-law pattern. The connectivity distributions are more clearly Gaussian, implying that either there are significant cost or ageing factors at play (Amaral et al 2000) or, less probably given the results observed for companies, that the network is stable. This observation led me to look at the inter-connection of locations through long-distance pipelines, thus generating a new classification of *production webs*.

2.2.3 Scale and Connectivity of Production Webs

Scale Metrics

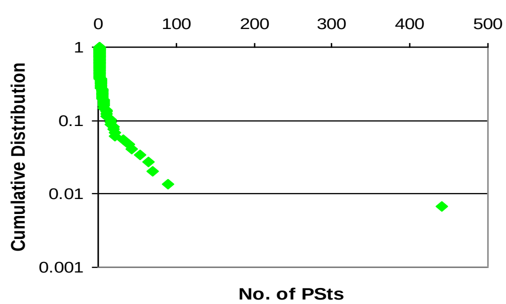


Figure 2.27– Prod. Web Cumulative Distribution of Product Streams (log-normal)

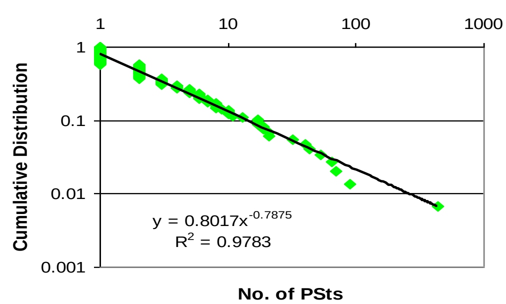


Figure 2.28 – Prod. Web Cumulative Distribution of Product Streams (log-log)

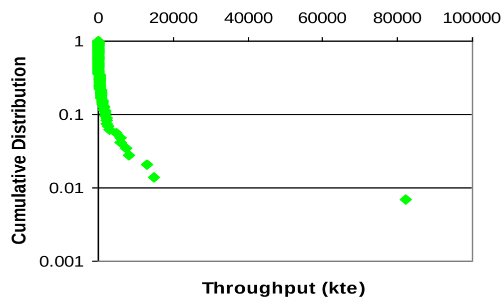


Figure 2.29 – Prod. Web Cumulative Distribution of Production Tonnage (log-normal)

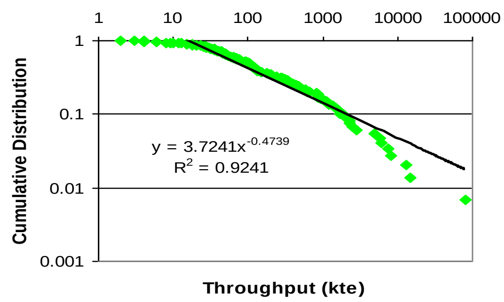


Figure 2.30 – Prod. Web Cumulative Distribution of Production Tonnage (log-log)

Connectivity Metrics

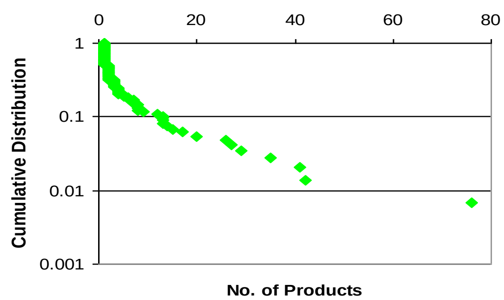


Figure 2.31 – Prod. Web Cumulative Distribution of Product Types (log-normal)

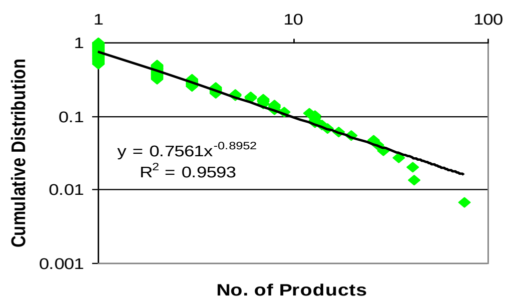


Figure 2.32 – Prod. Web Cumulative Distribution of Product Types (log-log)

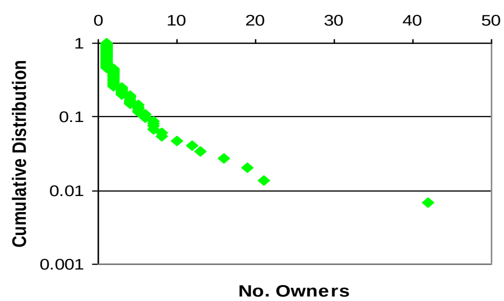


Figure 2.33 – Prod. Web Cumulative Distribution of No. of Companies (log-normal)

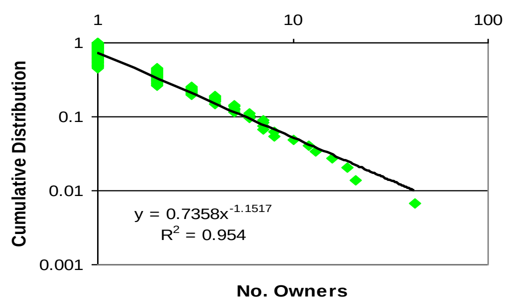
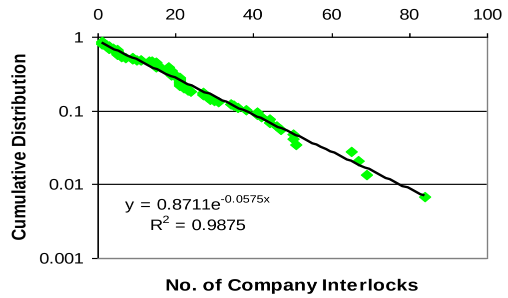


Figure 2.34 – Prod. Web Cumulative Distribution of No. of Companies (log-log)



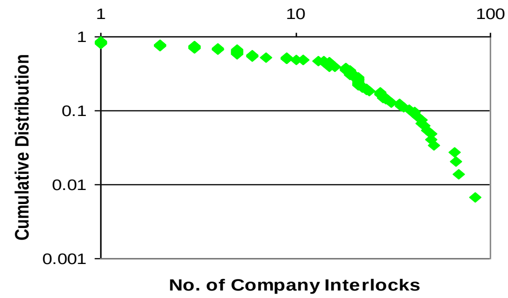


Figure 2.35 – Cumulative Distribution of No. of Production Web Interlocks (log-normal)

Figure 2.36 – Cumulative Distribution of No. of Production Web Interlocks (log-log)

Where pipelines collapse the physical distance between linked locations, power-law distributions of scale and connectivity re-emerge. As was found for companies, the interlocks between production webs show a Gaussian distribution.

