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A REVIEW AND CRITIQUE OF THE SMALL WORLDS HYPOTHESIS: THE BEST NETWORK STRUCTURE FOR INNOVATION?

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Abstract:
The properties of social networks have been used to explain the behaviour and performance of diverse economic and social systems. Recently, attention has been given to a class of network structures identified as 'Small-Worlds', due to their apparent efficiency in connecting different actors through short path lengths within a relatively sparse network. Intuitively, such network structures should also be conducive for innovation due to better flows of information and the possibility of new connections between skills and ideas. While there is some evidence for this hypothesis, we urge caution in interpreting the results of small-world studies of innovation and suggest future improvements for empirical research.

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A review and critique of the ‘small worlds’ hypothesis: The best network structure for innovation?

Abstract:
The properties of social networks have been used to explain the behaviour and performance of diverse economic and social systems. Recently, attention has been given to a class of network structures identified as 'Small-Worlds', due to their apparent efficiency in connecting different actors through short path lengths within a relatively sparse network. Intuitively, such network structures should also be conducive for innovation due to better flows of information and the possibility of new connections between skills and ideas. While there is some evidence for this hypothesis, we urge caution in interpreting the results of small-world studies of innovation and suggest future improvements for empirical research.

Introduction

Network analysis has a long tradition in the social sciences and the methods and models used in research studies have become steadily more sophisticated (Marsden, 1990; Wasserman and Faust, 1994; Snijders, 2001; Watts, 2004). Unsurprisingly, many innovation researchers have also turned to network analysis to address questions about the innovation process because it is highly dependent upon the flow of ideas, information and skills that create new combinations of knowledge and technology (Collins, 1974; Freeman, 1991; Macdonald, 1998; Burt, 2004; Mors, 2010). Networks can help us understand the flows of information and ideas, the interdependent connections between technologies and the diffusion of innovations.

In many instances, this network research is qualitative but statistical methods are also being deployed to examine the relationship between networks and innovation (Kastelle and Steen, 2010a). Whilst a wide variety of structural properties have been identified as being of interest to innovation researchers, the attention payed to a class of network structure identified by Watts & Strogatz (1998) as 'Small-World' has perhaps generated the most widespread interest. These intriguing structures seem to be very common in many systems and have the property of being highly connected in terms of short steps between actors in the network yet relatively sparse in terms of overall connections within the network (Buchanan, 2002; Watts, 2004).

It is the ‘small world’ notion of small distances (or more correctly, path length) between anyone in a network that has received attention from many innovation researchers. Intuitively this network structure is conducive to innovation because it creates information ‘short-cuts’ in large networks (Cowan and Jonard; 2004). For example, a scientist working in a community with a small world network structure should find it relatively easy to find an expert when faced with a new problem (Newman, 2001). In this review we examine the evidence for this hypothesis and also critically evaluate the empirical methods that have been used to investigate small worlds.

We commence by describing small world networks and the different network systems where small worlds have been demonstrated. Next we review the evidence for small worlds being facilitating factors in innovation. We find that while there is compelling support for the small worlds and innovation hypothesis, great care needs to be taken in terms of data collection, research design and the interpretation of results. We conclude with suggestions for improving this important area of innovation research.

Small World Networks

The first academic writing on small worlds appeared in the mid 1950s in an unpublished but widely circulated manuscript by Pool and Kochen (Pool and Kochen, 1978). Seizing upon the common observation that unacquainted people often had common associates, they endeavoured to show how degrees of separation (path lengths) could be modelled in a social network (Schnettler, 2009). Following the publication of the manuscript, Milgram (1967) took interest in the network explanation of small worlds and consequently designed an experiment to test the idea that small worlds existed in society and were more than urban mythology. By asking participants to send letters to someone they didn't know in another town by addressing the letter to someone who might know the final recipient, Travers and Milgram (1968) were able to show that an average of 6.4 steps was required to reach the final destination. Despite criticism of the experimental design, this result has entered the common lexicon in the form of 'six degrees of separation' (Buchanan, 2002).

