NIRSA Working Paper Series No 55 – January 2010

NIRSA
National Institute For Regional and Spatial Analysis
An Institiúid Náisiúnta um Anailís Réigiúnach agus Spásúil

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Social Network Analysis of the Irish Biotech Industry: Implications for Digital Ecosystems

Chris Van Egeraat, NUIM
Declan Curran, NUIM

John Hume Building, National University of Ireland, Maynooth, Maynooth, Co Kildare, Ireland.
Áras John Hume, Ollscoil na hÉireann, Má Nuad, Má Nuad, Co Chill Dara, Éire.
Tel: + 353 (0) 1 708 3350 Fax: + 353 (0) 1 7086456
Email: nirsa@nuim.ie Web: http://www.nuim.ie/nirsa

HEA
Higher Education Authority
An tÚdarás um Ard-Oideachas
Funded under the Programme for Research in Third Level Institutions (PRTLI), administered by the HEA

NDP
NATIONAL DEVELOPMENT PLAN

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Implications for Digital Ecosystems

Chris van Egeraat and Declan Curran

Abstract—**This paper presents an analysis of the socio-spatial structures of innovation, collaboration and knowledge flow among SMEs in the Irish biotech sector. The study applies social network analysis to determine the structure of networks of company directors and inventors in the biotech sector. In addition, the article discusses the implications of the findings for the role and contours of a biotech digital ecosystem. To distil these lessons, the research team organised a seminar which was attended by representatives of biotech actors and experts.**

Keywords-Digital Ecosystems; Social network analysis; Innovation; Biotech

I. INTRODUCTION

The Digital Ecosystem put forward by the OPAALS Research Consortium is a self-organising digital infrastructure established with the aim of creating a digital environment for networked organizations which is capable of supporting co-operation, knowledge sharing, the development of open and adaptive technologies and evolutionary business models [1]. The Digital Ecosystem provides structures of communication and collaboration that can facilitate collective learning, knowledge flow and innovation across SMEs and other actors.

In order to understand sustainable digital ecosystems of SMEs and the contribution they could make to competitiveness of SMEs and regional development, we need to understand in depth the processes of knowledge flow and innovation. This paper sets out to address two main research questions. Firstly, what are the structural characteristics of knowledge and innovation networks in the Irish biotech industry and are these conducive to knowledge flow? Secondly, what does this mean for the roles and the contours of a biotech digital ecosystem? The first question is explored with social network analyses, providing insight into the structural characteristics of both formal and informal networks. The second question was partly addressed through consultation of biotech actors and experts.

Section two of this paper presents the concepts and themes on which the study focuses. This is followed by the research design and methodology in section three. Section four introduces the biotech sector in Ireland. Next, section five presents the findings of the social network analysis. The paper ends with conclusions and a discussion of the implications of the findings for digital ecosystems.

II. DIGITAL ECOSYSTEMS AND NETWORKS

Recent studies of innovation emphasize the collective, collaborative processes that underlie innovation. The situation of slowly changing networks of organisations will be replaced by more fluid, amorphous and transitory structures based on alliances, partnerships and collaborations. These trends have been characterised as a transition towards 'open innovation' [2] and 'distributed knowledge networks' [3]

Knowledge economies can be thought of as ecosystems. Economic ecosystems are assemblages of interdependent institutions in which the welfare of the component organisms is dependent on the interactions between them. They tend to evolve towards an optimum state due to gradual adaptation. The evolution is accelerated by the promotion of higher and more efficient levels of knowledge flow/sharing. Towards this, *digital* ecosystems seek to exploit the benefits of new ICTs in terms of enhanced information and knowledge flow.

Economic ecosystems tend to be organised on a territorial basis as expressed in related concepts such as clusters [4] and regional systems of innovation [5]. Most territorial economic development concepts recognise that networks are an important aspect of innovation and clustering processes [6] Network theory and analysis can therefore lead to a better understanding of innovation and clustering processes [7].

