PERFORMANCE MEASURES AND MECHANISMS FOR INTER-ORGANIZATIONAL KNOWLEDGE MANAGEMENT

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Increasingly, research recognises that knowledge is through inter-organizational sharing and creation, and particularly that knowledge drawn from networks of multiple and geographically dispersed firms. Yet, research on performance measures and consequently, proliferating mechanisms, is still less developed, and the latter is essentially concerned with variances of forms of knowledge. We hence evoke techniques by proposing three sets of measures, focusing on inter-organizational alliances performance. Whilst the empirical results provide evidence that network (formation) asymmetry significantly reduces cost and generates economic gains for partners, the crucial importance of the quality (network) asymmetry yet, demonstrates that the "critical entropy" determines the alliances benefits. Further, when the tests of two sets of proliferation mechanisms are linked to implicit and explicit forms of knowledge, respectively, the simulated results supports our proposal that inter-organizational knowledge integration and knowledge segregation matters. The findings are not just concerned with the critical debate of knowledge transfer (or conversion) but how knowledge creation can be sustained in shared practice.

There is much that has been written within the knowledge management literature; knowledge offers value to organisations that is unique, acting as a barrier against attempts by rivals to imitate (Dierickx & Cool, 1989; Saviotti, 1998), knowledge dwells within social ties (Coleman, 1988; Burt, 1992; Ingram & Roberts, 2000; Weick, 1995), and knowledge resides among corporate research and development teams (Reagans & Zuckerman, 2008). Scholars also argue that knowledge conversion between tacit and explicit contributes to organisational knowledge creation (Nonaka & Takeuchi, 1995; Nonaka & von Krogh. 2009), knowledge percolates in networks of multiple and geographically dispersed firms (e.g., Burt 1992; 2007; Nahapiet & Ghoshal, 1998), knowledge proliferates at dyadic level of interactions (D'Eredita & Barreto, 2006), knowledge transfer by sets of mechanisms (e.g.,; Reagans & McEvily, 2003), and hence knowledge becomes less complex, and thus, more amenable to diffusion. Yet, prior literature, in general, shows the measures of proliferation for either tacit or explicit knowledge less explored. Consequently, it remains uncovered links between structural networks and knowledge either distributed or proprietary. The unattained issues consistently challenge inter-organizations in knowledge management. In contributing to reach on these problems, in this paper we develop three sets of examination.

In section two, we firstly construct an approach to insights of alliances performance. Whilst our multiple regress analysis is rather common, our interactive plot by increasing in scales and connections of alliance with change of performance landscapes of the partner firms is interesting. Yet, the contribution hereby is not the scales of differences of networks we examine but rather the argument that conversely may suggest the quality of alliance network matter. Whilst it is difficult to measure the quality of network, our simulation modelling of network measures not just attempt to make it (quality) visible but to demonstrate fundamentals of network structural effects linking to how actor bridging structure hole (Burt, 1992; 2007). More essentially, we employ the critical “entropy” (Edelman & Tononi, 1998; Balduzzi & Tononi, 2008) that provides insights of probabilistic network organizations in knowledge creation by knowledge integration (segregation). Thus, our novel contributions to knowledge management research are not just our application of network graph theories to demonstrate structural effects, but our implementations of the critical entropy in measuring the effectiveness of inter-organization knowledge creation.

In building the theoretical framework, we consider the wider implications for research into the structures of networks (e.g., Ahuja, 2000; Burt, 2007, Eden 2009; Gulati, Nohria, & Zaheer, 2000; Kogut & Walker 2001). On this basis, we propos both “online” knowing, which draws on the work of Polanyi (1958; 1962), Tsoukas (2002; 2003) and Weick and Roberts (1993), and “offline” knowing, a perspective which is exemplified in the work of Edelman (1987) and Hayek (1952). With these proposed mechanisms, we develop modelling to generate measures. We, in general, evoke both inductive and deductive methods to assess the propositions using both empirical analysis (panel data) and experimental simulation (e.g., Harrison, Lin, Carroll, & Carley, 2007). The multiple modelling and analysis techniques broaden our thinking in research on knowledge of various forms, and the methods offer a fresh approach to both quantitative and qualitative analysis for future studies.

With the above justification, we construct multiple examinations corresponding to the hypotheses generated in Section 2. In section three we illustrate the results from the analysis. In section four, we present a discussion in which we offer a number of proposals for knowledge measurement and how its evolving process is concerned with organisational knowledge networks. In the final section, we draw out the conclusions and indicate the research contribution for the knowledge literature. Simulation methods have been widely adopted in modelling dynamic landscapes (Rivkin, 2000; Rivkin & Siggelkow, 2007; Winter et al., 2007), and simulations are beginning to find wider applications in management research (e.g., Cowan & Jonard 2009; Martin & Rajshree, 2009). Simulation modelling is used extensively to examine neural systems (e.g., Balduzzi & Tononi, 2008) and learning (e.g., Arbib, Prudence, & Arbib, 2002). In modelling neural networks, Edelman and Tononi (1998) employ a set of measures based on information theory to evaluate the statistical dependence between multiple subsets of elements of interacting neural groups. It is these approaches have guided our innovative analysis.

SYSTEMATIC MODELLING

Asymmetry

We first study the alliance formation, and particularly examine the structures of airline networks that are presented by the route networks of the partners. Alliances are predicated on the belief that economic value stems from the ability of firms to combine mutually coherent sets of choices or activities rather than in the assembly of collections of individual components (Fiss, 2007). Network structures are also relevant to the studies of interdependent systems that have emerged as a prominent stream of thought, rekindling interest in ‘activity systems’ (Rivkin 2000; Siggelkow 2001; Porter & Siggelkow 2008), complementarities (Milgrom & Roberts 1990; 1995) and configurational approaches (Fiss, 2007). By emphasizing interdependencies, activity choice decisions necessitate a holistic or systemic view of strategy because the marginal benefits for the system as a whole from increasing or decreasing one activity will be dependent on its relationship with many other activities. In contrast, independent or loose-coupled systems are more susceptible to imitation.

