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Network Enabled Capabilities and Competitive Technology Clusters in Ireland

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Network enabled capabilities and Competitive Technology Clusters in Ireland

Abstract

The Network approach is a useful heuristic tool that enables us to focus on the network structure, inter-linkages between actors and help determining how the networks change over time. The present study used the network approach to understand the degree to which technology based clusters (TBCs); industries, firms and products are enmeshed and linked in a network. The study indicates the important features and structure of high-tech industrial organisation in Ireland. Various network-based measures of connectivity and embeddedness of these competitive technology clusters in the network are used to determine the behaviour, and the range of opportunities, influence, and power that the industries and TBCs have. The study also examines whether capabilities are transferrable across these TBCs and industries in an evolutionary manner through technological convergence. Demographics of 2280 high-tech firms that comprise 8 competitive technology based clusters in Ireland are used to construct this network and an extensive product classification is used to create linkages between the technologies and industries.

Network Enabled Capabilities and Competitive Technology Clusters in Ireland

1. Introduction

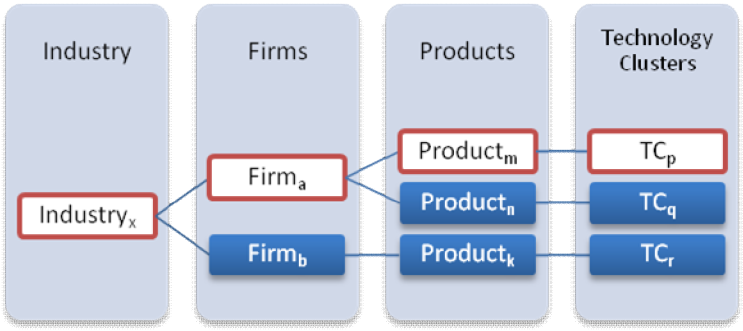
The Network concept is a key element of many of the spatial variants of growth models. Grabher (1993, 2006) provides a good synthesis of the use of the network concept in socio-economics. He explains, how a generic form of exchange called network obeys four basic features: reciprocity, interdependence, loose coupling and power. This opened up a relational view of the social context of economic action that largely became synonymous with Mark Granovetters (1985) paradigmatic notion of embeddedness. In this context Ter Wal and Bocshma (2009) argue that the network approach is now a useful heuristic tool to understand the dynamics of inter-organizational ties particularly in the context of industrial dynamics.

One of the key questions in this research is what does the structure of the technology-clusters look like? And what is the industrial composition of this structure? The network approach is a useful tool to answer these kinds of questions. It enables us to focus on the effects of certain network structure and one can distinguish between the effects of network on its individual actors at the micro level and the effects on the entire network structure as a whole at the macro level. Ter Wal and Boschma (2009) further point out that the network approach can also be a useful tool to understand how networks change over time. This paper provides a clear illustration of how the Lucerna database can be utilized to analyse the structure of the Irish high-tech sector using network analysis.

2. The Network Approach

As each individual firm in our database provides information about their main industry (2 digit level in Kompass Classification) along with their product portfolio (7-digit product level), which was used to define the technology-clusters, we used this information to construct a link between industry and our technology-clusters.

Industry Technology-Cluster Link



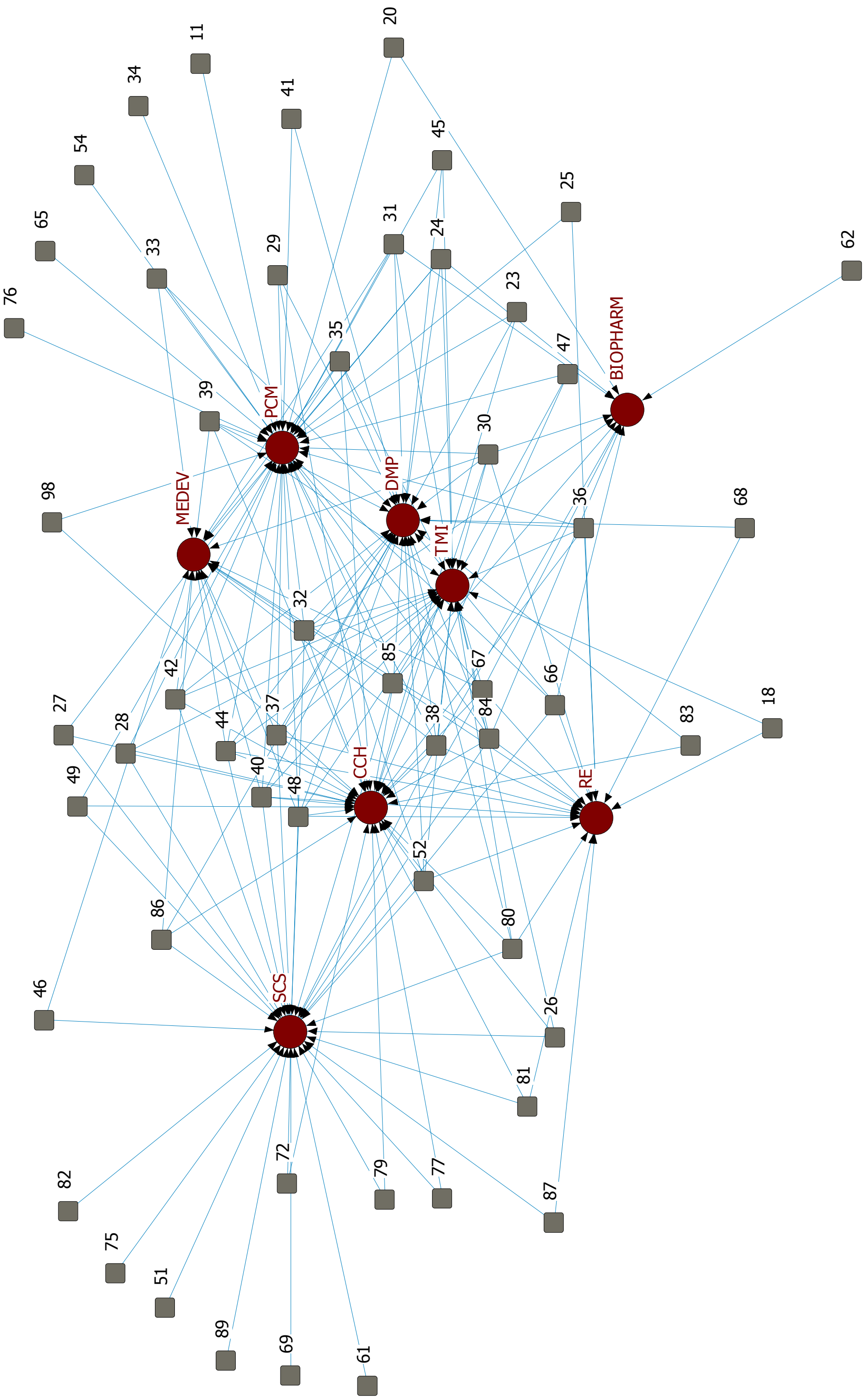
As illustrated in the above figure (an example Industry$_x$ is linked to three different technology clusters: TC$_p$, TC$_q$, TC$_r$) our dataset reveal a set of 2250 such ties. We used this relationship in network analysis using standard network analysis software. The basic idea of a network is very simple. It consists of a set of actors that may have relationships (or edges, or ties) with one another. In our case Industries and technology-clusters are such actors in Irish Industry-Technology net. The exact nature of this relationship is subjective and can be quantified with various variables: number of firms from a particular industry representing a particular technology-cluster or may be the share of industry employment in that technology-cluster. But the subjective nature of the relationship encompasses wider perspectives of industrial dynamics. One can argue that industries (alters) connected to a technology-cluster (ego) have greater interaction with each other in terms of exchange of people and trade. Possibly there are other non-tradable links of exchange of externalities and knowledge spillovers. Technology and science play an intermediating role in their capabilities development and they co-evolved with policy intervention.