The roots of the network concept and network theory go back to the end of the 19th century [8]. In sociology, anthropology, and psychology, network analysis was initially employed in a range of empirical context. For a long time surprisingly little attention was devoted to the role of networks in economic activity but this has changed drastically in more recent times. Since the early 1990s an increasing body of economists, economic sociologists and economic geographers have been focusing on the role of networks in economic activity, innovation and regional development. In this paper we focus on business/innovation networks. In broad terms a network can be defined as a set of actors linked through a specific type of connections [8].

A range of network forms and types can be identified. For the current research project we made a basic distinction between formal and informal networks (facilitating formal and informal knowledge exchange). Formal networks are configured as inter-organisational alliances while informal networks are based on inter-personal ties. In our view, formal networks include both the longer-term strategic networks based on strategic alliances and joint ventures, as well as the shorterterm project networks distinguished by [8]. In formal networks firms or institutions are linked in their totality, via, for example, joint research projects or buyer-supplier agreements.

In informal networks, the connected persons principally represent themselves. Because the persons are employed by firms and institutions, the links between these persons indirectly also link the institutions, providing a pipeline for (informal) information flow between these institutions. A large variety of informal networks exist including networks of former students, professional networks, networks of friends, members of sport clubs, networks of corporate board members, and so forth. Informal networks can develop on the back of formal business activity, as is the case with networks of former colleagues or former business relations that have developed a friendship. However, the characteristic of such informal networks is that the network is no longer based on these (former) formal relations. Informal networks have different levels of organisation or institutionalisation. Some professional networks (informal from the firms' point of view) can be strongly institutionalised while other networks, for example those based on friendship are virtually unorganised.

In this paper formal networks are seen as pipelines for formal knowledge exchange while informal networks are linked to informal knowledge exchange.

Rather than treating regional networks as a distinct type of network [8] we work from the perspective that all (types of) networks have a spatiality. Thus all, formal and informal, networks have a spatiality that may include local, regional, national and global aspects. During the 1990s, the interest in networks became strongly focused on regional networks. The cluster literature paid a great amount of attention to space of flows and the positive role of networks in regional clustering processes. However, it was assumed that the space of flows and the space of place showed a great deal of overlap [7]. The global aspects of networks tended to be ignored. Regions were treated as isolated islands of innovation.

Although remaining highly influential, these ideas became increasingly challenged by empirical studies that showed that firms in even the most developed clusters are often highly depended on non-local relations and networks for their knowledge. In fact, the non-local relations often play a crucial role in providing new (from the perspective of the region or cluster) knowledge. In the context of the biotech industry these ideas were supported by [9] [10] [11]. Recent contributions to the knowledge-based theory of spatial clustering specifically incorporate the idea that firms in clusters are connected to both local and non-local networks and depend on local and non-local knowledge flows through 'local buzz' and 'global pipelines' [12] [13]. Clusters are understood as nodes of multiple and multi-scalar knowledge connections [8].

This is not to say that the spatiality of the networks is irrelevant for the competitiveness of firms and regions. Firstly, from a neoclassical perspective one can point to the fact that proximity between actors in a network increases the efficiency of knowledge flow. Secondly, more important is the fact that the scale of some networks is strongly regional or national in character by nature. The membership of most regional/national professional organisations, chambers of commerce, industrial organisations etc, is nearly entirely regional/national. Many social networks, such as networks of former school-friends, are starting to include an increasing amount of globally dispersed members, but retain a strong national character. In particular, many informal networks tend to have a strong regional/national character, although some informal networks tend to have a significant international membership, e.g. epistemic communities.

Disagreement exists as to the salience or importance of the informal knowledge exchange both for the innovation capacity and competitiveness of firms and for regional clustering processes [14]. Some contributions argue that informal networks are important channels for knowledge exchange and that individuals in different firms and institutions informally provide each other with technical and market-related knowledge that can be of great value to the firm. Others are of the view that, although informal knowledge exchange does occur, the knowledge generally has limited commercial or strategic value. Individuals will only exchange general knowledge that is of relatively low value to the firm, for example information about new job openings. In addition, the knowledge may not flow freely throughout the local network but, instead, circulate in smaller (sub-) communities.