Resource asymmetry. The above discussion gives rise to the idea of resource asymmetry, which is a critical issue for firms in responding to market opportunities, those are likely to seek different access to what Denrell, Fang and Winter (2003) refer to as ‘the missing pieces of a puzzle' in accomplishment of the task. However, differences will exist between firms in their ability to access, and hence take the opportunity (Denrell et al., 2003). Different combinations will produce different outcomes depending on the 'pattern or profile' of the interactions within the system (Fiss, 2007). We firstly examine the economic gains with structures of networks, as such for instance, the density, connection, and geographical coverage that might explain firm performance asymmetries.

INSERT FIGURE 1 ABOUT HERE

Network asymmetry. Given resource asymmetry, benefits from alliances hence are concerned with formation of "asymmetry", which according to Cowan and Jonard (2009) is in degrees distribution of networks in which the vast majority of vertices (nodes) have smaller degree than the average, and a small proportion of hubs have may more links than average. In open milieu of an aerospace, for instance, it is important to connect to hubs and spokes canonical that are popular destinations, thus leading to a highly skewed distribution. Yet, due to formation cost, airlines can link only a finite number of cities relatively to the population. Also, for reason, relatively more links would need to be created and even if more are created those actually conveying relevant popularity to the set of all possible other links. Thus, in reality, a partnership at optimal overlap has a probability of success strictly larger than the cost of the partnership so any firms who have optional overlaps of their knowledge stocks, and hence will form an alliance but as firms overlap differs from the optimal level the probability than their alliance will be exceed its expected benefits, and hence successful alliances falls ($x - p$, $x + p$), as depicted in Figure 1. As such, partner performance may associate multiple structures of alliance networks, and that are differentiated

$$\ln Q_i^t \equiv \int_0^\infty e^{-rt} [\ln Q_i^t (A_i^t) - P_i^t (A_i^t)]\, dx ; \varepsilon_i^t ,$$
$$A \geq 1 \text{ allainces} \qquad (1)$$
$$A \leq 0 \text{ otherwise}$$

where $\ln Q_j^t$ is the logarithmic form of the performance of firm j at time t, and as there are infinitely-lived passengers with identical preferences of a basic reference service, $A > 0$ represents the extent to which a favourable service is over a unfavourable service, as a firm-specific (j)'s alliance, P_{tj} is the price per passenger kilometre, which is also subject to the alliances $A > 0$, and ε_i^t captures randomly distributed consumer preferences for a specific service. The above illustration leads to our first set hypothesis.

Hypothesis 1: In an alliance network, a firm's resource asymmetry and network structure asymmetry are positively interrelated.

Hypothesis 2: Network structure asymmetry significantly leads to reduced cost and increased economic gains of the alliance firm.

Structure Hole

Whilst strategic alliances in the airline industry have been further approaching the progressions of structural formation, we shall continue to examine the effects of network structures and activity systems, and such examination may not just measure partners' benefits but customers. Airline partner performance within the network is hence how the system is performed in term of services consistency, and that associates customers' satisfaction and hence economic gains. This suggests the reversed possibilities for network systems fit become significantly critical. However, the challenge is that in the quality formation of network, the structures might neither be able to be made explicit nor physically exist. Whilst what reflect inter-organizational value creation through shared knowledge and practice for instance, by partners flights exchanges of pilots, cabin crews, loading food from local destinations, and employing local staff at the transit and terminals airports, we contend that under such conditions, it is, how actors (firm managers) spinning structure holes that will significantly contribute to the quality of network. The argument ponders, in the modelling we hall not be confined to a demonstration of how network structures emerge but how value are sustained through the social production (airline partnerships).

We thus test the variants of the cross-sectional effects, and with a set of parameters, θ, in the set-up $\theta > 0$, acknowledging the extent to which greater revision possibilities lead to higher levels of network systems fit and an improvement on service quality, $\Delta S_{it,j}(\theta_{tj}) = dS_{it,j}(\theta_{tj}) / d\theta_{tj}$, which is expressed as follows:

$$\Delta S_{it,j}(\theta_{ij}) \equiv \Delta f(S_{it,j}) d\theta_{tj} \equiv \int_0^1 \Delta f \{(S_{it,j}) d\theta_{tj} [\Delta \exp(\delta_{tj}^{-\alpha t}, \gamma_{tj}^{-\alpha t})]\}, \tag{2}$$

where ΔS denotes a change of performance with respect to θ, parameterised by σ and γ, dual-asset of vectors of variables specified as: where α is a scaling factor, a >0, with a normal distribution N (0,1) and unknown variance, σ^2, i is passenger specific. The integral captures a passenger switching from a system $S_i \in [0,1]$ within an alliance network and without, and μ and v are stochastic disturbance that capture unobservable factors.

The above argument mirrors on an idea that a firm uses some of its links to bridge distant parts of the network in particular to which its neighbors are not well-connected. For this, we further use Burt's (1994) structure hole for the argument. Burt (1994) and Cowan & Johnard, (2009) noted that by doing bridging structure hols, the firms' network connections permit rapid access to knowledge in different parts of the network. In this sense, a network evolves to one that contains many structural holes, and hence firms may be more advantageous by increase in access to information that is not available in its local cluster. Benefits of firms from the network will be associated with the abilities of how actors bridge the structure holes.