The network perspective emphasizes multiple levels of analysis. At individual level differences among actors can be explained by the constraints and opportunities that arise from how they are embedded in networks; the structure and behavior of networks grounded in, and enacted by local interactions among actors. The differences among individuals in the way they are connected can also be extremely consequential for understanding their attributes and behavior. In general, high connectivity indicates that individuals are exposed to more, and more diverse, information and opportunities. Highly connected individuals may be more influential, and may be more influenced by others. At aggregate level, highly connected populations may be better able to mobilize their resources, and may be better able to bring multiple and diverse perspectives to bear to solve problems. Between the individual and the entire population, there is another level of analysis that focuses on ‘composition’. Some populations may be composed of individuals who are all pretty much alike in the extent to which they are connected. Other populations may display sharp differences. Differences in connections can tell us a good bit about the stratification order of different groups. Further most individuals are not connected directly to most other individuals in a population, it can be quite important to go beyond simply examining the immediate connections of actors and explore the distance between actors (or, conversely how close they are to one another). One major difference among different group is not so much in the number of connections that actors have, but in whether these connections overlap and constrain or extend outward and provide opportunity. Populations as a whole, then, can also differ in how close actors are to other actors, on the average. Such differences may help us to understand diffusion, homogeneity, solidarity, and other differences in macro properties of social groups.

3. Basic properties of Industry-Technology Net

Since networks are defined by their actors and the connections among them, it is useful to begin our description of industry-technology net by examining its simple properties. For present analysis, the Industry-technology net is based on a directed (asymmetric, not reciprocated –industries constitutes technology-clusters not other way round) relation where the ties are valued by the numbers of firms constituting the links. As we explained before the subjective natures of ties are ambiguous but they indicate a compositional structure. A di-graph illustrating the connection between industries and technology-clusters is given in figure 1. A careful interpretation of this graph can be very useful in getting an intuitive grasp of the important features of industrial organization of Ireland. Each 2-digit node refers to a Kopmpass 2-digit sector.

Figure 1 Network indicating Industry-Technology Cluster interaction in ROI



(Layout –Spring Embedding)

The descriptive statistics of a network indicate the number of actors present, the number of connections that are possible, and the number of connections that are actually present. Difference in size and manner of connection also indicate the cohesion, solidarity, density, and organizational complexity of the population. Individuals, as well as whole networks, differ in these basic demographic features. Individuals differ as the "sources" of ties or a "sinks" (actors that receive ties, but don't send them), or both. The number and kinds of ties that actors have are keys to determining how much their embeddedness in the network constrains their behavior, and the range of opportunities, influence, and power that they have. The following table 1 indicates various such measures of this industry-technology net.

The density of a network is simply the proportion of all possible ties that are actually present. This is an overall measure that may give us insights into such phenomena as the speed at which information diffuses among the nodes, and the extent to which actors have high levels of social capital and/or social constraint. For a valued network, like ours, density is defined as the sum of the ties divided by the number of possible ties. This is 0.652 (SD = 14.652) for this net. The value indicates the entire industry-technology net is well connected (comparative statistics from other regions may explain the difference). Connection is central to production system and a well connected network is a prerequisite for attaining greater competitiveness and open innovation model.

Results indicate the relative connecting power of different technology-clusters in I-TC net. SCS (M=18.42, SD = 108.75) scored highest mean value followed by PCM (M=6.21, SD=18.07) and CCH (M=6, SD=20.59) indicating they are central to Irish competitive technology. On the other side BIOPHARM (M=1.77, SD =10.19) and MEDEV (M=1.29, SD=5.61) which are dominated by foreign owned companies are least connected to diverse industries. Does a higher connectivity indicate a well embedded technology in Ireland? We will unfold the answer in next few steps. But the result points to technologies that are serving wider industries hence can be used as a point of departure for further studies and industrial and academic policies. Table 2 tells us about the role that each industry plays as a ‘source’ of ties. We only listed the top ten industries plus other three important sectors: 84-Technical offices and Engineering consultancies, Architects, 85-Research and Testing, 86-Education and Training to this table.