Small world research gathered further momentum when Watts and Strogatz (1998) were able to quantitatively describe small worlds using standard statistical approaches to network analysis. It is worth describing the way that 'small worldedness' is measured because this has implications for interpreting results from small world studies. The key measure, termed the small world quotient (Q) is the clustering ratio (CC) divided by the path length ratio (PL). In brief, clustering is a measure of fully connected structures and path length is the number of steps between actors within a network. In this calculation, both clustering and path length are compared to randomly generated networks of the same number of links and nodes. So, for example, if the CC ratio is greater than one it means that there are more densely linked substructures compared to a random network. If the small world Q is greater than 1.0 then the network could be described as a small world, with high levels of clustering and short average path length (Watts and Strogatz, 1998).

Small world networks have since been identified in a very wide variety of contexts, including nervous systems, power grids, film collaborations between Hollywood actors and investment banking syndicates (Newman, 2003; Schnettler, 2009). While it has been suggested that small world network structures are ubiquitous (Buchanan, 2002), there are many examples of networks that are not small worlds. For example, while the co-authorship network of economists from 1980-1999 fitted the small world definition (Goyal *et al.*, 2007), the co-authorship network within sociology from 1963 to 1999 didn't (Moody, 2004). Nonetheless, the fact that small world structures are relatively common suggests that the conditions for their formation are not very demanding (Schnettler, 2009). In a simulation study, Robins *et. al* (2005) were able to show how locally-specified processes at the actor level could result in the creation of small worlds. In particular, small worlds were likely to form if:

1. Individuals seek more than one network partner.
2. But the cost of maintaining partners is quite high so there is a tendency against very many partners.
3. There is a tendency for network partners to agree upon other network partners (driving clustering).
4. But this tendency is not too strong (stopping the creation of bridging ties between clusters) or too weak (preventing the formation of clusters) (Robins *et al.* 2005, p.923)

While more work is needed to understand how small worlds evolve, another interesting direction for small worlds research is to show how local processes and actor attributes affect the broader network (Guimera *et al.*, 2005). Longitudinal studies may show a coevolution of these micro and macro network variables (Baum *et al*. 2003; Corrado and Zollo, 2006). For example, the existence of knowledge brokers who can span different clusters in the network, may allow the formation of small worlds, which may then facilitate the emergence of more knowledge brokers who will enable the network to grow without losing connectivity.

Small Worlds and Innovation

While Schnettler (2009) has written an overview of the development of small world theory and research and Uzzi *et al.* (2007) have reviewed the contributions of small world research to management studies more generally, our particular focus in this essay is a review and critique of small world network in the field of innovation studies. Investigations of networks within academic research communities are excluded from this review as we are using the broad definition of innovation as the process of doing something differently that creates valuable outputs (Dodgson, Gann and Salter, 2005).

The first published paper on small world networks in an innovation context was by Verspagen and Duysters (2004). This paper examines a sample of technology alliances within the chemicals and electronics industries between 1980 and 1996 using the European MERIT CATI dataset. While the small-world coefficient is not calculated, the authors were able to describe both industrial networks as being highly clustered with a high degree of shortcuts through the network. A similar study of Italian inventors also examined clustering and path lengths and found that the collaboration networks in the electrical and chemicals industries were more highly connected than others (Balconi *et al.* 2004). This is an interesting observation because even though the Italian study inferred connections between inventors from patent data rather than alliances between established firms, the results are similar to the MERIT CATI study. This suggests that there are some characteristics within particular industries that support the generation of small-world networks across multiple levels.

Another study of alliances, this time in the biotechnology sector also found evidence for the emergence of small world networks (Gay and Dousset, 2005). In this sample of the antibody industry where 72% of alliances involved R&D agreements, the industry network demonstrates persistent small world properties, despite the changing roles of players within the network between 1990 and 2004. The robustness of small world structures in the main component of the network also suggests that there are aspects of the technology, and its relationship to the innovation process, which makes small worldedness a natural state of the network.

The notion of industry-specific innovation processes underlying the formation of small worlds can be better understood following the publication of a simulation study by Cowan *et al.* (2009) who showed that small worlds could form within innovation networks when embeddedness was a driver of alliance formation, thus creating clusters. However, technological interdependencies needed to be modular enough to allow connections to form across clusters. Embeddedness can arise through repeated interactions between firms that builds trust and a shared understanding, or through relational embeddedness due to shared partners. A recent review of the open innovation literature by Dahlander and Gann (2010) suggests that further research into the characteristics of technology, industries and interorganisational networks may be warranted.