One of the aims of this paper is to increase the insight into the quality of informal and formal networks in the biotech industry, notably whether the structure is conducive for knowledge exchange.

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III. Methodolgy and Data Sources

This paper sets out to address two main research questions:

1) What are the structural characteristics of knowledge and innovation networks in the Irish biotech industry and are these conducive to knowledge flow?

2) What does this mean for the roles and the contours of a biotech digital ecosystem?

The first research question was addressed through social network analysis. Social network analysis, one of the dominant traditions in network theory [8], is based on the assumption of the importance of relationships among interacting units or actors and that units don't act independently but influence each other. Relational ties between actors are viewed as channels for transfer or flow of resources [15]. The social network analysis tradition has developed a range of conceptual devices that can facilitate an analysis of regional business ecosystems, including structural equivalence, structural holes, strong and weak ties and small worlds. This paper focuses on the small world concept.

Networks of relationships between social actors, be they individuals, organizations, or nations, have been used extensively over the last three decades as a means of representing social metrics such as status, power, and diffusion of innovation and knowledge [16] [17]. Social network analysis has yielded measures both of individual significance, such as centrality [18], and of network efficiency or optimal structure [19]. Analysis of network structures becomes important when one is interested in how fragile or durable observed networks are. For example, what do network characteristics such as sparseness or clustering imply for the stability of the network structure? One established framework for analysing network structure is that of "small world" network analysis. Small world analysis is concerned with the density and reach of ties. A small world is a network in which many dense clusters of actors are linked by relationships that act as conduits of control and information [20] [21]. In keeping with the age-old exclamation "it's a small world!", this type of network allows any two actors to be connected through a relatively small series of steps or links – despite the fact that the overall network may be quite sparse and actors may be embedded in distinct clusters. As a result, actors in the network may in reality be "closer" to each other than initially perceived.

These small world networks, with high clustering and short global separation, have been shown by Watts [16] to be a general feature of sparse, decentralized networks that are neither completely ordered nor completely random. Small world network analysis offers us a means by which we can gain insights into network structures and the role of these structures in facilitating (or hindering) the flow of innovation and knowledge throughout the entire network. Watts [16] and Kogut and Walker [17] advocate comparing an observed network with a randomised network (i.e. a random graph) that has the same number of actors (nodes) and same number of relationships (links) per actor as the observed. Simulations by Watts [16] show that the structural stability of small worlds is retained even when a substantial number of relationships are replaced with randomly generated links. The network becomes more globally connected rapidly but the dense clusters are slow to dissolve. Thus, actors in the network can strategise and, rather than being disrupted, the small world structure is still replicated. In this way, networks that appear sparse can in fact contain a surprising degree of structure.

Small world analysis has been productively applied in the context of biotech clusters [22] and has important application in the context of regional biotech digital ecosystems. Knowledge will flow most efficiently in biotech ecosystems with small world characteristics. Where small world characteristics are absent, these can be created by adding a relatively small number of remote links to the network where the level of local clustering is already high [8].

The formal description of small world networks presented here is as per Watts [16], with the networks represented as connected graphs, consisting of undifferentiated vertices (actors) and unweighted, undirected edges (relationships). All graphs must satisfy sparseness conditions. The small world network analysis that follows in Section five is characterized in terms of two statistics:

Characteristics path length (L): the average number of edges that must be traversed in the shortest path between any two pairs of vertices in the graph. L is a measure of the global structure of the graph, as determining the shortest path length between any two vertices requires information about the entire graph.