2.2.4 Conclusions and Implications

Company scale and connectivity are power-law distributed, but with a distinct truncation beyond which scale effects suddenly dominate. It is commonly accepted that power-law distributions arise as a consequence of growth of a system or network, but the suggestion that there this is still significant growth in the industry is an unexpected result. The truncation might represent the point at which ageing or cost factors become significant (Amaral et al 2000), but I suspect that its abruptness is better explained as a consequence of competition authority regulation.

The results for locations are categorically different, in that location size and connectivity follow, if anything, a Gaussian distribution. This suggests that there are significant impediments to growth, particularly amongst the larger sites. The production web (locations linked by long-distance pipelines) results follow power-law distributions that match those of companies (albeit without truncation). The implication is that while individual sites become constrained in their ability to add new capacity or attract new companies, the industry uses long-distance pipelines to overcome these constraints and continue to expand and diversify.

The only consistently Gaussian distribution is of the number of interlocks. This implies that the networks of relationships between companies, between locations and between production webs is stable, and has a typical or optimum connectivity.

3. Network-enabled Sustainability and Network-driven Growth, Innovation and Information Exchange

Innovation and learning often involves the transfer of tacit knowledge (MacKinnon et al 2002), and the idea that knowledge and information forms one of the bases for competition is not new. However, that knowledge is not a public good and incurs significant maintenance and transmission costs is less well acknowledged (Kogut & Zander 1993).

A number of factors make the transference of tacit knowledge more straight forward, such as repeated interaction and a common architecture and understanding (Tallman 2003). Specialisation within firms is generally stable and self-preserving because it is based on incommunicable competencies (Kogut 2000), leading to the idea of identity. This concept, which is inherent in the structure of the firm, implies that idiosyncratic, tacit knowledge is more suited to intra-firm transmission than external codification and exchange (Kogut & Zander 1993). Buckley & Casson (1976 in Kogut & Zander 1993) suggested that firms act as secure, efficient networks for the transmission of knowledge and information, and Tallman (2003) claims a metaphorical and explanatory significance to the model of a multinational corporation as "a repository of knowledge rather than as a 'nexus of contracts'".

Interestingly these same factors serve to strengthen networks where they operate. In much the same way that firms can be viewed as social communities that provide "the cognitive representation of what constitutes the object of membership, that is, of identity" (Kogut 2000:408), so too can a long-established network, especially where that network is geographically defined. Thus networks have, to some extent, the ability to replicate the capabilities of firms to act as vehicles for information and knowledge transmission through close, often informal, interpersonal and inter-firm relationships which are the consequence of repeated and frequent interaction (MacKinnon et al 2002).

Where networks operate, their primary function "is to provide firms with access to information and other resources in the relevant environment" (Staber 2001:545) and firms "innovate and prosper through a collective learning process which depends strongly on existing synergies among a group of firms" (ibid:538). The norms of behaviour and culture within a firm limit the variety of options that it can pursue. By contrast, networks and markets are free to reorganise spontaneously, without any impact on the component specialisation provided by the member firms, allowing a far more diverse set of options. This leads to a "symbiotic interdependence" between the firms that enables "the rapid diffusion of new information and critical resources". Networks serve to coordinate an outcome that the individuals would be unable to achieve in isolation (Lado et al 1997) such as the development of capabilities that are properties of the network itself, and in turn promote the interdependence of the participating firms (MacKinnon et al 2002).

Local networks clearly play an important part in the development of competitive advantage, as Porter (1998:78) articulates: “the enduring competitive advantages in a global economy lie increasingly in local things – knowledge, relationships, motivation – that distant rivals cannot match”. But we must test the relative significance of the local environment and the wider geographical context:

> *“But how important is regionalization? Is the region somehow a necessary source of the dynamism of these production systems and, hence, of the developmental dynamics of contemporary capitalism itself? Or is regionalization merely an expression of, another interesting empirical dimension of, technological and organizational changes in successful production systems?”* (Storper 1997:4).

MacKinnon et al (2002) identify a number of studies which have demonstrated that spatial proximity enables network-wide learning. They report Saxenian’s (1994) articulation of “the contrast between the continuing dynamism of Silicon Valley and the relative stagnation of Route 128 as a product of the former’s reliance on cooperative networking arrangements, which promote flexibility and collaborative learning, and the latter’s experience of mounting organizational rigidities through its continuing orientation towards vertical integration and product standardization” (MacKinnon et al 2002:299). Kogut’s (2000:422) view has shifted subtly, and he now sees the boundaries between firms and networks as “malleable definitions determined by shifting identities and their coevolving capabilities”.

Thus, in attempting to explain different structural forms, it is critical that we understand and can test for the conditions that influence the relative efficiency of firms and networks in the creation and transfer knowledge.

3.1 Small Worlds

Small-world networks were identified by Watts & Strogatz (1998) as networks which:

> *“On the one hand, … display a large clustering coefficient, meaning that on average a person’s friends are far more likely to know each other than two people chosen at random. On the other hand … connect two people chosen at random via a chain of only a few intermediaries”* (Watts 2003:77).

Fragmentation, as seen in the petrochemicals industry, might enable “small-world” characteristics. The associated rapid diffusion of information and ideas might provide some explanation of its utility.

Watts and Strogatz's (1998, Watts 1999) propose a methodology of comparing average path length and cluster coefficients of actual networks against equivalent random networks of the same size and density to identify small-worldliness. Using UCInet (Borgatti et al 2002) it is possible to identify the actual average path length and clustering coefficients of real networks[8], and the equivalent figures for a random network can be derived using simple formulae (Watts 1999:502).

Small-world identification requires that $n >> k >> ln(n) >> 1$ (Watts & Strogatz 1998:440)[9], where n is the total number of actors in the network, and k is the average degree (i.e. number of links) of those actors. Furthermore, in order to ensure that the network is decentralised, not only must the average degree k be much less than n, but the maximal degree k_{max} over all vertices must also be much less than n (Watts 1999:496).

	n	k_{max}	***k***	***ln(n)***
Companies	117	25	6.66	4.76
Locations	143	16	12.27	4.96

Table 3.1 – Network Parameters for Small-Worldiness Assessment

It is clear from tables 3.1 and 3.2 that all of the conditions required for the analysis to be deemed valid are satisfied, and that along both dimensions the network formed between petrochemicals companies and locations is a small-world network.