While these early studies identified the existence of small world structures in an innovation context in relationships between firms, they did not demonstrate a relationship between networks and innovation outcomes. If small world networks are very common across many different systems then it is plausible that the structures have very little to do with the innovativeness of a community of actors. In the next generation of small world studies, researchers have endeavoured to show how small world structures influence innovation performance.

The study of small worlds in the Broadway musical industry by Uzzi and Spiro (2005) represents a significant step forward in terms of research design and analysis of the networks over time. In this study, the authors collected historical data on collaborations in the creation of musicals between 1945 and 1989. Since these musicals involve teams of creative artists such as musicians, choreographers and playwrights it is possible to construct an industry-wide network based upon who has worked on different musicals in a particular time period.

The dependent variable that acted as a proxy for creativity was constructed as a combination of profitability and critics' reviews of the musical. Uzzi and Spiro were able to show that an intermediate level of small world Q was most closely associated with financial and artistic performance. Thus they argue that the relationship between Q and performance is an inverted U shape. The strength of this relationship is significant to the point where the chances of a hit musical arising from the network, when Q is highest, are about three times greater than the network where Q is at its lowest value.

The fact that an increasing small world Q can be detrimental to performance was a surprising result but it makes sense in terms of previous findings by Granovetter (1973) on redundant information in networks, and Burt (2004) on innovation arising from the connections between disparate groups. Densely connected networks may lack diversity and novelty, resulting in decreased innovativeness across the network.

In a similarly designed study, Schilling and Phelps (2007) examined the network structure of technology alliances in 11 high-tech manufacturing industries between 1990 and 1997. Innovation performance was measured by patents in these industries but due to the time taken between generating an idea and producing a patent, this was measured as a lagged variable. In their model they also controlled for industry effects such as the prevalence of patenting. The interaction term 'clustering x reach', which captures the small world structure was positively and significantly ($p<0.01$) correlated with patents. These results were in general agreement with Uzzi and Spiro's (2005) Broadway study, but they did not test for the parabolic effect where high values of clustering and reach resulted in less innovation.

Most recently, a very large sample study has tested the small world hypothesis at the national network level using patent collaboration data from eleven countries (Chen and Guan, 2010). Like Schilling and Phelps (2007), they found that the small world Q was positively and significantly correlated with patents in the following year. Also, consistent with the Broadway study the authors were able to demonstrate an inverted U-shaped relationship between both clustering and patents, and Q and patents.

In contrast to these papers supporting the small worlds and innovation hypothesis, some other studies have empirically challenged the notion that small worlds enhance innovation. The most noteworthy of these is Fleming et al.'s (2007) careful analysis of the relationship between patent co-author networks in the Boston and Silicon Valley regions, and patent applications in the following year. While decreasing average path length across the network shows some correlation with innovation the authors found no linear correlation between patenting and the small world quotient. Interestingly though, they did not include a regression model that tested for the inverted-U relationship observed by Uzzi and Spiro (2005).

While not based on regression models, two other studies have emphasised the importance of understanding how the network functions rather than just demonstrating the existence of small world structures. Based on the observed small world structures in a range of product development networks, Braha and Bar Yam (2007) developed simulations to test the performance of the network in response to planned and unplanned modifications in the development process. A key to their model was the observation that real product development networks were asymmetric, with some nodes (product development tasks, in this instance) being aggregators and filters of information, with limited contact to other nodes. These simulations showed that product development small world networks performed well under planned perturbations, but unplanned disruptions, particularly those that occurred in the parts of the network that processed information, were detrimental to performance. Following a similar theme, Kastelle and Steen (2010b) were able to show that a small world structure could be demonstrated in a network of engineers designing a large industrial project. However, when the direction of ties in the advice and ideas network was taken into account it became apparent that senior project managers were playing a gatekeeper rather than a bridging role between different parts of the network. Both of these studies indicate that the type of interactions within the network potentially have far greater influence on innovation than the structure of the network.

The current state of the small world and innovation hypothesis is therefore undecided. However, as more research accumulates, there have been questions about the way that some of these studies have been designed and how the results have been interpreted. It is possible that some of the conflicting evidence results from the way that the empirical studies were conducted. In the following section we draw particular attention to three core issues in small worlds and innovation research. Specifically, these are research design, data collection and the interpretation of results.