Clustering Coefficient (C): if a vertex has k_v immediate neighbours, then this neighbourhood defines a subgraph in which at most $k_v(k_v -1)/2$ edges can exist (if the neighbourhood is fully connected). C_v is then the fraction of this maximum that is realised in v's actual neighbourhood, and C is this fraction averaged over all vertices in the graph. In this way, C is a measure of the local graph structure.

In order to determine what is "small" and "large" in this analysis, Watts [16] determines the following ranges over which L and C can vary:

1. The population size (n) is fixed.

2. The average degree k of vertices is also fixed such that the graph is sparse ($k<<n$) but sufficiently dense to have a wide range of possible structures ($k>>1$).

3. The graph must be *connected* in the sense that any vertex can be reached from any other vertex by traversing an infinite number of edges.

Fixing n and k enable valid comparisons to be made between many different graph structures. This also ensures that the minimum value for C is 0, while the maximum value for C is 1. The sparseness condition ensures that, while the network is sufficiently well connected to allow for a rich structure, each element operates in a local environment which comprises of only a tiny fraction of the entire system. Finally, the requirement that the graph is connected guarantees that L is a truly global statistic.

Data collection started with an inventorisation of biotech companies in Ireland (see the next section on the Irish biotech industry). Following this, two separate datasets were compiled for our social network analysis of the Irish biotech industry. In order to compile the first dataset, a rigorous internet search of official company websites and media sources has been conducted. In this way, it can be ascertained whether a director of a given Irish biotech company also holds a directorship on another Irish biotech company. Joint directorships are then taken to represent a conduit of informal knowledge flow between the respective companies. This dataset also contains information on the founders of each company; serial entrepreneurs, who form numerous companies; and spin-off companies. The database also identifies whether these spin-off companies emerged from existing private companies or universities. The date of establishment of all spin-offs and existing companies is also included in the dataset, allowing us to undertake an analysis of the evolution of the Irish biotech industry over time. We have endeavoured to verify the database through consultation with industry experts.

The second dataset has been compiled from patent data available from the Irish Patent Office (http://www.patentsoffice.ie/), US Patent and Trademark Office (http://www.uspto.gov/), and *Esp@cenet*, the European Patent Office (http://ep.espacenet.com/). For each Irish biotech company that that has registered patents, we can establish the researchers who worked on each patent; their employer at the time, and whether they were foreign-based or located in Ireland. We take this formal research collaboration to represent formal knowledge flow between Irish biotech companies.

Figure 1. Network of Irish Biotech Directors and Companies, based on directorship data