Table 1 Descriptive Statistics of Technology- Clusters in Industry-Technology net

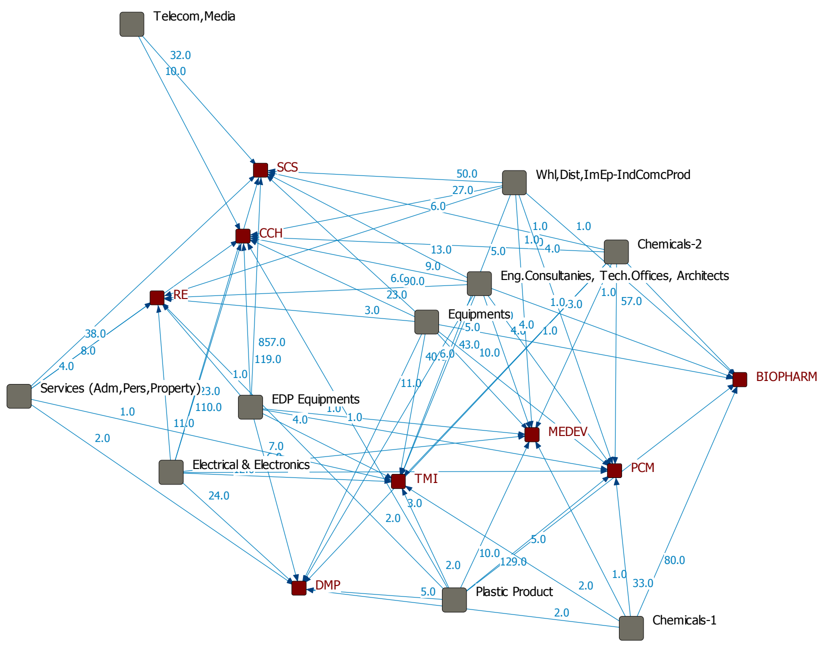
	PHARMA	CCH	DMP	MEDEV	PCM	RE	SCS	TMI
Mean	1.77	6	2.098	1.295	6.213	2.82	18.426	1.836
Std Dev	10.195	20.593	4.371	5.611	18.074	11.872	108.754	5.43
Sum	108	366	128	79	379	172	1124	112
Variance	103.947	424.066	19.105	31.487	326.66	140.935	11827.52	29.481
SSQ	6532	28064	1434	2023	22281	9082	742190	2004
MCSSQ	6340.787	25868	1165.41	1920.688	19926.23	8597.017	721478.9	1798.361
Euc	80.821	167.523	37.868	44.978	149.268	95.3	861.505	44.766
Minimum	0	0	0	0	0	0	0	0
Maximum	80	119	24	43	129	90	857	40
N	61	61	61	61	61	61	61	61

Table 2 Descriptive Statistics of Industries in Industry-Technology net

Rank	Industry	Mean	StdDev	Sum	Variance	SSQ	MCSSQ	Euc Norm	Min	Max	N
1	44	16.23	109.59	990	12010.01	748678	732610.8	865.262	0	857	61
2	37	3.279	14.624	200	213.873	13702	13046.26	117.056	0	110	61
3	30	2.557	16.401	156	269.001	16808	16409.05	129.646	0	129	61
4	38	2.295	8.035	140	64.569	4260	3938.688	65.269	0	43	61
5	84	2.115	11.563	129	133.708	8429	8156.197	91.81	0	90	61
6	31	1.934	10.917	118	119.176	7498	7269.738	86.591	0	80	61
7	67	1.541	7.201	94	51.855	3308	3163.147	57.515	0	50	61
8	32	1.148	7.263	70	52.749	3298	3217.672	57.428	0	57	61
9	80	0.869	4.931	53	24.311	1529	1482.951	39.102	0	38	61
10	79	0.689	4.237	42	17.952	1124	1095.082	33.526	0	32	61
22	85	0.23	0.663	14	0.439	30	26.787	5.477	0	3	61
26	86	0.197	1.157	12	1.338	84	81.639	9.165	0	9	61

The sum of the connections from the industry to TC (e.g. Industry -84 has 90 connection to various TCs) is called the *out-degree* of the point. Figure 2 illustrates the interaction of these to industries to various TCs.

Figure 2 Network indicating top 10 industries (degree) in Industry-Technology net.



While the previous section looked at the individual properties of the TCs and industries, the following section seeks to understand and describe whole populations by the "texture" of the relations that constrain its individual members. Embedding of actors in dyads, triads, neighborhoods, clusters, and groups are all ways in which the social structure of a population may display 'texture'. The smallest social structure in which an individual can be embedded is a dyad (that is, a pair of actors: Industry –technology link). We can characterize the whole population in terms of the prevalence of these dyadic 'structures'[1]. All of these forms of embedding structures speak to the issue of the "horizontal differentiation" of the population. However hierarchical structures in which individuals or sub-populations are not only differentiated, but also ranked, are extremely common in network. The degree of hierarchy in a population speaks to the issue of "vertical

[1] Even if it looks complex Industry-technology net is a very simple structure and only has dyadic relation between Industry and technology.

differentiation". Krackhardt[2] (1994) provided an elegant definition of the meaning of hierarchy, and developed measures of each of the four component dimensions of the concept that he identified. In this context the I-TC net shows following characters.

