Dynamic Evolution of Airline Industry – A Social Network Analysis of Airline Entry into Multipartner alliances (MPA), Evolution of MPA and Airline Industry Network Structure

Ritu Raj Kaur Virk

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Signed by the final examining committee

______________________________________ Chair
Dr. Saif Ullah

____
Examiner Dr. Rahul Ravi

____
Examiner Dr. Michael Carney

______________________________________ Supervisor
Dr. Kai Lamertz

Approved by

____
Chair of Department or Graduate Program Director

____
Dean of Faculty

____

Date

____

Abstract

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Ritu Raj Kaur Virk

Alliances in the airline industry have existed a long time, but it is only in the 1990s that airlines have entered into partnerships that are broader in scope in the sense that they involve more than two member airlines. These so-called "Multipartner Alliances (MPA)" are the topic of inquiry in this thesis, which aims to better understand the process of airline entry into MPAs, the development of MPA alliance network structure, and the evolution of the entire airline industry network from 1994 to 2007. Accordingly, the thesis undertakes analysis at three levels. At the firm level, I test how involvement in the industry alliance network structure predicts an airline's entry as a formal member in an MPA. The results indicate that prior direct, indirect ties and position of non-member airline play a crucial role in their MPA entry in the subsequent year. The findings also suggest that beyond exerting individual effects, the independent variables interact and exert a combined effect on the non-member airline MPA entry. At the MPA level of analysis, I explore changes in the structure of alliances that link the members of a given MPA. The results show that over time, on average, MPAs have become substantially larger in size, and their network structures have become less dense and more centralized. Finally, I explore the evolution of small world characteristics in the alliance network structure of the airline industry as a whole. The results of this macro-level analysis suggest that as MPAs have grown in size and changed their internal structural characteristics over time, the small worldliness of the industry network has declined. Finally, the thesis discusses the implications of entry and exit of airlines in MPA on the MPA and airline network structure and vice versa. The exploratory inter-level network analysis suggests that as airlines enter and exit the MPAs, they seem to modify the structural dimensions of MPA and airline network structure, which in turn, might impact the tie formation process among member and non-member airlines. Together, three levels of analysis, provide a holistic picture of the evolution of network structure of airline industry.

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Little by Little one travels far

- J.R.R. Tolkien

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Introduction

Most strategic alliances today are no longer confined to traditional dyadic alliances. In the last two decades, there has been an augmentation in multi-partner alliances (MPA)[1] (Das & Teng, 2002). They are voluntary associations formed by multiple autonomous firms that come together for the purpose of pursuing joint activities such as R& D, development and joint marketing of products and services (Lavie et al., 2007). They are different from conventional strategic alliances in the sense that they are characterized by formalized alliance processes (Lazzarini, 2007; Gudmundsson & Lechner, 2006). Prior research on strategic alliances is mainly concerned with investigating the effects of alliance formation on various aspects such as alliance performance (Das & Teng, 2003; Doz, 1996; Luo, 1997), the performance of firms entering into the alliances (Uzzi, 1997; Baum & Oliver, 1992). Relatively less importance has been paid towards studying the evolution of strategic alliances, notwithstanding the fact that emergence and evolution of alliances is a dynamic process (Gulati & Gargiulo, 1999). Understanding that alliances are not static but are constantly transformed with the addition of new actors, can have crucial implications (Gulati, 1998). For instance, envisioning the alliance structure beforehand can enable an organization to position itself strategically and be an active path creator rather than being passively path dependent (Gulati, 1998). Assessing the alliance outcomes without actually understanding the dynamics of how the alliance network evolved in the first place renders such an evaluation incomplete (Ahuja et al., 2012). While some scholars have undertaken the study of the evolution of alliances, they have done so primarily at the dyadic level. (Gulati, 1998; Powell et al., 2005; Provan et al., 2007). Extending our understanding beyond dyadic relationships is imperative as it is the whole alliance network that often guides the behavior of individual firms (Gulati et al., 2012). Investigation at network level has numerous implication both for individual actors and the whole industry. The evolution of interorganizational networks might provide a direction for the individual actors, as how the network could be best structured to fulfill individual actors interest (Provan et al., 2007). Gulati et al. (2012) also state that investigation of both micro-level - actor's network, and macro aspects – whole-network, are equally important to draw meaningful conclusions regarding the network dynamics. They base their aforementioned

[1] For the ease henceforth, Multipartner Alliances are referred as MPA in the subsequent sections of the thesis

proposition on the argument that the foundation of macro-level structure is created by the individual ties between the organizations and on the other hand, macro-level properties of network guide the behavior of individual actors.