	Average Path Length		**Average Clustering Coefficient**	
	Actual	Random	Actual	Random
Results for Petrochemicals Industry generated in this study				
Companies	2.23	2.51	0.82	0.057
Location	2.13	1.98	0.82	0.086
Watts & Strogatz's results (for comparison)				
Film Actors	3.65	2.99	0.79	0.00027
Power Grid	18.7	12.4	0.080	0.005
C. elegans	2.65	2.25	0.28	0.05

Table 3.2 – Results & Comparators for Small-Worlds Study

[8] I encountered a number of operational difficulties in this study. The theoretical approach is predicated on a very large, fully connected network. In this case, while the networks are large, they are not so large that individual actors do not influence the overall, averaged network properties.
A greater problem was that the real networks contain a number of unconnected actors and components. The average path length between these and the rest of the network has no real meaning, and becomes difficult to code for mathematically. My pragmatic response was to only consider the main connected component in each network, and to ignore the unconnected actors. The main components represented 84% of the companies (117 from the total of 140), and 86% of the locations (143 from the total of 167).
A second problem concerned pendants (actors that have only one link into the main component, and as such are only connected to one other actor) to the main components. There is no meaningful definition of the clustering coefficient for a pendant (since it is impossible to say whether it's single linked actor forms a dense cluster, or is totally isolated). In calculating the average cluster coefficient for the network I simply ignored all pendants. This seemed to be more reasonable than assigning them a clustering coefficient of 1, indicating a fully connected clique, or a value of 0, implying a totally dispersed structure, neither of which seem to properly reflect the 'real' situation.

[9] The first condition ensures that the network is sparse, and hence that the results obtained are meaningful, and the second condition ensures that the equivalent random network will be fully connected, and the third condition is the minimum requirement for a fully connected real network.

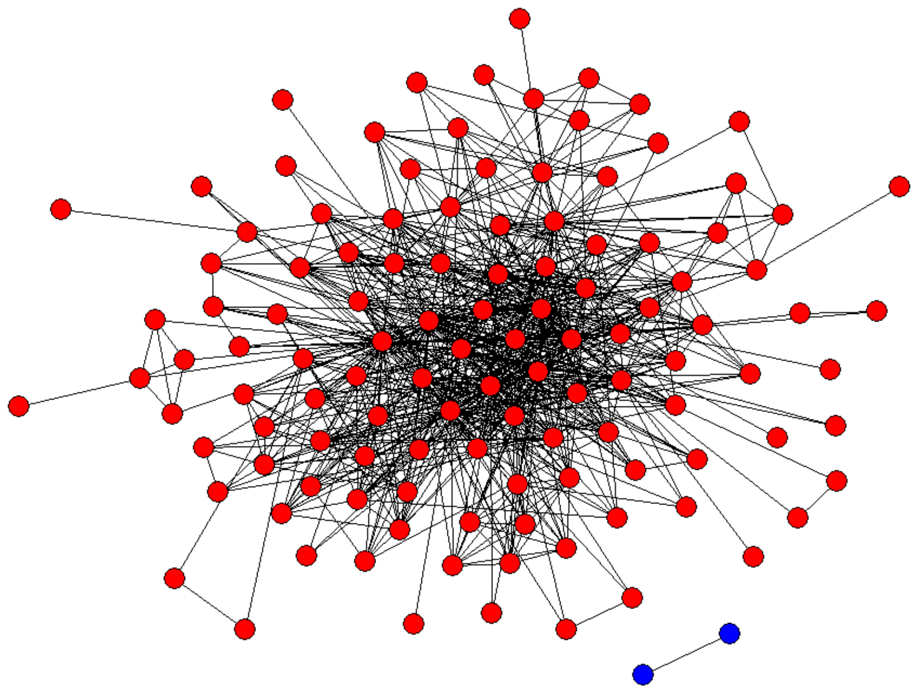


Figure 3.1 – Network of Companies Linked by Common Operating Location

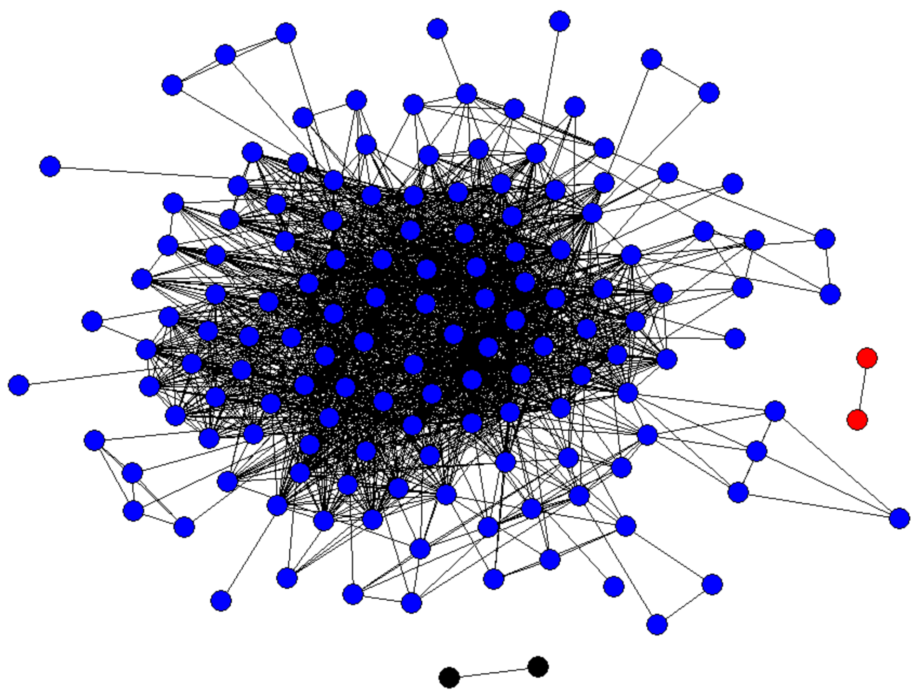


Figure 3.2 – Network of Locations Linked by Common Operating Companies

3.1.1 Conclusions & Implications

The petrochemicals industry does indeed fall into the "small-world" category of networks. This result is significant as it implies that all actors within the network, be they companies, locations or specific operating plants, have short links to the rest of the industry without knowing or realising this to be the case. This phenomenon informs the nature of the self-sustaining dynamics that might be responsible for sustaining such a structure, and is supportive of the idea that the transfer of tacit knowledge is significant.

3.2 Social Network Analysis Methodology and Tools

Network positions differ in terms of power and influence. Participants are not only advantaged by their membership in a collaborative network, but some of them are likely to be better placed to benefit by virtue of their position within it (Kogut 2000). Through the application of a variety of standard social network analysis (SNA) metrics I have been able to identify which features of network participation and connectivity can be associated with co-evolutionary economic success, and hence infer something about the dynamics at play within such systems.