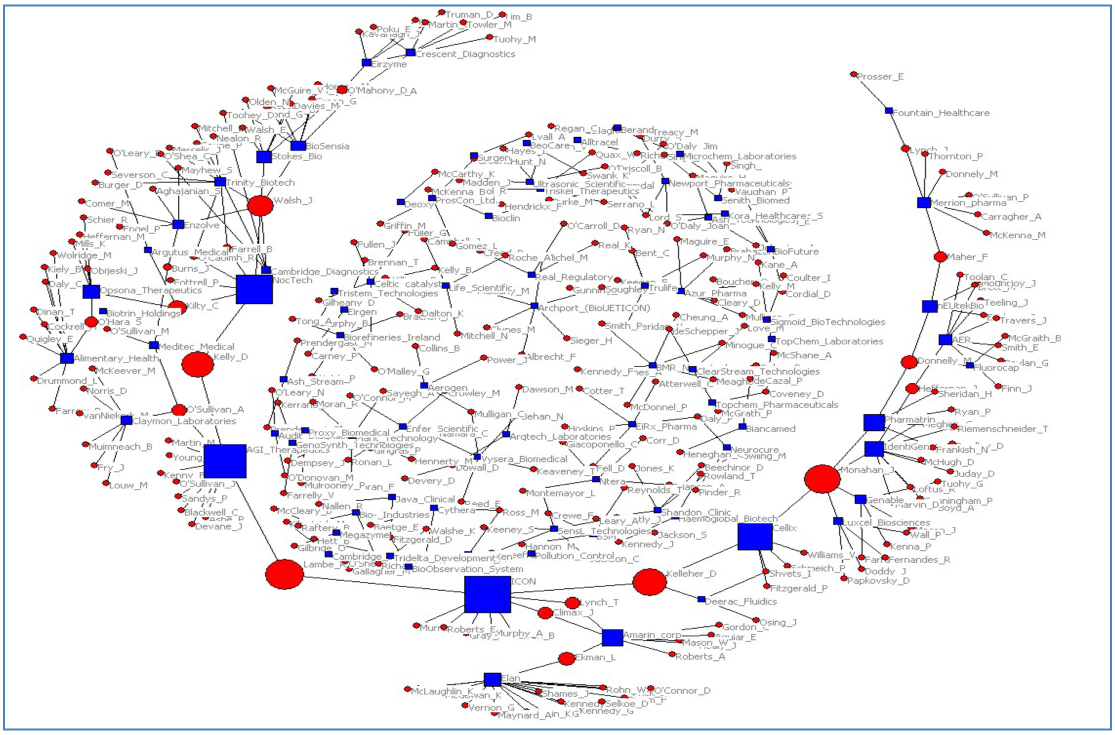
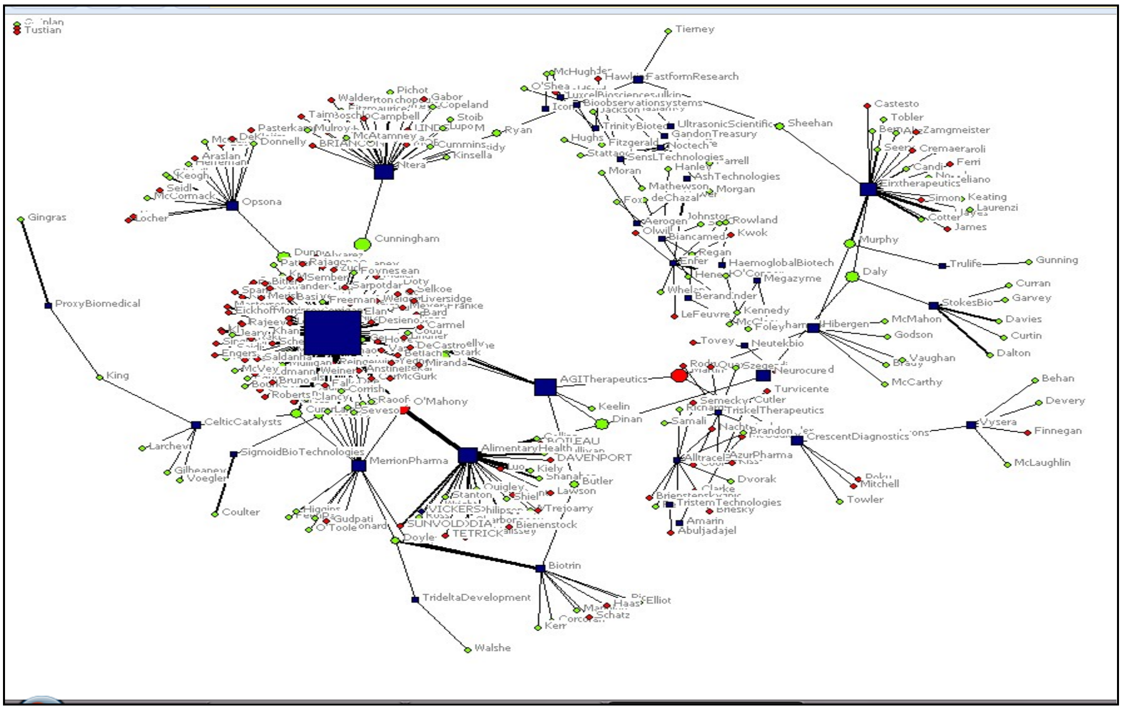


Figure 2. Network of Irish Biotech Directors and Companies, based on directorship data



Note: Green colour denotes researchers based in Ireland and red colour denotes researchers based abroad.