Table3 Density

Density	
Avg Value	0.6526
Std Dev	14.6527

Table 4 Embedding

Krackhardt GTD Measures	
Connectedness	1.0000
Hierarchy	1.0000
Efficiency	0.9290
LUB	0.0863

[2] Krackhardt defines a pure, "ideal typical" hierarchy as an "out-tree" graph. An out-tree graph is a directed graph in which all points are connected, and all but one node (the "boss") has an in-degree of one. This very simple definition of the pure type of hierarchy can be deconstructed into four individually necessary and jointly sufficient conditions. Krackhardt develops index numbers to assess the extent to which each of the four dimensions deviates from the pure ideal type of an out-tree, and hence develops four measures of the extent to which a given structure resembles the ideal typical hierarchy.

The main theme of embedding was to understand and index the extent and nature of the pattern of "constraint" on actors that results from the way that they are connected to others. These approaches may tell us some interesting things about the entire population and its sub-populations; but, they don't tell us very much about the opportunities and constraints facing individuals. In this section we are focusing on the individual technology clusters for detail understanding.

Table5 Egonet Analysis of Technology-Clusters

	Density Measure				Structural Holes	
	Size	Pairs	nWeakC	Brockers	Dya Cons	SH Constr
BIOPHARM	11	110	11	55	0.008	0.091
CCH	30	870	30	435	0.001	0.033
DMP	26	650	26	325	0.001	0.038
MEDEV	18	306	18	153	0.003	0.056
PCM	35	1190	35	595	0.001	0.029
RE	18	306	18	153	0.003	0.056
SCS	30	870	30	435	0.001	0.033
TMI	23	506	23	253	0.002	0.043

Different structural properties of individual technology clusters are summarized in the above table 5. The scores in this table indicate the following characters. Size of ego network (Size) is the number of nodes that one-step out neighbors of ego (plus ego itself). That is indicating the exact number of industries constituting the technology-clusters. PCM has the largest ego network that connects to 34 different industries followed by SCS and CCH, 29 each. BIOPHARM, MEDEV has the smallest networks and they constitute the members from 10 and 17 industries respectively. Number of ordered pairs (Pairs) is the number of possible directed ties in each ego network. This value has no meaning to present analysis as industries are not connected to each other in I-TC net. But it indicates the maximum available channels of connection within a TC, if industries are connected as in reality. Number of weak components (nWeakC) is the largest number of actors who are connected, disregarding the direction of the ties (a strong component pays attention to the direction of the ties for directed data).

Brokerage (Brockers) counts the number of pairs that are not directly connected. The idea of brokerage is that ego is the "go-between" for pairs of other actors. In an ego network, ego is connected to every other actor. If these others are not connected directly to one another, ego may be a "broker" ego falls on the paths between the others. It simply indicates the how much potential for brokerage there is for each actor.

Ronald Burt coined and popularized the term "structural holes" to refer to some very important aspects of positional advantage/disadvantage of individuals that result from how they are embedded in neighborhoods. Burt's formalization of these ideas, and his development of a number of measures has facilitated a great deal of further thinking about how and why the ways that an actor is connected affect their constraints and opportunities, and hence their behavior. Two such measures are used here in our analysis and scores are given in table 6.

Dyadic constraint (Dya Cons) is an measure that indexes the extent to which the relationship between ego and each of the alters in ego's neighborhood "constrains" ego. A full description is given in Burt's 1992 monograph, and the construction of the measure is somewhat complex. At the core though, A is constrained by it's relationship with B to the extent that A does not have many alternatives (has few other ties except that to B), and A's other alternatives are also tied to B. If A has few alternatives to exchanging with B, and if those alternative exchange partners are also tied to B, then B is likely to constrain A's behavior. In our example constraint measures are not very large, as most actors have several ties.

Constraint (Constra) is a summary measure that taps the extent to which ego's connections are to others who are connected to one another. If ego's potential trading partners all have one another as potential trading partners, ego is highly constrained. If ego's partners do not have other alternatives in the neighborhood, they cannot constrain ego's behavior. The logic is pretty simple, but the measure itself is not. It would be good to take a look at Burt's 1992 Structural Holes. The idea of constraint is an important one because it points out that actors who have many ties to others may actually lose freedom of action rather than gain it – depending on the relationships among the other actors.

Table 6 Structural Hole - Individual tech.cluster characters

Constraint	
Biopharm	0.091
CCH	0.033
DMP	0.038
MEDEV	0.056
PCM	0.029
RE	0.056
SCS	0.033
TMI	0.043

Network thinking has contributed a number of important insights about the power of actors. Perhaps most importantly, the network approach emphasizes that power is inherently relational. An individual does not have power in the abstract, they have power because they are connected to others (ego's power is alter's dependence). Because power is a consequence of patterns of (low density) not much power can be exerted; in high density systems there is the potential for greater power. Power is both a systemic (macro) and relational (micro) property. The amount of power in a system and it's distribution across actors are related, but are not the same thing. Two systems can have the same amount of power, but it can be equally distributed in one and unequally distributed in another. Power in social networks may be viewed either as a micro property (i.e. it describes relations between actors) or as a macro property (i.e. one that describes the entire population); as with other key sociological concepts, the macro and micro are closely connected in social network thinking. Network analysts often describe the way that an actor is embedded in a relational network as imposing constraints on the actor, and offering the actor opportunities. Actors that face fewer constraints, and have more opportunities than others are in favorable structural positions. Having a favored position means that an actor may extract better bargains in exchanges, have greater influence, and that the actor will be a focus for deference and attention from those in less favored positions.