Relative scale is a reasonable indicator of co-evolutionary success, and to this end I chose two readily available metrics for the petrochemicals industry: the number of product streams, which is very closely correlated with the number of production units, and as such is loosely indicative of employment generation capacity; and total production tonnage, this being the closest proxy for value generating potential that is available (accepting that there are a number of inherent, unsubstantiated assumptions being made).

The 'successful' companies and locations were identified and allocated to a division using a maximal differential technique, starting with the largest (because I am interested in success rather than vulnerability).

Table 3.3 identifies the companies in each division, together with their ranking in size order of product streams and tonnage[10].

	Company	Product Streams		Tonnages	
		No PSTs	Rank	Throughput Total (ktes)	Rank
Div 1	TotalFinaElf	151	1	17650	2
	BASF	148	2	17691	1
	ENI	123	3	14141	5
	Shell	116	4	14028	6
	BP	115	5	16160	4
	Dow	101	6	17004	3
Div 2	E-On	62	7	3345	15
	ExxonMobil	60	8	8041	7
	Bayer	58	9	4146	13
	Borealis	44	10	7072	8
	Solvay	43	11	4592	11
	Repsol	40	12	4406	12
	DSM	36	13	5923	10
	RWE-DEA	35	14	1794	21
	Rhodia	35	15	1517	22
	Ineos	34	16	6776	9
	PDVSA	30	17	1829	19

Table 3.3 – Divisions of the Most Successful Companies

[10] Figure 3.3 shows the results of this process for companies (only the first 40 largest companies are shown for ease of examination), and clearly identifies a distinct set of 6 highly successful companies. Examination of the results shows that these are the same 6 companies in both cases, so I have allocated these companies to the first division of successful organisations. The product stream map also shows a cut-point at the 17th company, and these show a reasonable fit with the ranked order of the tonnage list, so I have hypothecated the possible existence of a second division that contains the next 11 companies in the product stream list.

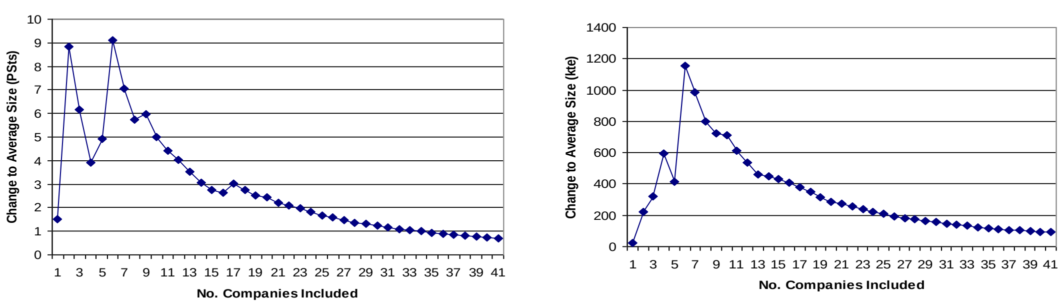


Figure 3.3 – Company Scale: Incremental Changes to Average Size (product streams and total production tonnage)

Exactly the same process was followed for locations, and the results are presented in table 3.4[11].

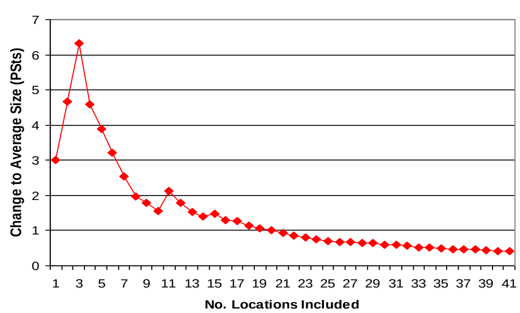
	Location	Tonnage		Product Streams	
		Throughput Total (ktes)	Rank	No PSTs	Rank
Div 1	Gtr_Antwerp	16013	1	85	1
	Gtr_Oberhausen	13059	2	79	2
	Gtr_Rotterdam	12912	3	52	4
	Gtr_Cologne	12483	4	68	3
Div 2	Gtr_Marseilles	8411	5	43	6
	Gtr_Terneuzen	8190	6	37	10
	Gtr_Teesside	6650	7	36	11
	Gtr_Mannheim	6328	8	48	5
	Tarragona	6194	9	39	9
	Gtr_Le_Havre	6052	10	40	7
	Gtr_Leipzig	5884	11	39	8

Table 3.4 - Divisions of the Most Successful Locations

Following the methodology established in earlier studies, the networks of companies sharing locations, and locations sharing companies are investigated separately from the networks formed by companies (or locations) linked through their product portfolios. This acknowledges the strength of formal networking organisations within the industry based on specific technologies and products.

I identified a set of network characteristic metrics that have a reasonably clear interpretation in this context (table 3.5). Many alternatives were available (Scott 2000:82,100, Hanneman 2001:60,77) but I selected those that were most suitable by virtue of having the most intuitive interpretation. Rank-order lists were generated for the actors in each network against all of these metrics.

[11] In this case (figure 3.4) there appears to be a very small core of 3 or 4 highly successful locations, and again these are the same locations in both cases. There is then a second cut-point after the largest 11 locations have been included.



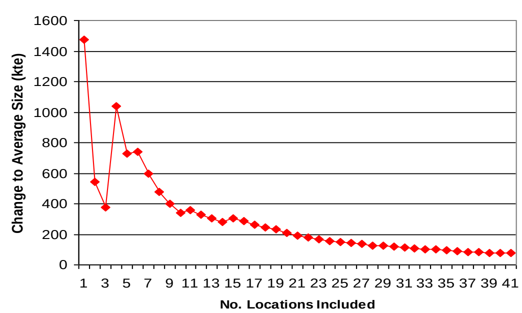


Figure 3.4 - Location Scale: Incremental Changes to Average Size (product streams and total production tonnage)

Metric	**Description**	**Interpretation**
Coreness Distance	The average geodesic distance between any particular actor, and every other actor in the network. Measured in terms of the smallest number of links between the two actors.	A small coreness distance indicates that the actor in question is closely linked to the all other actors in the network
k-core	A set of at least *k* actors, each of which has at least *k* links to other actors within the core. At its most trivial level, a 1k-core simply describes the whole network, but increasing values of *k* rapidly identifies the maximally inter-connected core of the network, and the value of *k* is indicative of the density of the core	Increasing k values indicate participation in an ever denser cluster. If the k value is close to the total number of members of the core this further indicates that the cluster is almost totally introspective with respect to the rest of the network
m-core	A set of actors who have ties between them of minimum strength *m*. A 1m-core simply describes the whole network, but increasing values of *m* rapidly identifies the most strongly linked actors.	This metric looks for groups that have a number of multiple links between them. It is the only metric in the study that differentiates between, for example, two companies linked by operation at a single location, and a different two companies that are linked through operation at 20 different locations.
Betweenness	The proportion of geodesics (i.e. the shortest paths between two actors) between all other actors in the network that pass through the actor in question	Indicates the influence of the actor in question over the efficient operation of the network
flow betweenness	The proportion of all paths between all other actors in the network, not only the geodesics, that pass through the actor in question	The influence of the actor in question over the operation of the network as a whole, irrespective of its efficiency
λ value from a *lambda sets* analysis	This value equals the minimum number of network links that need to be broken before any two actors can be isolated from one another	Indicative of the pervasiveness of the actors' linkages across the network, and hence the extent to which the actors in question are likely to be aware of each other's, and the rest of the network's activities

Table 3.5 – SNA Metrics used in Co-evolutionary Success Study

3.2.1 Company – Location Networks

Table 3.6 shows the characteristics of the most successful companies within the company-location network.