Research Design

Any research question that examines a link between networks and innovation performance faces the persistent problem of measuring innovation (David and Foray, 1995; Smith, 2005; Freeman and Soete, 2009). In nearly all of the studies that linked small worlds to innovation, the dependent variable was based upon patent counts. Although there is some support for using patents as indicators of innovation (Mansfield, 1985; Hagedoorn and Cloodt, 2003), others have suggested that the blanket use of patents to measure innovation is fraught with validity risks (Hinze and Dodgson, 2000; Smith, 2005). The use of other measures of innovation that are more closely tailored to the context of the study should be encouraged (e.g. Burt, 2004; Uzzi and Spiro, 2005)

One confounding factor in the relationship between patents and innovation is that some innovations can consist of a great number of patents, while other innovations may contain one or fewer patents. In a study of sectoral differences in patent intensity, Acs and Audretch (1988) found variations in the average patent per innovation between 0.6 and 49 across different industries. Since patents are count data and therefore liable to long-tailed distributions (Cameron and Trevedi, 2005) a small number of innovations may involve hundreds of patents. While patents may be part of an innovation, such evidence begs the question of what is actually being measured in patent counts. In some small-world studies where networks have been derived from patent co-authorship data, it is feasible that an industry with many patents per innovation will result in a very dense network as many technicians collaborate on a single innovation. This may result in subsequent patents due to the inherent complexity in the innovation driving further need for novel solutions, rather than a cause and effect relationship between social networks and innovation.

Confounding the relationship between patents and innovation further, Arundel and Kabla (1998) have demonstrated a wide variation in the incidence of patenting product and process innovations. For example, in the textile industry 8.1% of process and product innovations were patented, compared to the pharmaceutical industry where 79.2% of product innovations were patented and 46.8% of process innovations in the precision instruments industry. While larger firms were more likely to patent innovations, a significant factor in determining the likelihood of patenting was whether or not managers of a particular firm thought that patents were a good way to protect intellectual property

(Arundel and Kabla, 1998). In other words, firm-specific differences in IP strategy also distort the relationship between patents and innovation.

The problematic use of patents as a measure of innovation performance raises the issue of endogeneity in network regression models (Hamilton and Nickerson, 2003, Stuart and Sorenson, 2008; Bascle, 2008). A useful definition of endogeneity is when the error term correlates with an independent variable in the regression model (Hamilton and Nickerson, 2003). While endogeneity can arise for several reasons, the most challenging issue when using patents as a measure of innovation performance is that of missing variables in the model. For example, a firm's IP strategy or technological interdependency within the innovation (unmeasured variables) could correlate with patents but also affect the structure of the network.

Stuart and Sorensen (2008) suggest that network research in organization studies usually assumes that network structures are exogenous, whereby actors are randomly assigned to network positions. Actors and firms consciously make choices about partners and clearly the assumption that network positions are exogenous "…is, at best questionable and, at worst, violated in the majority of cases" (Stuart and Sorenson, 2007: 217). There are three approaches that may be used to deal with the endogeneity in network research (Stuart and Sorensen, 2008) that may be applied to the study of small worlds and innovation.

One of these is to select instances where the network position is genuinely exogenous. However, it is hard to envisage a situation where this may occur when studying networks and innovation. More feasible, but more difficult to design, is a study where network structures are linked to innovation, but the mechanisms that affect the evolution of the network are also modelled. Given the advances in statistically examining mechanisms of network evolution with software packages such as SIENA (Snijders, 2001, van de Bunt and Gronewegan, 2007), we suggest that this is promising research direction. Finally, econometric methods for managing endogneity may be deployed (Bascle, 2008; Stuart and Sorenson, 2007). The most popular method for dealing with endogeneity in innovation research is currently the Heckman correction, where endogeneity is treated as a self-selection problem (e.g. Aharonson *et al.* 2008) but care needs to be taken in using this approach (Bushway *et al.* 2007; Bascle, 2008). Another way to deal with the endogeneity problem is to use instrumental variables to control for endogenous regressors. In this instance, the Generalised Method of Moments (GMM) may be used (Windmeijer, 2000; Cameron and Trivedi, 2005).

While we will not go into this econometric method in detail, the choice of an instrumental variable is crucial in GMM estimations. The instrument should correlate with the theoretically justified missing variable (Windmeijer and Silva, 1997). For example, in the aforementioned situation where technological interdependency (a missing variable) could be determining network structures (independent variable) and patenting rates (dependent variable,) an instrument based upon patents per innovation for the particular industry could be deployed. An advantage of regressions using GMM is that the model does not assume strictly exogenous regressors, allowing the instrument to be used as a straightforward control variable (Windmeijer, 2000; Saloman and Shaver, 2005).