Baum et al. (2003) noted that strong firms consolidate their positions to insure the firms against technological surprise that may take place in a distance, or peripheral firms attempting to move to amore central position in a network. The discussion leads to our second set of conjecture.

Hypothesise 3: The quality of network is significantly related to how actors bridge the "structure holes".

Hypothesises 4: An actor' ability in spinning the structural holes significantly and positively contributes to an inter-organizational value creation.

Out hypotheses correspond to that how a firm in the network grows as actors tap into divergent and novel sources of knowledge, perhaps by reaching across structural holes (Burt, 1992; Kogut, 2000). Under such conditions, it is thus not the exposure to the diverse and novel sources of knowledge that is necessarily of the greatest significance, for as Burt (2008) notes, in the course of being exposed to novel and contradictory knowledge, actors develop the cognitive skills of analogy and metaphor, and importantly, the capacity to utilize information from multiple sources and use this to communicate across differences.

Critical Entropy

The discussion carried out above indicates that actors' cognitive skills in bridging structural holes are important. We hence introduce "entropy" (Tononi & Edelman, 1998; Baldulzzi &Tononi, 2008). The entropy we seek to explain is the probabilistic organization as knowledge sharing and creating organization in the network. This argument is concerned with how knowledge creates is realised by how the network enables knowledge functional integration, and at the meantime, knowledge functional specialisation cross firms within the network. This is because firstly, social capital and tacit knowledge will not be comfortably explained by dense networks, proliferation of tacit knowledge, for instance, needs interactions either with individuals (face-to-face) or objects/events. Secondly, we use R&D as the example. The joint ventures innovate in performance of robots that are guided by a set of rules produced by the human in the form of computer code. Yet, in this process, the sensory ordering of events cannot be explicated or parcelled out whilst it remains with the creators. The argument is that knowledge of such kind, in fact, is not transferred. The important point we give is that, in the absence of the information processing capacity of super-computers (or a computer programmer) that constitutes knowledge that has been made explicit. The computer can issue a set of rules for interpreting incoming signals "*a priori*" (Edelman, 1987: 44). Yet, actors, in effect, produce categorizations, such that, knowledge of a cabin crew about a customer and her preference sequences during services can only be defined "*a posteriori*" after the incoming signal has been received (Edelman, 1987: 44).

The above discussion is concerned with the distinction between knowledge transferred and emergent knowledge (Figure 2). The latter may be also related to personal skills and tacit knowledge. As so the proliferation will involve high sensorimotor skills, in that local context learning region, local clusters, and communities of practice are more applicable. Conversely, explicit knowledge transfer uses low sensorimotor skills, for instance, global supply chains, cross-border M&A/alliances, where geographical distance, relational distance, and institutional distance imply. We use Figure 2 to depict knowledge of various kind, and hence different mechanisms that the proliferation may concern.

INSERT FIGURE 2 ABOUT HERE

Our further argument is when distance increases, ambiguity and complexity increase in the process of knowledge diffusion, particularly for personal skills, and implicit knowledge.

Thus, D'Eredita and Barreto (2006) propose a specific mechanism by which tacit knowledge emerges based on "dyadic relationships", and Weick and Robert (1993) further note it is the "collective mind". To that end, we are able to further talk about knowledge "proliferation" within inter-organization.

The problems discussed so far raise the issue that within an inter-organizational network, where there will be a greater probability of knowledge divergent. Yet, it might be also such process offering chances for knowledge to become more differentiated and specialized. Knowledge functional segregation creates advantages of complex knowledge. Individuals dispersed imagination with the evolving nature tacit knowledge may contribute to unarticulated rules in the network for inter-organisational knowledge creation. It can be hence argued that a differentiating network is a self-organizing system and as the network grows, it increases the amount and diversity of knowledge in the system. At the meantime, we also propose an integrating network. Such network is a result of constantly reconfiguring connections, actors develop the capacity to integrate distributed, specialized and novel sources of knowledge.

Thus, in a network, our emphasis under these conditions is not so much, "knowing what" but "knowing how" (Ryles, 1949). Networks hence become tacit rules that underpin the cognitive and emotional skills that stem from making connections to actors with divergent beliefs and practices that matter (Burt, 2008). The rules are a 'by-product' from making connections (Burt, 2008: 11) and thus, it is the skills and competences in coordinating ambiguous, contradictory and novel sources of knowledge that form the source of a firm's advantage.

Yet, in what follows, how can we assess the ability of a system to be both differentiating and integrating, and through which how does new knowledge emerge? One way to assess how much knowledge is generated by a network is to measure the capacity of the system to generate knowledge over and above that which is generated by a connected/disconnected system, in either case, the minimum amount of effective knowledge that can be exchanged across a bipartition of a subset within the network (Tononi, 2004). For an organization to constitute a knowledge creation network, the knowledge generated must be greater than what can generated by the sum of its parts (Tononi, 2008). The total knowledge generated by a network that is decomposable into a number of separate subsystems would simply equal the sum of the components that make up the system.

We adopt the relative entropy H (p-) and we let it to be captured by the *effective information ei*. It is generated by the network system when, through causal interactions among its elements, it enters state x_i and thereby specifies a set of knowledge of "*a posteriorie*" distribution with respect to "*a priories*" X_0 distribution (Balduzzi and Tononi, 2008). Thus, we let

$$ei(X_0 \to x_1) : H[p((X_0 \to x_1) \| p^{\max}(X_0)], \qquad (3)$$

simplify

$$ei(X_0 \to x_1) = H(p^{\max}(X_0)) - H(p(X_0 \to x_1)). \quad (4)$$

where $H(p(\text{-}))$ is the entropy of probability distribution p, a system of n binary elements generates at most n bits of information, depending on state x_1.