	Company	Owners Linked Through Location					
		Coreness Distance Rank	K_Core Rank	M_Core Rank	Betweenness Rank	Flow Betweenness Rank	Lambda Set Rank
Div 1	TotalFinaElf	5	17	5	2	3	3
	BASF	3	1	1	4	10	1
	ENI	8	1	8	7	2	14
	Shell	2	17	1	9	15	5
	BP	1	1	3	5	4	6
	Dow	4	17	5	1	1	1
	No. ranked in top 6	5	3	5	4	4	5
	proportion ranked in top 6	0.833	0.500	0.833	0.667	0.667	0.833
Div 2	E-On	6	1	5	13	12	8
	ExxonMobil	7	17	3	21	24	9
	Bayer	12	1	8	8	8	4
	Borealis	22	17	20	6	9	13
	Solvay	13	1	10	17	31	12
	Repsol	56	1	20	12	7	52
	DSM	21	1	20	10	16	11
	RWE-DEA	11	17	12	32	42	28
	Rhodia	16	17	12	3	5	7
	Ineos	19	1	12	15	14	10
	PDVSA	17	1	10	28	43	17
	No. ranked in top 17	7	11	8	8	7	9
	proportion ranked in top 17	0.636	1.000	0.727	0.727	0.636	0.818
Overall							
	No. ranked in top 17	13	17	14	14	13	15
	proportion ranked in top 17	0.765	1.000	0.824	0.824	0.765	0.882

Table 3.6 – Network Characteristics of the Most Successful Companies

There is a strong correlation between rank position and co-evolutionary success across all of the metrics chosen. It should be noted that the highest k-core identified was a 13-core with 16 members; a k-core rank of 17 simply indicates that the company is a member of the second largest k-core.

By contrast, the results for locations (table 3.7) show a more varied picture. There is a strong correlation between success and coreness distance and k-core rank, but the correlation with the betweenness metrics is far less compelling.

Location		Locations Linked through Ownership					
		Coreness Distance Rank	K_Core Rank	M_Core Rank	Betweenness Rank	Flow Betweenness Rank	Lambda Set Rank
Div 1	Gtr_Antwerp	1	1	1	3	8	1
	Gtr_Oberhausen	4	1	6	2	5	3
	Gtr_Rotterdam	5	1	1	15	17	11
	Gtr_Cologne	3	1	6	27	28	12
	No. ranked in top 4	3	4	2	2	0	2
	proportion ranked in top 4	0.750	1.000	0.500	0.500	0.000	0.500
Div 2	Gtr_Marseilles	2	1	1	19	41	4
	Gtr_Terneuzen	31	1	18	35	27	25
	Gtr_Teesside	13	1	8	4	6	6
	Gtr_Mannheim	19	45	14	52	73	36
	Tarragona	15	1	17	9	9	21
	Gtr_Le_Havre	7	1	8	22	39	5
	Gtr_Leipzig	10	1	17	11	26	1
	No. ranked in top 11	3	6	3	3	2	4
	proportion ranked in top 11	0.429	0.857	0.429	0.429	0.286	0.571
Overall							
	No. ranked in top 11	9	10	7	5	4	7
	proportion ranked in top 11	0.818	0.909	0.636	0.455	0.364	0.636

Table 3.7 - Network Characteristics of the Most Successful Locations

3.2.2 Product Portfolio Networks

The same analysis was undertaken, but considering companies or locations to be linked if they produce the same product(s). The intention was to assess the extent to which particular products are associated with success.

	Company	Ownership Linked Through Products					
		Coreness Distance Rank	K_Core Rank	M_Core Rank	Betweenness Rank	Flow Betweenness Rank	Lambda Set Rank
Div 1	TotalFinaElf	5	1	5	2	2	1
	BASF	1	1	1	1	1	1
	ENI	4	1	5	4	5	4
	Shell	3	1	3	6	7	5
	BP	2	34	3	5	6	6
	Dow	6	1	1	3	3	1
	No. ranked in top 6	6	5	6	6	5	6
	proportion ranked in top 6	1.000	0.833	1.000	1.000	0.833	1.000
Div 2	E-On	7	34	7	10	8	7
	ExxonMobil	8	34	9	16	14	14
	Bayer	19	57	11	7	4	11
	Borealis	15	34	11	37	54	27
	Solvay	9	34	17	18	21	17
	Repsol	10	34	8	11	12	10
	DSM	11	34	10	9	10	9
	RWE-DEA	16	34	11	24	26	15
	Rhodia	21	1	16	8	9	8
	Ineos	27	67	24	35	36	56
	PDVSA	12	34	14	32	60	23
	No. ranked in top 17	8	1	10	6	6	8
	proportion ranked in top 17	0.727	0.091	0.909	0.545	0.545	0.727
Overall							
	No. ranked in top 17	14	6	16	12	12	14
	proportion ranked in top 17	0.824	0.353	0.941	0.706	0.706	0.824

Table 3.8 – Production Portfolio Network Characteristics of the Most Successful Companies

Again, we see that all of the network characteristics are closely associated with company success, particularly with the Division 1 companies (table 3.8). It is interesting to note that the Division 1 and Division 2 companies are differentiated by their k-core and betweeness ranks.

The results of the analogous study for locations (table 3.9), shows a strong correlation between success and the coreness distance, k-core and m-core ranks, but far weaker correlations with the other parameters.