Table 7 Degree Centrality of different Industry in Industry-Technology Cluster net of ROI

		Freeman Degree			Bonacich Power
Rank	Industry	Degree	NrmDegree	Share	Bon. NorValue
1	44	990	1.894	0.201	57.907
2	37	200	0.383	0.041	11.698
3	30	156	0.298	0.032	9.125
4	38	140	0.268	0.028	8.189
5	84	129	0.247	0.026	7.545
6	31	118	0.226	0.024	6.902
7	67	94	0.18	0.019	5.498
8	32	70	0.134	0.014	4.094
9	80	53	0.101	0.011	3.1
10	79	42	0.08	0.009	2.457
22	85	14	0.027	0.003	0.819
25	86	12	0.023	0.002	0.702

Three different approaches have been used in network analysis to understand power: Degree, Closeness and Betweenness. Each of these three ideas: degree, closeness, and betweenness, has been elaborated in a number of ways. Linton Freeman developed basic measures of the centrality of actors based on their degree, and the overall centralization of graphs. The scores of this measure for Industries and TC are presented in table 7 illustrating the degree centrality values. Phillip Bonacich proposed a modification of the degree centrality approach that has been widely accepted as superior to the original measure. The original degree centrality approach argues that actors who have more connections are more likely to be powerful because they can directly affect more other actors. This makes sense, but having the same degree does not necessarily make actors equally important. Bonacich argued that one's centrality is a function of how many connections one has, and how many the connections the actors in the neighborhood had. Bonacich proposed that both centrality and power were a function of the connections of the actors in one's neighborhood. The more connections the actors in your neighborhood have, the more central you are. The fewer the connections the actors in your neighborhood, the more powerful you are. This concept is particularly useful to understand the role of different industries in industry-Technology net. The Bonacich power (Bon.NorValue – a normalized value) for top 10 industries plus STECS is given in table 7.

Degree centrality measures might be criticized because they only take into account the immediate ties that an actor has, or the ties of the actor's neighbors, rather than indirect ties to all others. One actor might be tied to a large number of others, but those others might be rather disconnected from the network as a whole. In a case like this, the actor could be quite central, but only in a local neighborhood. Closeness centrality approaches emphasize the distance of an actor to all others in the network by focusing on the distance from each actor to all others. Depending on how one wants to think of what it means to be "close" to others, a number of slightly different measures can be defined. The values of this measure are presented in table 8.

Path distance calculates the far-ness of each actor from all others. Far-ness is the sum of the distance from each ego to all others in the network. Far-ness is then transformed in to nearness as of reciprocal far-ness. relations, the amount of power in social structures can vary. The score of these measures for technology-clusters are given in table 8 and indicating the values for different industries. Figure 3 is an illustration of this value. Reach is another way of thinking about how close an actor is to all others is to ask what portion of all others ego can reach in one step, two steps, three steps, etc. An index of the "reach distance" from each ego to (or from) all others is calculated. Here, the maximum score (equal to the number of nodes) is achieved when every other is one-step from ego. The reach closeness sum becomes less as actors are two steps, three steps, and so on (weights of 1/2, 1/3, etc.). These scores are then expressed in normalized form by dividing by the largest observed reach value in table 8 and 9 for Tc and industries. *Hubbell, Katz, Taylor, Stephenson, and Zelen Influence measures* - The geodesic closeness and Eigen value approaches consider the closeness of connection to all other actors, but only by the "most efficient" path (the geodesic). In some cases, power or influence may be expressed through all of the pathways that connect an actor to all others. The Hubbell and Katz approaches count the total connections between actors (ties for undirected data, both sending and receiving ties for directed data). Each connection, however, is given a weight, according to its length. The greater the length, the weaker the connection. How much weaker the connection becomes with increasing length depends on an "attenuation" factor. In our example, below, we have used an attenuation factor of

.5. That is, an adjacency receives a weight of one, a walk of length two receives a weight of .5, a connection of length three receives a weight of .5 squared (.25) etc. scores are presented in table 9 and subsequently schematically in figures 4 to 7.

Table 8 Degree Centrality of different Industry in Industry-Technology Cluster net of ROI

	Degree Centrality			Closeness Centrality-Path Distance				Reach, Influence, Information			
	Deg	NrDeg	Share	inFrness	outFrness	inClness	outClness	IndwReach	nIndwReac	Inf.Score	Infor
BIOPHARM	108	0.207	0.022	3111	3782	1.961	1.613	12	0.194	109	3.824
CCH	366	0.7	0.074	1952	3782	3.125	1.613	31	0.5	367	4.085
DMP	128	0.245	0.026	2196	3782	2.778	1.613	27	0.435	129	4.006
MEDEV	79	0.151	0.016	2684	3782	2.273	1.613	19	0.306	80	3.905
PCM	379	0.725	0.077	1647	3782	3.704	1.613	36	0.581	380	4.077
RE	172	0.329	0.035	2684	3782	2.273	1.613	19	0.306	173	3.962
SCS	1124	2.15	0.228	1952	3782	3.125	1.613	31	0.5	1125	4.086
TMI	112	0.214	0.023	2379	3782	2.564	1.613	24	0.387	113	3.984

Table 9 Closeness Centrality of different Industry in Industry-Technology Cluster net of ROI

Closeness				Reach			Influence Score			Information		
Rank	IND	outFarness	outCloseness	IND	OutdwReac	nOutdwRea	Rank	IND	Row	Rank	IND	Inform
1	38	3294	1.852	38	9	0.145	1	44	991	1	44	4.081
2	84	3294	1.852	84	9	0.145	2	37	201	2	37	4.048
3	85	3294	1.852	85	9	0.145	3	30	157	3	30	3.999
4	30	3355	1.818	30	8	0.129	4	38	141	4	38	3.997
5	32	3355	1.818	32	8	0.129	5	84	130	5	67	3.956
6	37	3355	1.818	37	8	0.129	6	31	119	6	84	3.94
7	40	3355	1.818	40	8	0.129	7	67	95	7	32	3.879
8	44	3355	1.818	44	8	0.129	8	32	71	8	31	3.854
9	48	3355	1.818	48	8	0.129	9	80	54	9	80	3.825
10	67	3355	1.818	67	8	0.129	10	79	43	10	79	3.747
11	42	3416	1.786	42	7	0.113	11	81	43	11	81	3.739
12	52	3416	1.786	52	7	0.113	12	48	36	12	48	3.717
13	24	3477	1.754	24	6	0.097	13	40	33	13	40	3.672
14	31	3477	1.754	31	6	0.097	14	28	31	14	28	3.648
15	35	3477	1.754	35	6	0.097	15	42	30	15	42	3.631
16	36	3477	1.754	36	6	0.097	16	35	28	16	35	3.603
17	39	3477	1.754	39	6	0.097	17	39	28	17	52	3.575
18	66	3477	1.754	66	6	0.097	18	18	27	18	39	3.554
19	80	3477	1.754	80	6	0.097	19	52	27	19	18	3.463
20	28	3538	1.724	28	5	0.081	20	27	20	20	66	3.411
21	86	3538	1.724	86	5	0.081	21	66	20	21	27	3.408