In general, relative entropy measures a particular system state, and the difference between probability distributions between actual state (X_0) and the potential state (x_1). The "relative entropy" H is also known as the theory of Kullback-Leibler (1951) divergence, a discrete function though which we seek to assess new elements of knowledge generated by actors in the connectivity of the network systems.

INSERT FIGURE 3 ABOUT HERE

From the above discussion, we need to redefine the probabilistic function (Figure 1), and hence we present Figure 3 to show that this measure can be used to identify the subsets of a system that are integrating knowledge. The discussion leads to our final set of hypothesis.

Hypothesis 5: In sets of system, when new knowledge evolves, the network shows significant and positive entropy H (p-) >0.

Hypothesis 6: Inter-organisational knowledge creation is a probabilistic organisation in distributed knowledge as well as in undistributed and unarticulated rules.

THE EMPIRICA INVESTIGATION METHODS

Data and Measures

The panel data sources for the empirical analysis of airline performance were obtained from Traffic *by Flight Stage, Digest of Statistics* (ICAO 1989-1998); *Airline Annual Reports* on CDRom (IATA 1996-2005). Overall, the empirical analysis contained more than 5,500 cross-sectional data sets. The alliance data collection was based on Airline Business 1989-2000 monthly issues and *Airline Alliance Survey, Special Report, Airline Business* (1999a 2000, 1999b 2000).

The questionnaires were collected at the passenger lounges at four major international airports, Melbourne, Sydney, Singapore, and London Heathrow. The survey covered 700 routes within Asia, Europe, North and South America, and Asia-Pacific regions, and included 57 airlines, including both connecting services (131) and city-pairs (82). The data covered the period from July 2001 to July 2005. A total of 504 (73% response rate) valid data questionnaires were used. Passengers travelling outside alliances were also considered for a comparative analysis. The random sampling included passengers travelling for a variety of purposes (e.g., tourist, business), boarding on first-class, business, and economy flights. The further interview of managers' through structured questionnaires at Customer Services of American Airlines, British Airways, Singapore Airlines and Lufthansa at Singapore International Airport compromised the customer survey data for further information.

Analytical Techniques

The empirical investigation incorporated multiple regressions and sensitivity analysis, with the parameters adjusted in order to improve the model's ability. Such methods build on previous studies by adding refinements that address a number of measurement problems, particularly in empirical tests relating to resource and capability research (Levitas & Chi 2002, Peteraf, & Reed 2007). We introduced an error term (ε) to capture unobserved effects and vectors of variables (control variables) that proxy for measures of different aspects.

Simulation Considerations

In studying different network structures, we use node v, and links e in a network, and hence we generate different sample regions to examine diffusion probabilities, measuring changing values of the graph data (e. g., cluster coefficients, graph distance, and degree distribution). The simulation modelling are also related to the landscape generation by Winter *et al.* (2007), which uses v (vertices), similar to Rivkin's (2000) binary string of N bits, which corresponds geometrically to the unit hypercube in N space. To search graph distance requires a search strategy that depends less on incremental improvements and more on the ability of mechanisms to detect whether there is any correspondence (alignment) between a new, and perhaps novel combination of events, and the current configuration. The different network structures reflect the differences in these properties.

There are three important properties in studying graphs that must be considered in the computations; the clustering coefficient, the average path length and the degree distribution (Barabási & Albert 2002). The degree of a vertex is the number of edges connected to that vertex and the degree distribution relates to how the edges are distributed across the network. Degree distribution is a measure of the density of the network and in this paper we consider only undirected edges. Average path length represents network power (graph content) and is related to graph distance. Graph distance distinguishes vertices that are close-in to the initial combination from those that are more distant. We adopted the concept of Barabasi and Albert (2002) in the assessment, and the equations are shown together with the results in Figure 4.

RESULTS

Test of the Alliance Network (Asymmetry) Effects

The results (Table 1) firstly show that the alliances, significantly contributed to an in increase in Q, passenger market growth in the observed population and period (1989-2005). The analysis considered other factors influencing market growth, such as T, the time series (insignificant); and ε, the volatility factor (significant but negative) and service activity variables prior/post alliance (significant), which contributed to a better model fit. However the critical point we found were not just the gains but lost for some airlines without being able to entry alliance due the reason depicted by Figure 1 in the modelling section. Forexample, we found evidence that carriers (e.g., Air India, Pan American) on the same routes (e.g., Chicago-Frankfurt), operating reciprocal bilateral services, had a higher propensity to exit due to significant reductions in their share of the market (in 1995) once the larger carriers had entered one of the alliance groupings.

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INSERT TABLE 1 ABOUT HERE

The sensitivity estimation (in Figure 4) showed the results in general, passenger market grew (Adj. $R^2 = 0.93^c$, $p < 0.0001$) and (in Figure 4) and price changed (Adj. $R^2 = 0.50^c$, $p < 0.0001$) in a system, J (K_1), with parameter $s \in s \subseteq K_1^{rt}$, where k was an open set, then the system's output function is $J(K) = E_{Y|k}[Y(s)]$, where, s (alliance) is a random vector with known probability density function, f(s; K_1), and Y was a performance measure. The results demonstrate that an increase in the degree of alliance was associated with an increase in the levels of market performance for alliance partners, for example, the mean value for joint activities was 4.8 but the mean for bilateral service rights was 4.1. The results in general support our first set of propositions.

INSERT FIGURE 4 ABOUT HERE

Critically, we found evidence to support the second set of hypothesis where δ, the vector variables associated with network system fit, was significant and positive, ($R^2 = 0.84$, $p < .0001$; and $R^2 = 0.55$, $p < .0001$), and γ, the vectors of variables associated with the integrative flexibility, was also significant (Adj $R^2 = 0.82$, $p < .001$; Adj $R^2 = 0.73$ $p < .001$). The results reflect inter-organizational value creation through shared knowledge and practice. The results also reflect managers' cognitive skills in bridging structural hotel for creating the "seamless" services critically important.