Going beyond the issues surrounding dependent variables and endogeneity, another problem with the design of small world and innovation studies is that they tend to treat innovation as an event rather than a process. So, for example, what does it really mean when we say that small worlds are correlated with innovation? Are we talking about search processes, idea generation, or product development? While some network structures may enhance idea generation, the network structures for turning ideas into new products may be quite different (Ohly *et al.* 2010). Given that the innovation process is different between industries and is also in a state of flux in response to factors such as competition and innovation technologies (Dodgson *et al.* 2005; Freeman and Soete, 2009), far more care needs to be taken in describing the context of small world studies and the type of innovation processes that may be affected by small world networks.

Data Collection

Another characteristic of small-world studies of innovation is that they overwhelmingly rely upon the use of secondary data. The use of secondary data, such as patent collaborations and alliances, has the obvious attraction of being able to generate large-n data sets without the concerns and effort surrounding surveys or interviews. However, the use of these data in network research brings in a particular set of problems that are not widely discussed in published studies. These relate to the collection of strong ties in the form of official collaborations, rather than more informal networks that may have a critical role in the innovation process.

Within social networks the interdependencies that are easiest to identify are strong ties (e.g. members of boards; a person's wife/husband) due to their relatively stable, structured and systemic nature (Montgomery, 1994). Conversely, weak interdependencies within a network (e.g. cartel behaviour; a friend's friend) are more problematic to identify due to their inherently dynamic, quasi-random and subtle nature (Granovetter, 1973). Since the publication of Granovetter's (1973) article on the strength of weak ties, it has been understood that these more transient links are more likely to act as bridging ties between clusters. Conversely, strong ties within dense clusters are more likely to provide closure (Burt, 2005). Focusing on the strong ties within the network is thus likely to present us with a distorted picture of the innovation process (Breschi and Catalini, 2010).

This distortion of the innovation process has significant implications for studying small worlds. The selective sampling of strong ties is likely to systematically bias the small world characteristics of the network. In some cases, the removal of weak ties from the dataset may cause a network to fragment into several smaller components. Even without this fragmentation, if weak ties tend to be bridging ties then it is reasonable to expect that the average path length will increase and clusters will appear more independent, resulting in the small world coefficient to be spurious.

The problem of biasing the small world Q through missing weak ties has been empirically studied by Shi *et al.* (2007). Using two real social networks they looked at the effect of removing weak ties and noticed a small increase in path length but in both cases they did not observe widespread fragmentation of the network into several components. While this result suggests that strong-tie bias does not affect the small world coefficient to a great extent within these two networks, we suggest that future research should check the relative importance of both strong and weak ties in the particular innovation context that is being studied. Missing data and respondent reliability is a general problem in network research and may become a significant issue in small world studies if researchers rely more heavily on network surveys for data collection in future (Marsden, 1990).

One aspect of data collection and analysis often overlooked in small world studies is the issue of disconnected components. In the situation where this happens, the average path length will be infinite and the small world quotient will be 0. The pragmatic solution is to analyse the largest component (Uzzi and Spiro, 2005; Fleming *et al.* 2007; Chen and Guan, 2010) but this is problematic for two main reasons. One of these is that there is evidence that innovative outputs are correlated with the size of the component (Fleming *et al.* 2007). If this is the case then sampling the largest component will artificially inflate innovation performance. The other problem is that some industries have very fragmented networks, depending upon how ties are measured. For example, Rosenkopf and Schilling (2007) used alliance data to construct networks in several different industries. Even in technologically dynamic industries such as engines and turbines, household audio and video equipment, and motor vehicles, there is great variation in the proportion of the network that is within the largest component. Most probably, analysing one particular component within a fragmented network and then correlating it with the innovation performance of the industry will generate spurious results (Schilling and Phelps, 2007).

Interpretation

The final problematic theme in small world studies of innovation surrounds the interpretation of network data. Putting it simply, just because a network map can be constructed doesn't mean that information, knowledge or other resources necessarily flow freely in all directions along the map. As mentioned previously, actors will regulate and filter the interactions between other actors (Braha and Bar-Yam, 2007; Kastelle and

Steen, 2010). In particular, if we impute ties from secondary data such as patent co-authorship, we have no way of knowing if a densely connected node is a disseminator or filterer of information.