There is a shortage of studies exploring MPAs (Lazzarini, 2008). More specifically, the alliance processes associated with MPA growth and evolution are understudied (Gudmundsson & Lechner, 2006). Prior research has focussed on investigating the competitive dynamics (Gomes-Casseres, 1994), cooperative strategies (Zheg & Chen, 2003) and member benefits with respect to MPA (Lavie et al., 2007). A modest amount of research on MPA has also focused on investigating the factors which might lead initial bilateral ties among airlines to culminate eventually into formalized MPAs (Lazzarini, 2008). However, this line of research stops short at investigating merely the formation of MPAs. What happens to the MPAs after their formation – how do they evolve over time in terms of their structure and accepting new members? How does the actor level relationships impact the network structure of MPA overtime? How does the change at actor level as well at the MPA level affect the whole-network structure of the airline industry? What impact does the whole-network structure, in turn, has on relationships that exist between individual actors? Such questions remain unexplored.

In the light of existing gaps in the alliance literature, I intend to study the evolution of a network of individual airlines, multipartner alliances, and the whole passenger airline industry, over a period of 19 years. The airline industry is a prototype of such a phenomena, where at present three large MPAs, Star Alliance (28 members), Oneworld (19 members), SkyTeam (13 members) account for more than 77% of the world Airline Capacity (Wang, 2014). Moreover, besides MPAs there exist non-member airlines which share bilateral ties to numerous MPA airline members (Lazzarini, 2007). Studying both the evolution of formal MPA as well bilateral ties of non-member airlines with the MPA members would provide a complete picture of the evolutionary dynamics of airline alliances.

In studying the evolution of airline MPAs, I adopt the embeddedness perspective which advocates that organization's behavior and decisions are impacted by the web of relationships they are involved in (Gulati, 1995; Uzzi, 1997). Explicitly, an organization's direct and indirect relationships with its partners, its position in the alliance network and the properties of entire industry network structure influence its reputation, status and behavior as well as the opportunities it has regarding access to resources and fine grain information. (Gulati, 1995, Uzzi, 1997; Dacin et al., 1999; Podolny, 1993). I use this logic to run –

- Actor-Level Analysis to undercover the process of airline entry into the airline MPA
- Meso-level Analysis to map the structural changes of MPA and the airline industry network structure
- Whole-network Analysis to examine whether airline industry exhibits a peculiar pattern

Although the intent of the research is primarily exploratory, I do undertake the predictive analysis at actor-level. I investigate how embeddedness of individual airlines in the airline industry network relates to their entry into an MPA. On the exploration side, I account for the MPA development regarding the entry of non-member airlines and the evolution of MPA and airline industry network structure from 1994 to 2007.

Theory

Multipartner Alliances Evolution

MPAs are "alliances formed by multiple autonomous firms which collaborate among themselves and compete against other groups of firms for both clients and members" (Lazzarini, 2008, p. 20). Their increasing presence can be ascertained by the mere fact that out of a database of 1570 alliances collected by Dyer and Singh (1998), one-third were multipartner alliances (Das & Teng, 2002). Despite their increasing popularity, management scholars have underexplored them (Lazzarini, 2008). In general, alliance literature in the past have explored various dimensions such as alliance performance (Das & Teng, 2003; Doz, 1996; Luo, 1997), performance of firms entering into the alliances (Uzzi, 1997; Baum & Oliver, 1992) and alliance formation (Gulati, 1995; Gulati & Gagiulo, 1999). As far as the evolution of these alliances is concerned, there has been little work done in this direction (Gulati & Gargiulo, 1999).

In general, the majority of research has considered the phenomena of alliance evolution as determined by exogenous factors (Gulati & Gargiulo, 1999). Scholars probing into the causes of alliance formation have majorly considered organizational resource based factors (Peffer & Salzanik, 1973), isomorphism, legitimacy or improving strategic position (Gulati, 1995) as the leading causes. Likewise, the knowledge-based view contends that firms ally with each other to learn and innovate (Powell et al., 1996 ; Kogut and Zander, 1992) Although, this "exogenous " approach is apt in determining why firms would ally with each other, it falls short of suggesting whom should firms partner with (Gulati & Gargiulo, 1999; Gulati, 1995). The interdependence approach of tie formation is indecisive in informing firms about the new opportunities that might arise regarding alliance formation as well as the behavior of potential partners which might be essential for alliance formation (Gulati, 1995; Gulati & Gargiulo, 1999; Gulati et al., 2012). Strategic alliances are a voluntary form of organization, which do not possess the advantage of hierarchal rules and regulations and hence are prone to vulnerabilities (Gualti, 2007). Researchers have well documented the fact that firms in alliances are prone to various vulnerabilities like free-riding, spillovers, cheating, and distortion of information (Gulati, 1995). These vulnerabilities result from the fact that firms have imperfect information about their potential partners regarding their resources, needs, objectives and capabilities (Baum et al., 2004). Das and Teng (2001) define these vulnerabilities as “relational risk” which firms should overcome before entering into alliances. Thus, for the purpose of forging new relationships, how do firms learn about the behavior, capabilities and needs of their potential partners and overcome above mentioned potential risks? Researchers have advanced Granovettor (1985) embeddedness logic in answering the above question (Gulati, 1995; Gulati & Gargiulo, 1999; Uzzi, 1997).