Figure 3: Network indicating Industry-Technology Cluster interaction: Degree centrality of nodes

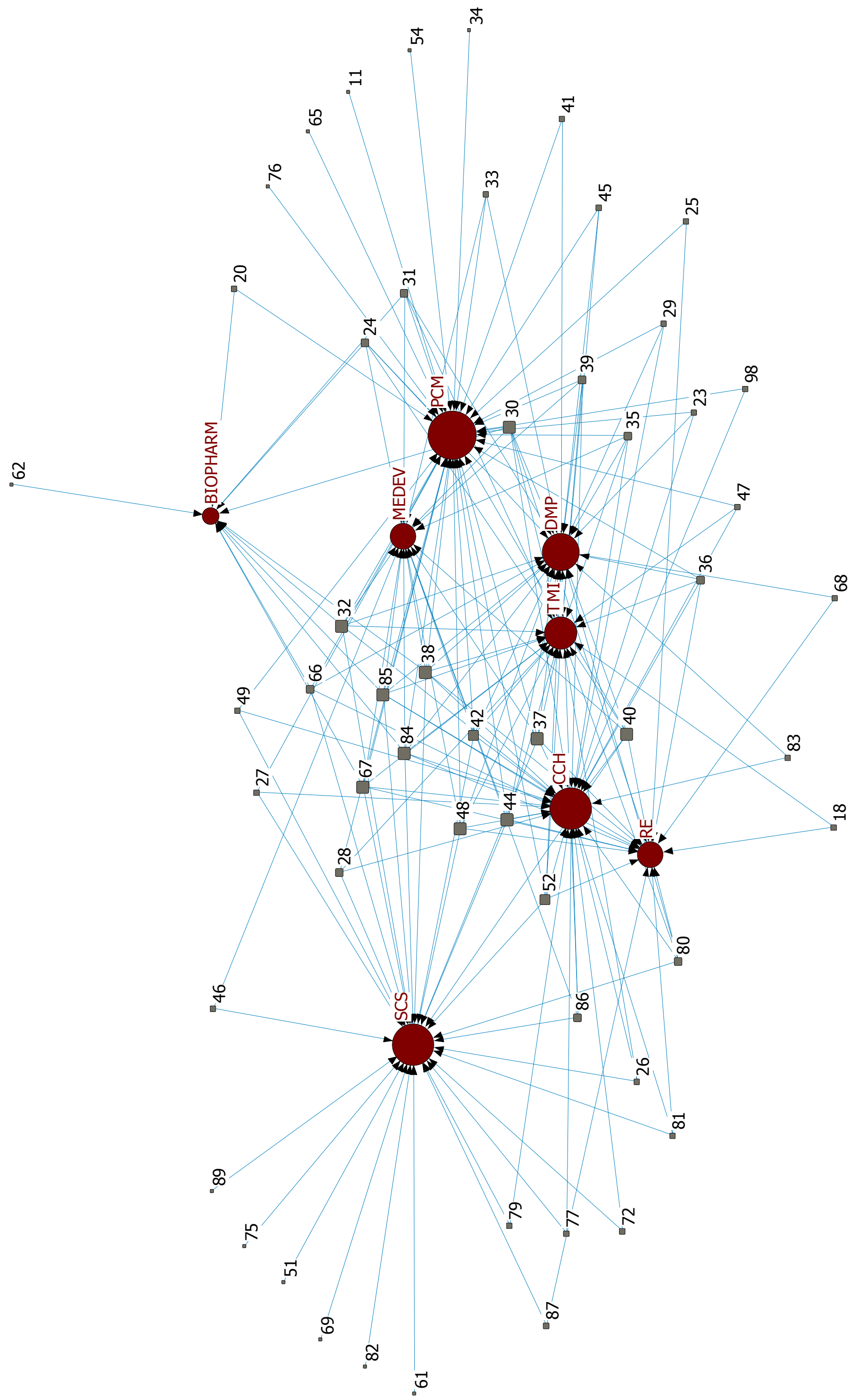
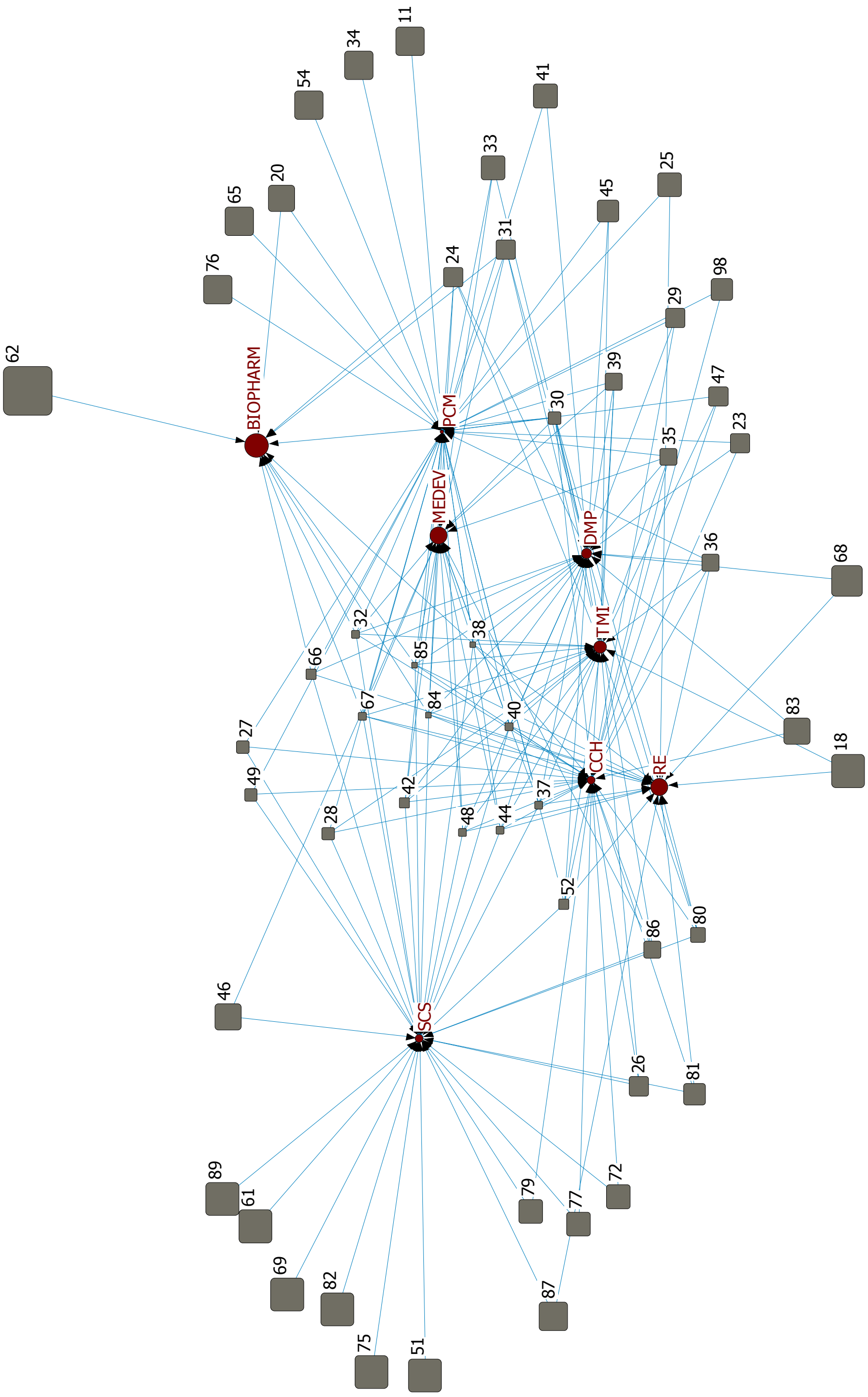