This issue is taken up by Rosenkopf and Schilling (2007) in their study of small worlds in industrial alliances. While some of their networks show clustering around key firms in a network, "…these central actors may have neither the capacity nor motivation or economic interest to share information" (Rosenkopf and Schilling, 2007: 207). What appears to be a small world in a diagram may not be a small world in the reality of the actors that are being studied. One particular study from the biological sciences has shown how networks that can be mapped as small worlds may not function as small worlds. While metabolic pathways within bacteria can be represented on paper as small worlds, radioactive tracing of the interactions between enzymes and metabolites show that the metabolic network within the cell is not a small world (Arita, 2004). It is quite possible that a similar comparison of small worlds from industry alliance data, with surveyed responses from the industry about the actual nature of contacts, may reveal a similar absence of small world structure.

Related to the issue of inferring real connections from network maps are the analytical challenges surrounding bipartite (dual mode) networks (Wasserman and Faust, 1994). When actors are connected by membership rather than direct contact the overall density of the network can be greatly inflated but the actors may not actually know each other. A common example of a bipartite network is patent co-authorships. While there may be several authors on a patent application, some of these authors may not have actually worked together directly (Balconi *et al.* 2004; Fleming *et al.* 2007). Uzzi and Spiro's (2005) Broadway musical study is also an example of bipartite network analysis. Clearly, the analysis of bipartite networks must be different from singe-mode networks (see Newman et al. 2001 and Robbins and Alexander, 2004 for more detailed technical discussion).

Also, the underlying dynamics of bipartite small worlds are different from single mode small world networks. Whereas highly connected people drive clustering in one-mode networks, it is team composition that drives clustering in bipartite networks (Robins and Alexander, 2004; Uzzi et al. 2007). In other words, small-worlds in patent-co-authorship may be occurring because there are many authors per patent, and these authors are also party to other patents (Uzzi et al. 2007). Some aspects of the industry in question such as authors per patent and technological interdependency are therefore likely to influence the formation of these bipartite small worlds.

Conclusion

The past several years has seen a maturing of network analysis research within the innovation studies field. From initial enthusiasm about the discovery of a major determinant of innovation, researchers have since become more reflective about the findings from their research and what it means for innovation performance. In his critique of what he calls the ‘new social physics’, Urry (2004) warns of the temptation to search for simple explanations of complex social processes. In light of this warning, and based on our findings, we would like to make three proposals about the future direction of network analysis in innovation studies.

The first is that researchers must become more aware of endogeneity issues when conducting this research, particularly if they are using regression analysis to correlate network variables with innovation measures. This is one of the fundamental issues with research design that is apparent in the current state-of-the-art studies. One implication of this is that we recommend a move away from large-network analysis. Problems surrounding causality, data collection and interpretation are not likely to be solved with further analysis of very large datasets. Rather than addressing the universal question of small worlds and innovation, researchers are more likely to ask the questions of when small worlds form and under what conditions and then relate this to a particular innovation context where performance can be gauged more accurately.

Moving from large networks addresses the primary issues with the network variables. However, it is apparent that there are also significant issues with the dependent variables used to measure innovation. As discussed, there are substantial difficulties in using patent count data as a proxy for innovation, both at the level of the firm and of the region. Process, service and business model innovations are also very important economically, and if we are to develop a better understanding of the relationships between network structures and innovation outcomes, we need to use metrics that capture these forms of innovation more effectively.

Finally, we propose that network analysis of innovation needs to move beyond a focus on structure to a focus on process. There are problems with the assumption that all ties are created equal. Analyses that include weak tie data may reveal different important network structures. Similarly, research that develops a better understanding of the nature of the relationships within the network will provide better insights into the interactions between network structures and innovation outputs. In particular, greater use can be made of bipartite networks by linking actors through their use of common meanings and shared cognitions (Cambrosio *et al.* 2004; Bourret *et al.* 2006).

The possibility of extending small world studies to examine the relationship between the micro and macro levels of the network is particularly exciting. For example, how do technological interactions in virtual space affect the formation of small worlds? How does trust and perceived social risk between individuals affect the macro-structuring of the network - and innovation as a consequence? As Urry (2004) has suggested, once we go beyond the relatively simple sociology of connection, implied by the majority of small world studies, there remains a very rich social physics that has yet to be developed.

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