Assess the Structure Holes and Effects

In the experiment, the first set of graph data generated has similarities to a disconnected network (Figure 5A) with infinite (∞) path lengths due to the absence of connections. The second graph generated (B) had a small world structure. Of the graph data properties examined, the small world had the greatest cluster coefficient (0.22), suggesting that a closed group has the greatest potential for the diffusion. But its degree distribution (0.49) was the weakest and the value of the average path length (2.05) was the largest.

Comparatively, the segregated cluster graph (C) appeared to be relatively advantageous due to its lower average path length (1.8) and the higher structural density, as measured by the degree distribution (0.56). However, the graph data properties do not necessarily indicate that knowledge diffusion would be effective in such a geographically dispersed network. We could see that the graph distance between the two nodes, 9 and 13, was g(9, 13) = 3 and g(16, 13) = 5, respectively. The dynamic structure of the network (D) demonstrated greater network graph (content) power, compared with the other three, as its graph data properties had the smallest average path length (1.65) but had the highest degree distribution (0.60).

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INSERT FIGURE 5 ABOUT HERE

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The in/outgoing edges showed that the central nodes (actors) are spanners, bridging structural holes, which suggests that information flows improve, as the greater degree distribution, and the greater clustering coefficient suggest the greater were network opportunities, in that most related mechanisms were able to "communicate" with each other. It is also noteworthy that this network graph had the highest diffusion probability ($p < 0.78$). The differences between network structural effects challenge inter-organisational knowledge management not just formation but interactions between actors. An our results suggest the latter be more important.

Test of the Entropy

We present Figure 6 from multiple observations of the *effective information* (*ei*). It (D) shows when X_0 enters x_1: one out of eight states (2^3), the other seven perturbations are ruled out. As the entropy of the "*a priories*" repertoire is 3 bits and that of the "*a posteriories*" is 0 bits, so 3 bits of effective information are generated by the system. Thus, figuratively, the system's mechanism and state generate information by sharpening the uniform distribution into a less uniform one. Balduzzi and Tononi (2008) define that the more different they are the higher the relative entropy, and this is how much uncertainty is reduced. Relative entropy H (p-) is zero if the repertoires (distributions) are identical, suggesting no information generated. In comparison, in A (copy), the information generated is little given the systems repertoire is also too small. In B and C**,** many states lead to the current outcome either by "always firing" or "at random" (when noise dominating). When choices are either joint presence or joint absent, no alternatives are ruled out, no information is generated.

INSERT FIGURE 6 ABOUT HERE

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CONCLUSION AND IMPLICATIONS

The paper builds on theoretical arguments and systematic modelling. In the study, we evoke three sets of analysis to demonstrate the social production of knowledge as an emergent property of network systems and contingent on the context from which it is generated. We have found significance of inter-organisational knowledge creation through knowledge integration rather than its conversion. Codified knowledge, as Kogut and Zander (1992) note, enables actors to structure knowledge into a set of identifiable rules and relationship that can be communicated. Conversely, personal skills implicit knowledge may not have theory but rather take the form of a set of subsidiary particulars; unarticulated rules (Hayek, 1967;

Tsoukas, 2003). The knowledge characteristics suggest that organizations in network assist these rules that can form a set of interaction in complex ways through which knowledge creates. This is why we have proposed both structure holes and the entropy for measurements.

The research findings challenge inter-organizational knowledge management of how they develop a micro-behavioural foundation of social knowledge that as Loasby (2006) and Teece (2007) indicate, should be used in explanations of performance asymmetries, and the sustainability of competitive advantage. We hence suggest further justification through future empirical work; sorting out individual from collective-level effects.

The paper also challenges inter-organisations of managing knowledge of macro level. Such organizational capabilities in the current management literature are thought to be a socially constructed phenomenon. Given knowledge may be kept proprietary or may not diffuse for reasons, in this context the capability-based literature and empirical findings could stir further debates on collective-level effects. This is the other reason why this paper integrates the organisational knowledge and strategy with dispersed and personalised specialised knowledge, and demonstrates that managerial mental models and cognitive hierarchies strongly impact on the ways of firms deploying resource (formations of types of alliance), and that result in performance asymmetries. Previous research on strategy emphasise that managerial strategic behaviours are concerned with the protection and sustainability of economic rents, but how rents are created in the first place and constantly accumulated will require a better understanding of the link to opportunity. And in social capital theories, how opportunity is created are through social interactions and shared community practice. In those contacts, individual knowledge and knowledge of organisations are co-evolving as coherent systems. Towards this argument this paper additionally generates several implications for future research, as follows.

Implication for Inter-Organisational Knowledge Creation

Our analysis by entropy demonstrate that by knowledge conversion or transfer, actors might commit to an isomorphic presentation. Knowledge conversion also may only offer some temporal and symmetric resources. Balduzzi and Tononi, (2008) recognise that strictly modular and homogeneous systems can not generate high values because the former lacks integration, whereas the later lacks information. Congruence between the external problem and knowledge heterogeneity suggests actors in a network develop knowledge with higher-order consciousness. The experiments explain actors' creative capacity co-emerges with organisational environment verges that continuously build models of the world and of itself. The entropy with the *effective information* measure studied in this paper suggests the importance and possibility of actors enhances a capacity in endogenous dynamics with stimuli from the external world; including challenge from the network. For systems have no underlying causal architectures are merely copy or replay activity states (Balduzzi and Tononi, 2008). Such dynamics suggest actors by actively and positively engage with inter-organizational partnership can go beyond the information given to generate new knowledge.