In his classical paper, Granovettor (1985) gives a detailed account of how economic activity is embedded in a network of social relationships which has an impact on actions that actors pursue and he terms this phenomenon as “embeddedness”. He claims that “behavior and institution to be analyzed are so constrained by ongoing social relations that to construe them as independent is a grievous misunderstanding” (Granovettor, 1985, p. 482). Thus, by understanding the phenomenon of how firms get embedded in the network of relationships, forming a particular structure over a period, which in turn affects firm’s behavior, could provide us some insights with regards to the above mentioned concerns. Organizations, in order to mitigate the hazards associated with alliances and to reduce information costs regarding their potential partners create stable relationships and over a period of time these relationships culminate into an embedded network which serves as a repository of information concerning the capabilities and reputation of potential partners (Gulati, 1995; Gulati, 1998; Gualti & Gargiulo, 1999; Uzzi, 1997). I use this logic of embeddedness to investigate the process of airline entry into the MPA

Research Setting – MPA in the Airline Industry

Since the deregulation of U.S. airlines and privatization of airlines in Europe and East Asia (Lazzarrini, 2007), collaboration among airlines have occurred on a scope broader than ever before (Evans, 2001). Within five years (1994-1999), the number of non-equity airline alliances was more than double - 222 in 1994 to 460 in 1999 (Evans, 2001). Although bilateral ties have existed in the airline industry since long, it is in the 1990s that broader alliances consisting of more than two airlines came into existence (Lazzarrini, 2007). These ties are formally known as multipartner alliances. The first multipartner alliance was formed between Delta, Singapore and Swiss Airways in the 1990s (Vaara et al., 2004). As of today, there are three truly global multi partner alliances – Oneworld, SkyTeam and Star Alliance (Hanlon, 2007, p. 303). Among these three, Star Alliance is the largest in terms of passengers carried and destinations served (Fan et al., 2001). They are a group of airlines that come together and perform activities such as codesharing, joint marketing such as frequent flier programs, provide joint access to airport facilities controlled by individual members (Lazzarrini, 2007). They are also referred as the explicit *airline constellations,* and the agreements between them are multilateral in nature in the sense that they apply to more than two members (Lazzarrini, 2007). Moving beyond multilateral agreements in the airline industry, there exist bilateral ties between members of explicit airline constellation and non- members[2]. For instance, in 2000, various non - member carriers such as British Midland Airways, Emirates, Malaysian Airlines, South African Airways and Virgin Atlantic had bilateral ties to various members of Star Alliance (Lazzarini, 2007). These bilateral ties are also known as implicit grouping (Lazzarini, 2007). Previous research has explored how the interaction between these implicit grouping lead to the formation of formalized MPA (Lazzarini, 2008). The existence of explicit constellation and implicit bilateral ties of non-members to members of MPAs creates multiple forms of linkages within the airline industry and to only consider explicit alliances while disregarding the implicit bilateral relations would provide us an incomplete picture of the network structure of entire airline industry (Lazzarini, 2007). Thus, my research takes into consideration both the formal MPAs as well as the bilateral

[2] Non-member airlines are those airlines that are not formally part of any MPA within the airline industry (Lazzarini, 2007). In the current study, henceforth, the airlines that are part of any MPA are referred as member airlines and the airlines which are not part of any alliance are referred as non-member airline.

ties that non-member airlines share with member airlines in studying the evolution of MPA and the airline industry.

As far as research on multipartner alliances in the airline industry is concerned scholars have explored them with respect to

- causes of alliance formation - economies of scale (Bruckner, 2001), risk sharing, access to assets, global competition, information revolution (Evans, 2001)
- airline performance - effect on airline's productivity and profitability (Oum et al., 2004), decreased cost and increased passenger traffic (Park & Zhang, 2000).
- competition among various Multipartner Airline Alliances (Lazarinni, 2007)
- the culmination of bilateral ties into multipartner airline alliances (Lazarinni, 2008)

As pointed out earlier, scholars have mainly considered exogenous factors while considering the formation of alliances. Equivalently, research about alliances in the airline industry has followed the above mentioned approach. Scholars have contended that alliances in the airline industry are a response to institutional factors such as restrictive bilateral air service agreement or resource based factors such as cost reduction and global reach (Park & Zhang, 2000). Although these factors justify why airlines should enter into strategic alliances, they do not explain with whom should airlines ally?