The second research question deals with the meaning of the results of the social network analysis for the roles and contours of a biotech digital ecosystem. To distil these lessons, the research team organised a seminar. This seminar was attended by 14 representatives of biotech companies, industrial promotion agencies, third-level colleges, venture capital companies, software companies, the OPAALS community and other industry experts.

IV. THE IRISH BIOTECH INDUSTRY

The OECD [23] defines biotech as the application of science and technology to living organisms, as well as parts, products and models thereof, to alter living or nonliving materials for the production of knowledge, goods and services. In order to narrow the definition to 'modern' biotech the OECD employs a list based definition that includes various techniques and activities: synthesis, manipulation or sequencing of DNA, RNA or protein; cell and tissue culture and engineering; vaccines and immune stimulants; embryo manipulation; fermentation; using plants for cleanup of toxic wastes; gene therapy; bioinformatics, including the construction of databases; and nanobiotech.

Partly due to the lack of official statistics and partly due to the ambiguous nature of the definition it is difficult to determine the size of the Irish biotech industry. Our 'universe' of firms in the modern biotech industry in Ireland was based on existing survey material [24], the list of firms included on the 'Biotechnology Ireland' website (hosted by Enterprise Ireland), information from interviews with industry experts and internet search.

The final list included 80 biotech firms. Fifty two of these companies are Irish-owned. All but two of these indigenous companies are small or medium sized. It is estimated that the majority of indigenous companies in the list are micro-enterprises, employing less than 10 staff - often start-up companies or campus companies. The majority of the other indigenous companies are small enterprises, employing less than 50 staff.

V. RESULTS OF SOCIAL NETWORK ANALYSIS

Figure 1 presents a sociogram of the network connections in the Irish biotech industry, using data on directorships. Some directors are director of more than one company, providing links or ties in the network which can support information flow and diffusion of the digital ecosystem concept. Figure 2 presents a sociogram of the network connections in the Irish biotech industry, but now using patent data. On the face of it the sociograms would suggest that the networks have a low density.

However as discussed in the methodology section, the structure of the networks may be such that despite low overall density, short path length and high clustering may still be features of the network. This would suggest that rather than being a sparse network unsuited for swift flows of knowledge, there may actually be potential for rapid diffusion of knowledge (and adoption of a biotech digital ecosystem) through the network if the right actors are targeted. Using both datasets, both informal knowledge flows and formal knowledge can be analysed and their resulting network characteristics compared. The results of the small world network analysis are now presented.

Table 1 presents the results from the Irish biotech network of directors and companies, analysing the directors and companies separately (i.e. deconstructing a 2-node network into its constituent 1-node networks). While directors may be connected to each other by virtue of being on the board of the same company, this type of intra-company link is avoided by analysing the company-only 1-node network. Thus, presenting the results of both 1-node network analyses serves as a useful robustness check. In keeping with the formal description of small world networks presented in the methodology section, two central findings can be gleaned from Table 1. First, it is clear that both directors and companies are highly clustered (C = 0.948 and 0.669, respectively). This is particularly evident when compared to the low degree of clustering generated by a random network with the same number of nodes and ties as the highly structured observed networks (C = 0.039 and 0.062, respectively). Second, though the director and company networks are highly clustered, they are not characterised by long path lengths. This is in keeping with Watts' [16] findings that even as a network moves from a structured to a random graph, the path length decreases rapidly but the clustering is persistent. For the purposes of our Irish biotech study, this highly clustered/short path length characteristic of the directors network and the network of companies connected via directors has practical implications for the diffusion of informal knowledge and tacit knowledge throughout the entire network. It indicates that while knowledge is capable of travelling rapidly through the entire network, the challenge is get the knowledge to flow between the distinct clusters. It is exactly this challenge that a digital ecosystem can help overcome.