Implication for Network Structures

We may urge although only limited knowledge could be directly distributed in a network, the significance for a knowledge network is in the individual's capacity to develop "endogenous dynamics". As new knowledge and novel ways of knowing are generated through the interplay between reflection, thematization and experience within situated interactions, inter-organisational context becomes crucial. This thus challenges research on network structural effects. The difficulties of knowledge percolation are manifest in several ways. First, knowledge creation evolves more effectively from those areas: direct (social) links (Burt 2007; Eden 2009), and shorter (neural) fibres and closer memories in time distance

(Sporns, Chialvo, Kaiser, & Hilgetag, 2004). Second, the innate states of individual accounts in cross-correlation studies of “free-scale” (dynamic connectivity) functional brain networks (Sporns et al., 2004), the robust properties of networks relate to shorter path lengths.

Furthermore, given the variants of cognitive variables, in the global environment, there are linkages between markets, institutions and individuals, and international spillovers. There are factors related to the “global mindset”, “knowledge criticality” and “absorptive capacity” (Eden, 2009: 178). The interactivity emphasized by Weick (1995) and D’Eredita and Barreto (2006) suggest that tacit knowledge is interpreted, constructed and contextualised.

More critically, it is widely acknowledged that actors have an incentive in keeping knowledge proprietary by restricting the types of resources/capabilities that are to be included in an exchange. This action will have an impact on how knowledge diffuses in a network, and furthermore, it raises questions concerning value distribution among participants. Kogut (2000) argued, whilst we trying to understand why benefits are not distributed more widely among industry participants, we necessarily recognise that networks act as a *qualitative barrier*, and hence the tacitness only be shared with possible partners working closely together, and that also signifies why firms also wish to *cooperate* rather *defect* in a cooperative game setting.

Thus, although there is evidence in the literature that offer the points the advantages of highly connected network systems, our analytical results do not however suggest that geographically dispersed networks for knowledge percolation are easily achieved, unless we can think of a way of unlocking the models. This is the reason we have promoted the cognitive model (the endogenous dynamics), and knowledge integration, and our analysis showed that these models are plausible to play the role in bridging the gap.

Implication for Research Analysis

"Stimulation modelling provides a powerful methodology for advancing theory and research on complex behaviour and systems" (Harrison, Lin, Carroll, & Carley, 2007: 1229), and its standing in history has been shown by the publications in the *Academy of Management Journal* (e.g., Lomi & Larsen 1996), *Organisational Science* (e.g., March, 1991), *Management Science* (e.g., Revikin, 2000). Yet, Harrison et al. (2007: 1229) recently provided data to show a much smaller proportion of simulation articles, "it has embraced more slowly in management than in some associated social science disciplines", and "part of the reason is that stimulation methods are not well understood".

To make a contribution in this area, we have innovated in the simulation to investigate dynamic, nonlinear, complex behaviours to process copious amounts of data and communicate ideas. Prior management literature shows research as largely employed surveys and secondary data and the use of statistical applications for analysis (e.g., regressions or linear models) though those methods have high generalizability and are low in realism and precision (MacGraph, 1982; Scandura & Williamn, 2000). This paper demonstrates that creative search broadly oscillates between domains that vary in their distance to the endogenous forces.

The methods open the way for alternative approaches to unobservable phenomena and the measurement of intangibles. Studies emphasise that knowledge-based work has been on nurture, collective and environment (e.g., Nahapiet & Ghoshal, 1998: 247; Spender, 1996: 53). To this prospective, the three sets of measures developed in our study provide fundamentals of insights into more competitive analysis in the future, both in terms of selecting appropriate experiments and generating measures for testing. Our research design and analysis suggest that future studies may not only be confined to firm performance measures (e.g., quantitative or large secondary statistical data) but also seek the insights underlining qualitative factors.

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FIGURE 1

Cost, Benefits of an Alliance as a function of Asymmetry of Network (Resources) Structures