Location		Locations Linked through Products					
		Coreness Distance Rank	K_Core Rank	M_Core Rank	Betweenness Rank	Flow Betweenness Rank	Lambda Set Rank
Div 1	Gtr_Antwerp	2	1	3	4	6	4
	Gtr_Oberhausen	1	1	1	1	2	1
	Gtr_Rotterdam	4	1	1	6	7	6
	Gtr_Cologne	3	1	4	7	4	8
	No. ranked in top 4	4	4	4	2	2	2
	proportion ranked in top 4	1.000	1.000	1.000	0.500	0.500	0.500
Div 2	Gtr_Marseilles	7	1	7	13	9	17
	Gtr_Terneuzen	12	1	12	8	8	6
	Gtr_Teesside	11	1	9	9	10	7
	Gtr_Mannheim	5	1	4	2	1	3
	Tarragona	8	1	9	14	12	11
	Gtr_Le_Havre	9	1	8	18	17	14
	Gtr_Leipzig	6	1	4	3	3	1
	No. ranked in top 11	6	7	6	4	5	5
	proportion ranked in top 11	0.857	1.000	0.857	0.571	0.714	0.714
Overall							
	No. ranked in top 11	10	11	10	8	9	9
	proportion ranked in top 11	0.909	1.000	0.909	0.727	0.818	0.818

Table 3.9 - Production Portfolio Network Characteristics of the Most Successful Locations

3.2.3 Conclusions & Implications

This analysis only identifies correlations not causality. The results might be indicative of self-reinforcing feedback loops, but cannot identify their initial origin.

There is an overwhelmingly strong relationship between network position and co-evolutionary success within the system. This is perhaps not very surprising, but there are insights to be gained where this relationship breaks down.

Betweenness indicates the degree of influence that an actor has over the network. The results indicate that influence is a significant feature of the most successful companies, but is apparently much less important for locations. Whether this implies that the most influential companies are actively making use of their influence to manipulate the industry, and whether such manipulation would be legitimate, are questions beyond the scope of this study.

A second, perhaps related, question is raised by the k-core differentiation of Division 1 and Division 2 companies with regard to their production portfolios. The Division 1 companies have a common core production portfolio that links them together very closely. Missing part of this core portfolio is a serious impediment to evolutionary success as the Division 2 companies demonstrate. The Division 1 companies exercise far greater influence over the operation of the network, as indicated by their betweenness scores. This might be an indication of an oligopoly in action (Holm et al 1996).

3.3 Stability

Understanding network structure enables an investigation of the ability of the network to absorb new ideas, to transmit information and innovation and coordinate its on-going development (Watts 2003). It also enables the identification of actors who are critical to the effective operation of the network, and those best placed to influence it. Hence, by utilising conventional network analysis tools it is possible to draw conclusions concerning the future viability of an industry, sector or cluster.

3.3.1 Information Cascades

Watts' (2002 and 2003:153) model of information cascades assumes that a new idea or innovation is only adopted by an actor if a threshold proportion of the other actors to which it is linked have already adopted the change. "In threshold models the impact of one person's action on another's depends critically on what other influences the other has been exposed to" (Watts 2003:230). As such, it offers a model for diffusion of ideas, innovations and new ways of working through the industry. Amongst his conclusions is the observation that for global cascades to occur there must be a pervasive core of low threshold "early adopters" throughout the network. Furthermore, there is a link between the average degree (i.e. the average number of connections within the network) and the average threshold value necessary for global cascades to occur. This yields a lower threshold for cascades (where the average degree ~ 1) and an upper threshold, above which the density of connections prevents the threshold value ever being reached for most actors. "Cascades can still be forbidden by the network itself, in two ways – either it is not well connected enough or (and this is the surprising part) it is *too well* connected" (Watts 2003:237).

A rigorous quantitative application of the model requires detailed knowledge of the response of the actors to change (the threshold at which they will adopt an exogenous change), and of their propensity to associate with similar actors, neither of which is known. Nonetheless, it is possible to assess the implications and assumptions that underpin the model in a qualitative way.

Only the network of companies (linked through location) was considered. The interpretation of modes of innovation and information transmission through this network is clear (a mechanism whereby companies generate and own innovations that are transmitted to other companies through partnerships, contacts between personnel etc. is intuitive). An analogous interpretation of locations acting directly as active generators or adopters of innovations is less clear.

The core of the company-location network (i.e. the *13k-core* identified previously) is actually formed by a 16 member *1-plex* (Scott 2000:118) which is the largest in the network. This means that the central 16 companies in the network are linked to one another, and each has only one connection outside this group. If we accept the threshold conjecture for the adoption of new ideas, the implication is that it is very unlikely that this core group will act as early adopters, as their influence threshold can never be reached.

It is still possible for companies within this core to instigate change, but they are unlikely to be involved in the early-stage propagation of any change that was not internally generated. But, because the core provides many of the short-cuts across the network, removing these actors from the potential pool of early adopters significantly increases the size of the early adopter network necessary for global cascades to occur and increases the distance across which innovations need to be transmitted. This has the dual impact of reducing the likelihood of the existence of a pervasive network of early adopters and of reducing the probability any transmission being successful (Watts, Dodds & Newman 2002).

Furthermore, the average degree of the connected component in the company-location network is over 13. At this level it is clear that the network is well above the lower threshold, and is likely to be close to, or even above the upper threshold (Watts 2003:238) for information cascades to be possible.

3.3.2 Sector Influence

Another potential evaluation that can be made concerns the vulnerability of the network to node interference (Borgatti 2003). I used Keyplayer software (Borgatti 2003) to identify the actors (companies and locations) that offer the most pervasive overview of, or opportunity to influence, the network as a whole.

The following tables (3.12 and 3.13) display the results of this analysis focusing on the influence of an increasing number of coordinated nodes[12]. Adding more nodes beyond the number shown generated lists in which the consistency breaks down, as very subtle and inconsequential differences begin to dominate.

[12] This analysis maximises the number of other actors that can be reached by the starting set. For this study only direct contacts have been considered, as we are primarily concerned with early-stage propagation of ideas through direct contact and influence.