Figure 4: Network indicating Industry-Technology Cluster interaction: Power of Nodes

Figure 5:



Network indicating Industry-Technology Cluster interaction: Farness of Nodes

Figure 6: Network indicating Industry-Technology Cluster interaction: Betweenness of Nodes

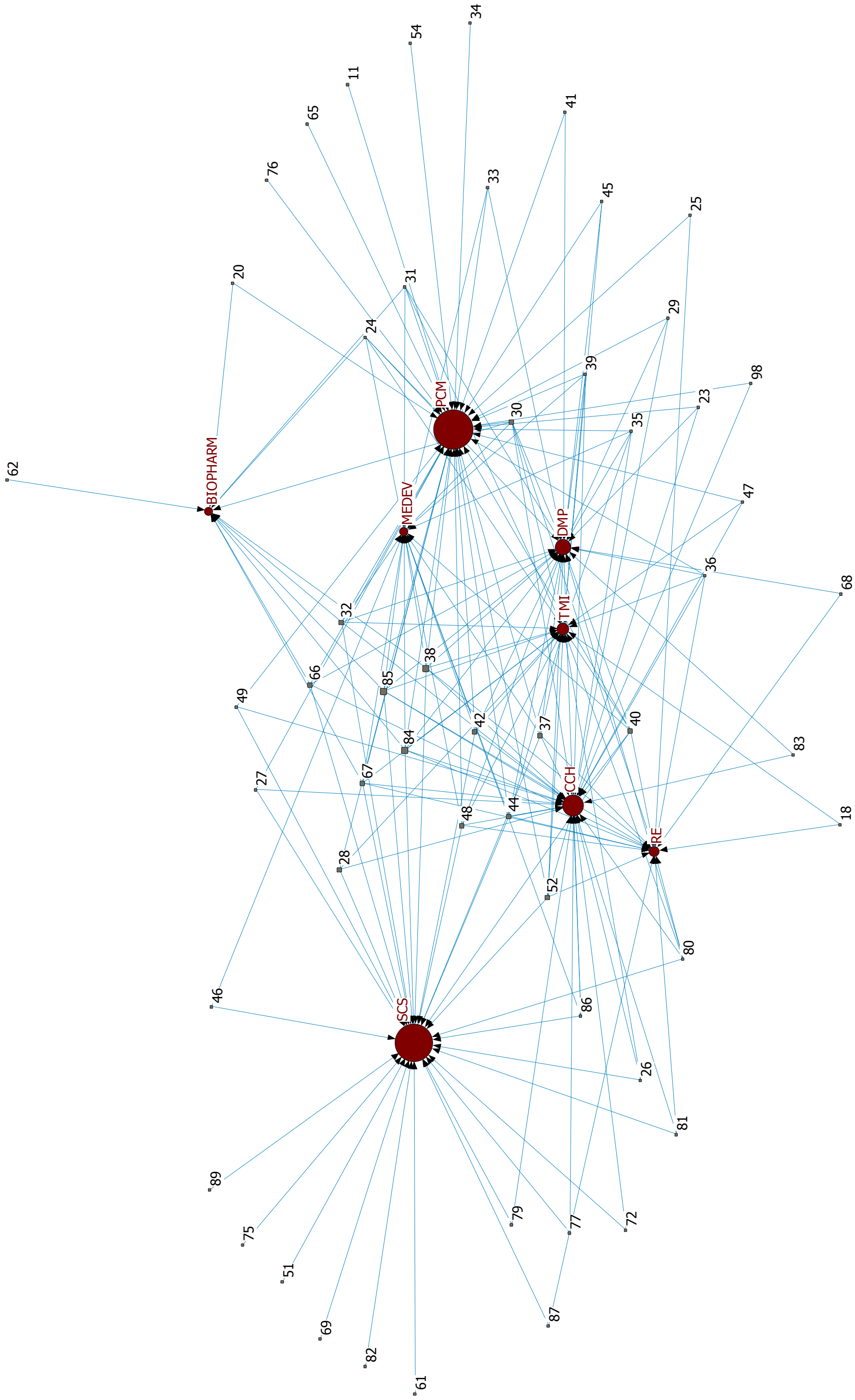
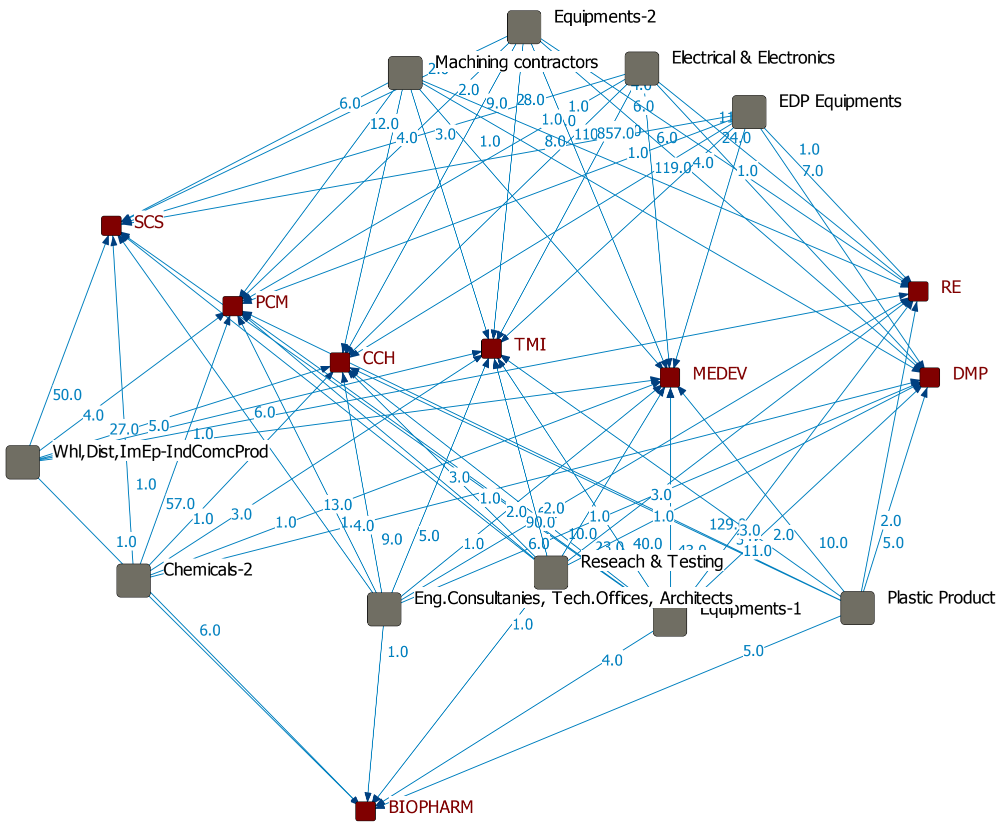


Figure 7: Network indicating top 10 industries (Centrality value) in Industry-Technology Cluster interaction in ROI



4. Conclusion

Existing official data sources provide valuable insights into industrial change in Ireland. For example, official data sources can be used to “reveal” comparative advantage and estimate industrial location quotients within Ireland. We have developed a complementary, business-enterprise centered research methodology to go inside the existing aggregative indicators of industrial dynamics.

We deploy a product classification system to assist in the identification of seven key technology-based clusters. A consistent methodology is developed so that key industry clusters do not overlap and are mutually exclusive in terms of data. Each year the data can be updated so that emerging trends can be anticipated and benchmarked internationally. Thus the Lucerna database methodology provides a general framework for investigating and understanding the evolving Irish economy. This paper utilizes the data to analyse the structure of the Irish high-tech sector employing network analysis.

Nevertheless, the interaction of business organisation, technological change and innovation is inherently complex. To more fully understand the dynamics of emerging, rapidly growing, and maturing clusters requires a considerable amount of qualitative investigation using case study and other research techniques. Nanotechnology and renewable energy, for example, may be emerging industrial clusters that operate at the intersection of two or more of the technology-based clusters that presently exist in Ireland. For another example, as the next chapter illustrates, the rapid growth of medical devices in the 1990s has led to the repositioning of companies once classified in instruments and to the convergence of medical delivery devices and drugs. No classification system can predict in advance the twists and turns of industry fortunes consequent upon innovation and technological change. Uncertainty will always prevail. The virtue of the Lucerna research methodology is that the site where these changes impact on the economy is the business enterprise; consequently, the macro level of industrial change can be examined in terms of the technologies, processes, products and services that enterprises design, develop, produce and market at the micro level. This paper has provided practical examples of hoe the databases can be utilized for network analysis that reflects the structure of the Irish high-tech sector.