TABLE I. IRISH BIOTECH INDUSTRY DIRECTORS AND COMPANIES (VIA DIRECTORSHIPS) NETWORK STATISTICS

Variable	Directors	Companies
Density		
Density (for all directors/firms)	0.018	0.016
Total no. of ties	1,622	118
Average no. of ties (between those connected)	5.5	2.7
Clustering		
Cluster coefficient	0.948	0.669
Random Cluster coefficient	0.039	0.062
Path Length		
Average Path length among those connected	3.538	2.912
Random Average Path Length	3.127	4.111

Note: No. of directors: 302; No. of firms: 86; no. of connected firms: 43

TABLE II. IRISH BIOTECH INDUSTRY RESEARCHER AND COMPANIES (VIA PATENTS) NETWORK STATISTICS

Variable	Researchers	Companies
Density		
Density (for all researchers/firms)	0.163	0.041
Total no. of ties	16,110	64
Average no. of ties (between those connected)	52.5	2.78
Clustering		
Cluster coefficient	0.975	0.439
Random Cluster coefficient	0.570	0.099
Path Length		
Average Path length among those connected	2.091	2.256
Random Average Path Length	2.013	3.264

Note: No. of researcher: 315; connected researchers: 307; No. of firms (that have registered patents): 40; connected firms: 23

Comparable results emanating from the network of Irish biotech researchers and the network of Irish biotech companies via patents are presented in Table 2. While the findings outlined above can be interpreted as capturing informal knowledge flows, the results of Table 2 are based on patent data and therefore refer to formal knowledge flows. Once again, the salient findings are those of high clustering and short path lengths for both the researcher and company networks. However, in this instance the company network is noticeably less clustered via patents than it was through directors. This suggests that formal knowledge flows through the network in a different, slower, manner than informal knowledge. This may also have important practical implications both for understanding the process of knowledge diffusion in the Irish biotech industry and for ensuring optimal design and operation of a digital ecosystem in such a setting.

Finally, Table 3 presents a comparison of small world networks identified in a range of existing studies and allows us to assess "how small" the networks in the Irish biotech industry are. The small world network statistics of the Irish biotech industry are compared with comparable statistics from a study of networks of German firm owners [17] and a study that reported on three types of networks [25]: a network of film actors connected by participation in films; a power grid network representing links between generators, transformers, and substations in the western United States; and *C. Elgans*, which is the completely mapped neural network of a worm. Comparison across the networks illustrates once again the strong small world characteristics of the director network and the network of companies connected via directors, as well as the lesser degree of clustering in the small world network of Irish biotech researchers and the network of Irish biotech companies via patents.

VI. CONCLUSIONS AND IMPLICATIONS FOR THE IRISH BIOTECH DIGITAL ECOSYSTEM

Previous case study based research on innovation processes in the Irish biotech industry [26] showed that individual innovation projects involved little collaboration and informal information flow between regional actors. From this, one might have anticipated low density, sparse and weakly clustered networks. However, the social network analysis shows that networks do exist in the Irish biotech industry and that both the formal networks, connected through patents, and the informal networks, connected through directorships, have small world characteristics. This means that the network structures are conducive to knowledge flow. However the formal network is noticeably less clustered than the informal network, which suggests that the informal networks are far more conducive to knowledge flow than the formal networks. Knowledge in the formal network will flow and diffuse in a different, slower manner. The results also suggest that in both types of networks there remains scope for improving the structural characteristics of the network by creating links between distinct clusters in the network.

The social network analysis has provided new insight into network structures of the Irish biotech industry. At the same time one must not lose sight of the fact that the results are in most cases only suggestive of efficient knowledge flow. It remains unclear how much knowledge flows through the links and how far the knowledge travels through the network [14]. In addition, some knowledge is more strategic than other. It is therefore important that future research investigates what actually flows across the links [8]. This is, of course partly dependent on the type of actors in the network.