Number of Nodes Engaged	1	2	3	4	5	6	7	8	9
Engaged nodes with maximum impact	Dow	Dow TotalFinaElf	Dow TotalFinaElf Borealis	Dow TotalFinaElf Borealis DSM	Dow TotalFinaElf Borealis Akzo_Nobel ENI	Dow Borealis Akzo_Nobel ENI BP Rhodia	Dow Borealis Akzo_Nobel ENI BP Rhodia BASF	Dow Borealis Akzo_Nobel ENI BP Rhodia BASF Repsol	Dow Borealis Akzo_Nobel ENI BP Rhodia BASF Repsol Maerkishe_Faser
Number of Co's Influenced	**61**	**80**	**91**	**98**	**103**	**107**	**109**	**111**	**113**
Proportion of all Co's influenced	43.6	57.1	65.0	70.0	73.6	76.4	77.9	79.3	80.7

Table 3.12 – Company Network Engagement – Most Critical Nodes

Number of Nodes Engaged	1	2	3	4	5	6
Engaged nodes with	Gtr_Antwerp	Gtr_Bilbao Gtr_Oberhausen	Gtr_Antwerp Gtr_Bilbao Gtr_Oberhausen	Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona	Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre
Number of Co's Influenced	**76**	**106**	**114**	**121**	**125**	**128**
Proportion of all Co's influenced	45.5	63.5	68.3	72.5	74.9	76.6

Number of Nodes Engaged	7	8	9	10	11	12
Engaged nodes with maximum impact	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna Gtr_Teesside	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna Gtr_Teesside Estarreja	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna Gtr_Teesside Estarreja Schwarzheide	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna Gtr_Teesside Estarreja Schwarzheide Aalesund	Gtr_Antwerp Gtr_Oberhausen Gtr_Monza Gtr_Stenungsund Tarragona Portalegre Ravenna Gtr_Teesside Estarreja Schwarzheide Aalesund Barbastro
Number of Co's Influenced	**131**	**133**	**135**	**137**	**139**	**141**
Proportion of all Co's influenced	78.4	79.6	80.8	82.0	83.2	84.4

Table 3.13 – Location Network Engagement – Most Critical Nodes

These results provide some guidance as to which sets of companies or locations are most likely to be able to activate an early-adopter network, and hence have the greatest chance of instigating change within the industry. In fact, it is quite possible that alliances between these companies might obviate the need for a pervasive early adopter network, given that they effectively form a pervasive network themselves. “This much larger population is still stable with respect to individual innovators, but once the entire vulnerable cluster has been activated, these initially stable nodes become exposed to *multiple* early adopters” (Watts 2003:242).

3.3.3 Conclusions & Implications

With the information available it is impossible to assess which side of the global information cascade upper threshold (Watts 2002) the industry lies, but if such cascades are still possible, then they will be very rare and almost impossible to forecast. Near this upper threshold:

> *"global cascades become larger, but increasingly rare…….the system will in general be indistinguishable from one that is highly stable, exhibiting only tiny cascades for many initial shocks before generating a massive, global cascade in response to a shock that is a priori indistinguishable from any other."*(Watts 2002:5770)

The network formed by the industry is highly resilient to disruption., but with this comes the penalty that it is difficult, if not impossible, for innovations to propagate through the industry. Studies (Grabher 1993 and Glasmeier 1994 cited in Staber 2001:546) have demonstrated that tight linkages become self-reinforcing over time leading to 'cognitive and political lock-in', and the domination of large core firms in the formulation of strategy with the outcome that the existing network hierarchies are preserved. Lock-in is a real risk.

An appropriate choice of companies and/or locations allows access to the bulk of the industry through the influencing of surprisingly few actors. This small group has direct linkages to almost the entire network. But without the cooperation of this set, and the core of the most highly connected companies, it would appear to be very difficult to initiate industry-wide change.

4. Implication for Research & Practice

4.1 Implications for Theory & Application

4.1.1 Tools, Techniques and Methodologies

The power of SNA tools and techniques is unquestionable. The ability to describe networks in matrix form enables the use of matrix algebra. The resultant ease with which the desired information can be generated from a base set of data, and the ability to inspect the results using network visualisation software, is enormously powerful.

The small world study exposed some of the shortcomings of the conventional approach to SNA when applied out of context. Notionally SNA software can generate path length and clustering coefficient information, but there is no established convention for dealing with isolates (which have a theoretically infinite path length to the rest of the network), nor pendants (for whom the clustering coefficient has no real meaning) in real systems[13]. It would be useful if a standard approach could be established and the limitation understood.

Similar issues are encountered when focussing on specific network properties. In deciding on which of the multitude of standard SNA measures to use I was minded of Scott's (2000:101) invaluable advice:

> *"The choice of a particular characteristic depends on the researcher's decision that a particular mathematical criterion can be given a meaningful and useful sociological interpretation. Unfortunately, this is rarely made explicit, and far too many researchers assume that whatever mathematical procedures are available in social network programs must, almost by definition, be useful sociological measures."*

Power-laws provide an extremely powerful diagnostic tool for the identification of underlying dynamics and structures. Most correlations are clear and easily identifiable by eye, but where they are ambiguous, a readily deployable significance test would be invaluable. Standard R^2 statistics are unhelpful, as they fail to account for the systematic deviation from a trend line that is misapplied.

4.1.2 Study Specific Questions

The fragmentation study identified a convergence in the level of integration as company and location size increased. It is no surprise that locations show a higher average level of integration than companies (which might invest in production facilities that are not internally integrated for some strategic reason), but that there should be an optimal value for the degree of integration merits further investigation.

[13] For this study I chose to only examine the properties of the main component as a pragmatic way to work around the first limitation, and I simply ignored pendants when calculating the average network cluster coefficient.

The network structure of the industry enabled the discrete dimensions of diversity advocated by Stirling (2004) to be given a rigorous interpretation. One of these suggested an optimal level of redundancy for the industry[14]. This might indicate the point at which the costs associated with the maintenance of the redundancy equal the benefits in terms of robustness (Staber 2001), thus enabling a quantification of these robustness benefits.

The dominant and perhaps most surprising findings of the power-law study was the implied growth in the sector (Barabasi & Albert 1999). This is apparently at odds with the stagnation of the industry that is generally accepted (Chapman 1991). One possible explanation might relate to the on-going merger and acquisition activity within the sector. While being a zero sum activity, it does represent growth for the acquiring companies.

Finally, a clear correlation was established between size and dominant network position. It would be useful to be able to identify the direction of the causality in this correlation, and to make a judgement on the how deterministic network position has been.

4.2 Implications for Stakeholders

4.2.1 Industrial Stakeholders

A tentative conclusion of the fragmentation study was an upper limit on the size of the fully integrated production fragment that any company can manage successfully, and most companies opt for configurations much smaller than this. Whether this conclusion is valid or not, it is clear that company growth occurs not through specialisation and consolidation, but through the addition of new products at new locations. In fact, the more disparate a company's configuration, the larger it is likely to be. What's more, the largest companies operate relatively more, rather than larger, production facilities, and they grow through diversification, building out from their established production chains, but at new locations with new products.

The core of the industry exhibits multiple redundant routes for information transfer. This structure encourages cooperation and information exchange because it is likely to render any attempt to protect knowledge and innovation futile. Further emphasising the point, the industry's structure exhibits small-world characteristics[15]. The crucial implication is that close linkages between geographically distant production facilities are not anomalous exceptions – they are normal and common. Hence, information is easier to find that most companies think, nothing stays secret for long, and reputations are quick to spread.