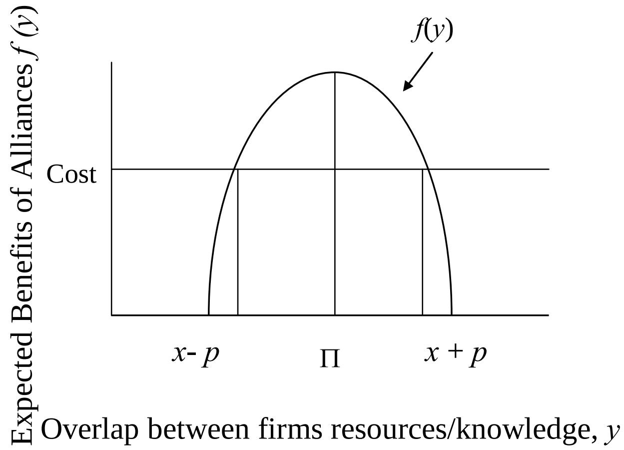


FIGURE 2

Knowledge of Various Kinds and Mechanisms Functioning in a Network

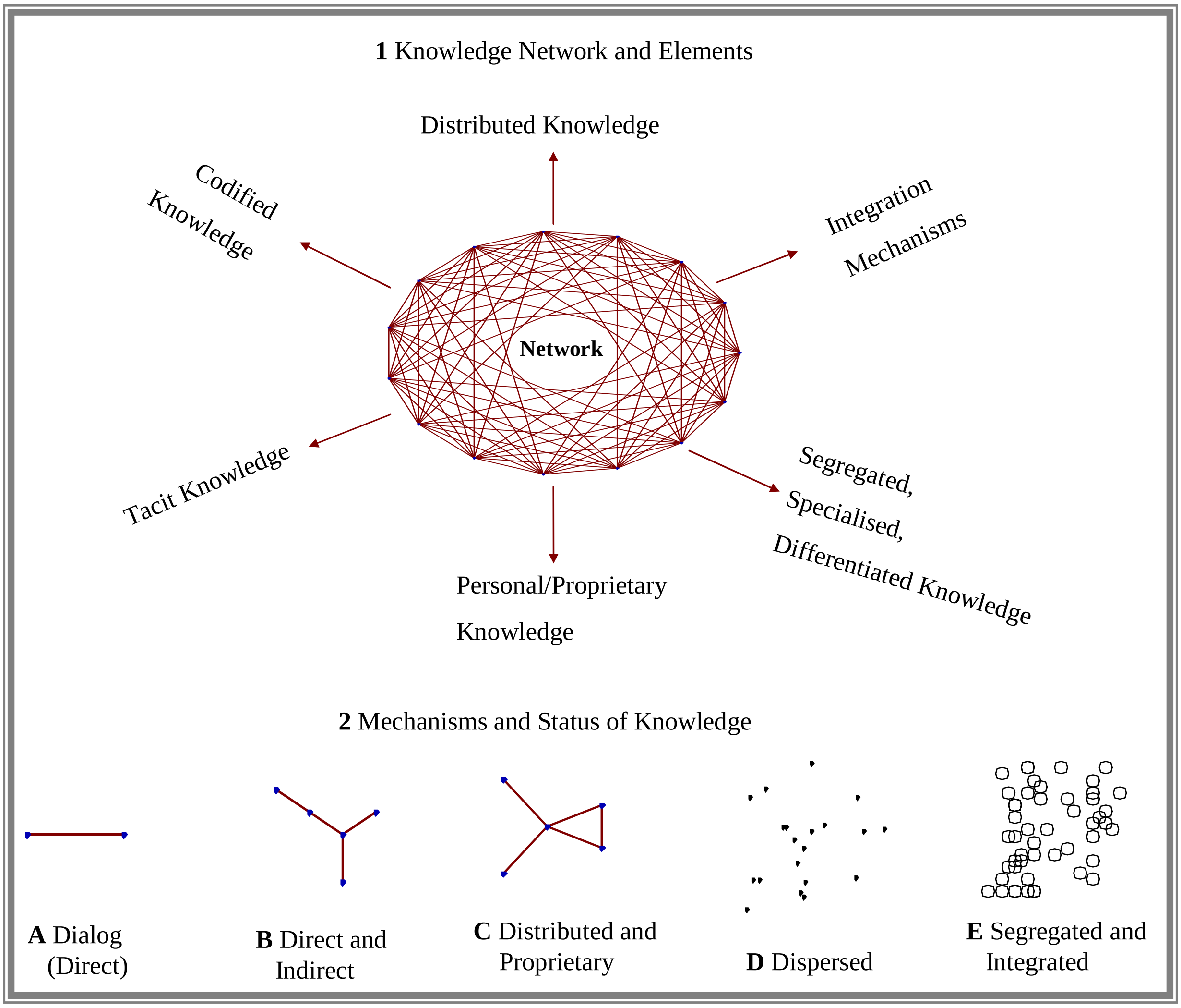
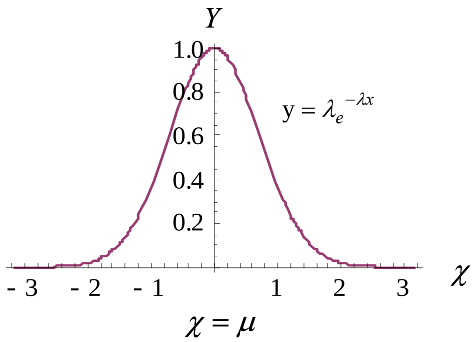


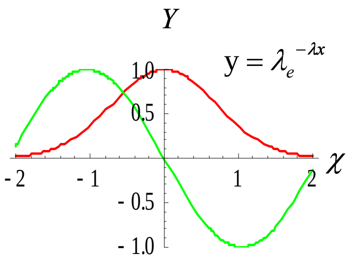
FIGURE 3

Benefits of Alliances as a Function of Probabilistic Inter-Organization Knowledge Integration/Differentiation



$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma}} d(\frac{x-\mu}{\sigma}) = 1$$

$$\text{let } P\{-1 \le \chi \le 3\},\ p(x) = \begin{cases} 2e^{-2x} \chi \ge 0 \\ 0 \quad \chi = 0 \end{cases}$$



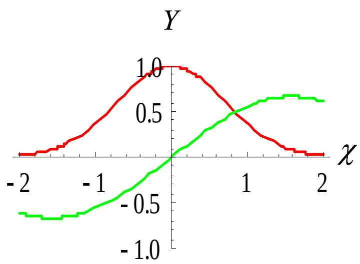


TABLE 1

Airlines Competitiveness with Annual Total Alliances

Variables	Observed Variable (Number of Alliances)	
	Reg. coefficients	t- values
(Constant)	1.57[c]	22.14
Network share	1.32 [c]	5.88
Passenger market (*Q*)	0.50 [b]	7.28
Number of routes	-1.56 [c]	-7.14
Total flights	0.28 [b]	5.10
City pairs	0.20[a]	2.79
T Time Series	-0.07	-1.2
ε	-0.47[b]	3.23
Model Fit	R^2: 0.51	p< 0.00

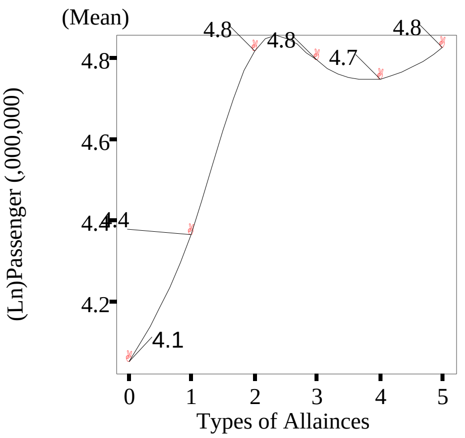
Note: Service Activities, Data 1989-2005 of 24 Major Carriers

[a] $p < 0.05$. [b`] $p < 0.01$. [c] $p < 0.001$.