The findings, and the discussion of these findings with industry actors and experts, suggest important implications for the role and structure of a digital ecosystem in the Irish biotech sector. In the Irish biotech industry, a digital ecosystem is unlikely to play a significant role in promoting regional development by facilitating efficient and secure communication and knowledge flow between regional actors (partners), collaborating in a specific innovation project (i.e. as a project management tool). The actual numbers of collaborations is simply too small for a digital ecosystem to have a significant impact on regional development in this way.

In the Irish context, a digital ecosystem is more likely to stimulate regional development by acting as a more general communication tool and knowledge resource, connecting all regional players in the biotech industry (irrespective of whether or not these actors are partners in a specific innovation project). It could provide a more efficient medium for existing networks of individuals and firms to exchange informal knowledge, thereby better exploiting these existing networks.

The digital business ecosystem in the biotech industry should involve the entire social world of the firms, linked to the specific inter-firm networks that firms have and, more importantly, also to the loose web of ties that people within innovation projects share with others in the industry.

TABLE III A COMPARISON OF SMALL WORLD NETWORK STATISTICS

Network	Path Length		Clustering		Actual-to-Random Ratio for:	
	Actual	Random	Actual	Random	Length	Clustering
Irish Biotech Directors	3.538	3.127	0.948	0.039	1.131	24.31
Irish Biotech Companies (via directors)	2.912	4.111	0.669	0.062	0.708	10.79
Irish Biotech Researchers	2.091	2.013	0.975	0.570	1.039	1.711
Irish Biotech Companies (via patents)	2.256	3.264	0.439	0.099	0.691	4.434
German Firms[1]	5.64	3.01	.84	.022	1.87	38.18
German Owners[1]	6.09	5.16	.83	.008	1.18	118.57
Film Actors network[2]	3.65	2.99	.79	.001	1.22	2,925.93
Power Grid network[2]	18.70	12.40	.08	.005	1.51	16.00
C. *Elegans* network[2]	2.65	2.25	.28	.05	1.18	5.60

[1] Kogut and Walker [17]; [2] Watts and Strogatz [25]

Innovation seems to be driven strongly by engagement with public spaces and 'communities' where information sharing is relatively open. Innovation remains rooted in an engagement with a community that involves accessing diverse sources of knowledge through decentralized networks, loosely defined ties, and quasi-public spaces. Public spaces are crucial to innovation. A digital ecosystem could play the role of a new type of 'public space' [27]. The digital ecosystem environment can also actively be employed to stimulate or create new links between distinct clusters in a network.

A biotech digital ecosystem in Ireland should include strong assistance/support functionality. Companies and individual actors provide information about their knowledge assets and requirements. One of the central questions becomes "what knowledge that could be of value to me do you have, and are you willing to share?" This may be particularly beneficial, to young companies and new actors, but not exclusively so.

The digital ecosystem should provide a multi-level data/communication structure. Some levels are shared by all firms and individual actors while others are only accessible to smaller groups. The different levels mediate knowledge and information with different levels of sensitivity, requiring different levels social proximity and trust.

Given the important knowledge generating role of the universities, one of the most valuable roles of a digital ecosystem in the biotech industry is to facilitate knowledge transfer from these universities and research institutions. Universities and their lead scientist would therefore be the most important players and potential catalysts in a digital ecosystem organised on a regional basis.

On the basis of the proceeding of the seminar with industry actors and experts, we suggest that the following digital ecosystem applications have the greatest potential in the Irish biotech industry:

- A forum for regional actors (in universities; research institutions and private enterprise) to consult each other on a reciprocal basis about the location of (regional and extra-regional) actors and sources of knowledge.
- A regionally-based science forum for biotech scientists and technicians. Here biotech scientists and technicians in companies and universities can ask for advice about, and interactively discuss, scientific and technical problems.
- A biotech sector dedicated electronic interactive labour exchange, matching skilled people to jobs.
- A directory tool, providing information about regional actors, and promote Ireland as a biotech region.

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