[14] The disparity dimension of production diversity appeared to converge as the size of the companies and locations increased. This implied an optimal level of redundancy of 3 product streams per product for companies, and 2 for locations.

[15] A small world network shows short links between any two actors, despite those actors not necessarily being aware of them. As a result the companies (or locations) are likely to have an unrealistic view of how affected they might be by actions elsewhere in the system. For example, Enichem at Fawley, UK probably believe that they are largely isolated from the actions of Borealis in Schwechat, Austria, but in practice they are likely to be linked through surprisingly short ownership and location chains, and have a far greater chance of being affected than they would ever imagine.

The strength of the network core confers massive robustness, but this comes at the price of significant resistance to change (Kogut 2000). Networks of similar actors, presumably with similar knowledge, offer very little in terms of access to new knowledge, ideas or information to their participants. However, by allowing a certain amount of local autonomy, it is possible that companies use their geographical fragmentation to bypass the threshold requirement for corporate level adoption of innovation and change (Watts 2003). Cumbers et al (2003) identified that innovations are often not so much 'new to the world' as 'new to the market' (i.e. the local competitive environment).

The flip-side of the structure that has emerged is that the entire industry can be influenced with the cooperation of only a small set of companies and/or locations - a fact that must be of value to suppliers and innovators alike.

One final consideration that industrial stakeholders should consider is the role of long-distance pipelines, which, according to the power-law results have become the dominant factor in location decisions. Coupled with the speculation that the truncation of the company size distribution is a consequence of regulator action, a clear implication for the largest companies is that a controlling interest in these pipelines represents an accessible growth option in the face of anti-trust opposition to manufacturing expansion.

4.2.2 Public Sector Stakeholders

Local government bodies and development agencies should be interested in the swathe of results that suggest that fragmentation is a vital ingredient within the industry. The implication is that, while the strength of local networks is critical, the quality of long-range networks differentiates the most successful regions from the rest. The danger of lock-in, particularly in regions that are dominated by a single, vertically integrated manufacturer are real, but can be actively managed with sufficient foresight.

Public bodies need to be cognisant of the observation that networks have no authoritative capability other than reinforcement. "It is interesting that relationship commitment is influenced by understanding between the partners rather than by the profitability achieved in the relationship" (Holm et al 1996:1048). Development agencies have a key role to play in promoting such relationships, but they must be inclusive, and not focus exclusively on SMEs.

Links of this type are likely to exist between Enichem at Fawley and most other companies at most other locations, and should be expected.

At a national and European level the implications of the results are worrying. The industry has evolved a structure that is highly concentrated amongst a few large companies and locations. Consequently, common perspectives, unconsciously embedded in the network's processes, inform the actors' interpretation of their social environment. This results in a reinforcement of the interpretation of group behaviour, "(the causality of the probable) which provides the illusion of immediate understanding" (Gorton 2000:281) and generates a self-sustaining dynamic of misplaced mutual reassurance. While robust to any amount of disruption, it is also likely to be highly resistant to change and subject to stagnation – indeed according to the threshold model of information transfer, it is possible that information and innovation cascades are already impossible.

Nonetheless, the core is so powerful and influential that attacking or excluding these companies will inevitably be unsuccessful.

Which brings me to the implications for regulators. Many of the research findings *might* be interpreted as being consistent with the active operation of an oligopoly. Theoretical evidence supports the idea that oligopolistic action can protect the structure of a mature industry (e.g. Chapman 1991). This is the critical point, it does protect the industry which would otherwise disintegrate under uncontrolled competitive pressure, and regulation might prove counter-productive. We have learned that behaviours become encoded in the structure itself over time (Kogut 2000), so, if an oligopoly is operating (and the research methodology cannot demonstrate this either way) it might not be deliberate, and in any respect would prove extremely difficult to influence.

Regulators might also give some consideration to the origin and implication of the truncation of the company size distribution in the power-law study. The absence of a similar truncation of the production web size distribution, despite the North European ethylene and propylene grids (which yield the enormous outlier in the data) implies that long-distance pipelines mitigate the constraints that otherwise restrict growth.

5. Conclusions

This work clearly demonstrates the validity of a methodology that considers a well defined industrial sector as a network that exists across a disparate set of geographical scales. The tools of social network analysis lend themselves, with careful interpretation and consideration, to an economic and industrial context and prove invaluable. Nonetheless, there is scope to improve and enhance their usability as has been described.

The model that emerges from both the theory and the results of the petrochemicals study is of a series of local networks where intense formal and informal linkages facilitate information and knowledge exchange and innovation. The critical feature though, is that large, multinational corporations enable the transfer of new capabilities between locations, thereby generating new opportunities for innovation within the locations themselves. This gives large corporations a legitimate role in the development of regional agglomerations, but in a way that forces a consideration not only of the quality of the local networks, but also of the linkages to the wider and more geographically dispersed industry. The ability of the regional clusters to learn from their multinational corporations becomes a critical factor (MacKinnon et al 2002).

I found that the form and structure of the network was consistent with that which is suggested by a co-evolutionary interpretation of industrial sectors and regions. In doing so, I believe that I have been successful in demonstrating the applicability of network and co-evolutionary theories to mature industries, and the importance of considering local and distant linkages together.

Fragmentation is one of the methods utilised to generate the necessary levels of diversity for effective learning and evolution. But this fragmentation also creates a network of interconnected companies and locations. If the companies indulged in vertical integration at single-owner dominated locations, no such network would exist. It is clear from the power-law study that connectivity is seen as attractive within the industry. This is clear evidence that existing connectivity is an important factor in making location decisions. Thus local agglomeration is promoted, the level of fragmentation is enhanced, and the network develops further.

Chapman (1991) identifies a mechanism for the diffusion of information along two interrelated dimensions: between competing firms and from one geographical location to another. It is my contention that internal company resources and local geographical resources provide a two dimensional search lattice (Watts, Dodds & Newman 2002) within the industry, creating an environment more conducive to learning and problem solving than a single organisational hierarchy.

There are no examples of companies that have grown to significance through a process of specialisation or local vertical integration. Given the multitude of reinforcing positive feedback loops that have generated the current industry structure, it is difficult to see how or why such a strategy might be more successful in the future.

This work potentially provides a basis for future research. A comparative study on a sector with a different structural form (e.g. the automotive sector in which the critical linkages might be expected to be between the first-tier suppliers) would provide an invaluable insight into the specificity of my findings, and of the methodology and tools themselves. There is also a need to demonstrate the operation of the hypothesised self-perpetuating behavioural and cultural dynamics that underpin much of the theoretical basis of the work described in this paper. Finally, it is only through a formal longitudinal study that many of the inferences can be properly tested.

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