FIGURE 4

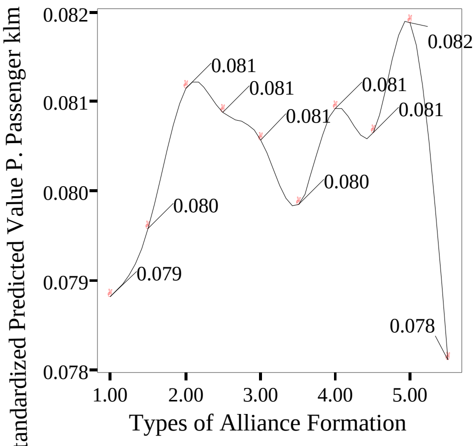
Passenger Market Growth and Price (US cents) Change

(Per Passenger Kilometre, 1989-2005)



Types of Alliance Formation

Data sets 5,500, Carriers 174, F-value: 6,620, R^2: 0.93, *P*<.0001



Data Sets 5,500, Carriers 174, F-value 1,147, R^2: 0.64, *P*< 0.001

TABLE 2

Structural Holes and Seamless Services: Evidence from Customer Survey (504 customer survey)

	Dependent *SerQ*	
vari. associated with systems fit	Model 1 (*within*)	Model 2 (*without*)
Coefficients		
(Constant)	0.50[c]	0.60[c]
	(3.23)	(3.11)
ScaleConnectivity	0.08	0.44[c]
	(1.56)	(7.27)
InforTransfer	0.57[c]	0.25[c]
	(12.40)	(4.94)
NetworkConsi't	0.04[a]	0.16[c]
	(0.84)	(5.35)
In-flightCoordi'n	0.05	0.24[c]
	(1.16)	(4.63)
AirportCoordi'n	0.52[c]	0.37[c]
	(9.38)	(7.21)
CustomerBenefits	0.26[c]	0.10[c]
	(3.83)	(3.37)
$\mu_{t;j}$	0.42[c]	0.16[c]
	(3.34)	(2.92)
Model statistics		
R^2	0.85	0.56
(Adj.^{2})	(0.84)	(0.55)
F value	93.90[c]	49.52[c]

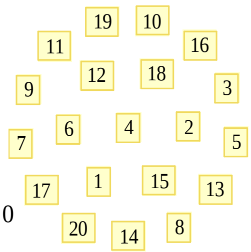
The numbers in parentheses are *t* values.

[a] $p < 0.05$. [b`] $p < 0.01$. [c] $p < 0.001$

FIGURE 5

Knowledge Percolation and Structures of Network Effects

A Actors in Isolation



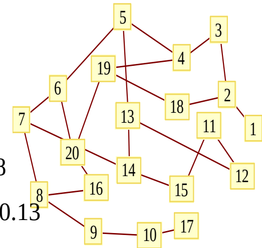
Graph distance

g(1,2)=0, g(1,3)= 0

Coefficient (cluster) = 0

Aver. path length = ∞

B Actors in a Group



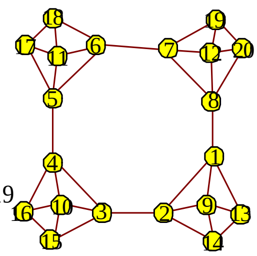
Graph distance

g (1,3)=2, g (12,17)=8

Coefficient (cluster)=0.13

Aver. path length=1.53

C Actors in Segregated Clusters



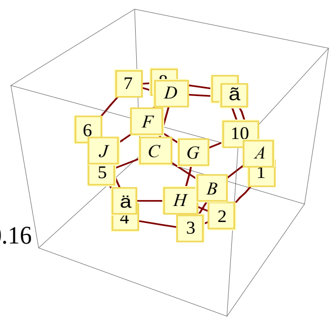
Graph distance

g(1,2)=1,g(1,4)=3

Coefficient (cluster) = 0.19

Ave. path length = 1.80

D Actors in a Relative Dynamic Group



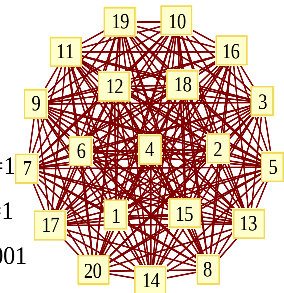
Graph distance

g (1,3)=1, g (1,4) = 1

Coefficient (cluster) = 0.16

Ave. path length = 0.71

E Actors in Greater Density & Dynamics



Graph distance

g (1,10) =1; g (2,10)=1

Coefficient (cluster)=1

Ave. path length =0.001

The analysis used randomised graph data and set equally 20 vertices for all of the graphs, where graph distance is a connection (e.g., v_1, v_3). If connection exists between two vertices (individuals), then they are to be adjacent. The estimations are mainly based on Barabasi and Albert's (2002) statistical measures, and the average path length is given as, $L_G = 1/n_i(n_i - 1)\sum_{i,j} d(v_i, v_j)$, and the clustering coefficient for undirected graphs is,

$C_i = 2|\{e_{jk}\}|/k_i(k_i - 1): v_j, v_k \in N_i, e_{jk} \in E.$

FIGURE 6

Probabilistic Knowledge Creation Organisation: Effective Information (Knowledge) Generated by Entering a Particular (Network) System State