The Logic of Embeddedness

A prominent logic behind embeddedness is that a firm's behavior regarding building strategic relationships is affected by a network of social relationship that a firm is embedded in (Gulati, 1995). Prior research has well established that being embedded in such networks have informational and signaling benefits. The network serves both as an information conduit and provides a signal of an actor's status (Podolny, 2001). On informational side, such a network acts as a reservoir of information availability regarding the behavior and capabilities of potential partners thus minimizing risks and uncertainties associated with future relationships (Gualti & Gargiulo, 1999; Uzzi, 1997). The signaling effect of a network provides cues to other network members as well as any actor within the industry regarding a focal actor, based on who are it's current affiliations (Podolny, 2001). Prior research showcase that most firms are part of various networks such as board interlocks, trade association or research consortiums and often getting embedded into such kind of network influences firm's decision regarding identifying potential partners by providing members with timely informational as well signaling resources. (Gulati & Gargiulo, 1999; Podolny, 2001). The embeddedness logic enables us to understand the network dynamics regarding how a given network undergoes structural changes over a period (Halinen & Tornroos, 1998). At individual actor level, the direct, current and past relationship that an actor is embedded in, known as relational embeddedness, provides a source of information regarding the future ties and, consequently, the formation of new ties leads to the development and changes in the firm's network (Gulati, 1995; Gulati & Gargiulo, 1999). Moving beyond an actor's direct ties, firms are also embedded in a web of indirect relationships which impacts their decision making regarding future partnerships (Gulati, 1995; Gulati & Gargiulo, 1999). In such a process, technically known as structural embeddedness, firms obtain information regarding future partner's behavior and reputation through their common partners. Again, the formation of new ties is impacted by structural embeddedness which in turn also affects the network structure in which the firm is embedded in. Finally, due to the formation of direct ties and indirect ties, individual firms come to occupy a particular position in the network. The position that a firm gets embedded in over a period, in turn also influences firm's ability to access information regarding future partners, as well as, also impacts the status and visibility of the focal firm among other firms as a potential partner (Gualti & Gargiulo,1999). Thus as stated above a network works as an information reservoir as well as a signaling mechanism regarding the status of an actor. This notion is best explained by referring to networks as 'pipes and prisms' (Podolny, 2001). As pipes, networks facilitate the network communication and as prisms, they reflect its member's status (Podolny, 2001). When drawing a parallel between network as pipes and prisms and various level of embeddedness, it can be inferred that relational embeddedness would serve as pipes through which network members get acquainted with each other first-hand due to their previous direct relationships. Structural embeddedness would reflect network as being both, a pipe through which information about a potential partner flows through a common partner towards focal actor and, a prism signaling the potential partner's reputation. Positional embeddedness would be a prism which mirrors a member's status by way of reflecting its affiliations with other actors in the network.

In the context of airlines, relational embeddedness would comprise of direct dyadic alliances between member and non-member airlines (Figure 1), whereas structural embeddedness would comprise of all indirect relationships among member and non-member airlines (Figure 2). In the case of positional embeddedness, uncovering how central an airline is in the network would be worthwhile (Figure 4). Although direct and indirect ties, as well as the position the firm occupies in the network , all embed firms in a given network, the mechanism through which they impact the evolution of ties among actors are somewhat distinct. Sharing direct ties provides the opportunity for actors to get acquainted with each other's behavior which reduces uncertainty (Gulati, 1998) and as a result, greater trust and cooperation develops between actors, which eventually fosters ties in the future (Gulati, 1995; Gulati & Gargiulo, 1999). On the other hand, sharing common partners in past and present impacts the development of future ties via reputational lock-ins and signaling effects (Gulati & Gargiulo, 1999). Sharing a common partner could indicate that potential partner is capable of cooperating in a similar manner as it cooperates with the common partner. (Gulati & Gargiulo, 1999). Thirdly, positional embeddedness, which measures how central a firm is in the network has been equated with the status of the firm (Podolny, 1994, 2001). A particular status signals a specific behavior, such that, members of a specific status behave in certain ways towards their partners (Gulati, 1998). Moreover, an actors status is impacted by who they associates with (Podolny, 1994; Gulati & Gargiulo, 1999). Being associated with firms that have a high status or members that are more central in the network tends to enhance an actor's status. Thus, positional embeddedness dictates that actors that have a high status or are more central in the network are more desirable as potential partner by the firms.

To summarize, the previous and current direct and indirect relationships as well as the position of the firm in the entire network in which it is embedded creates a relational architecture of new relationships, which, subsequently cause changes in the network structure in which the firm is embedded. Thus, I aim to investigate how direct and indirect embedded ties of airlines and the position of airline in the airline industry triggered the formation of new ties among non- member and member airlines and facilitated the entry of non-member airlines in the MPA. Also, I intend to map the structural changes in the MPA and airline industry network structure over a time period of 13 years from 1994 to 2007. In studying how embeddedness fosters new ties I use social network analysis, a technique widely used to study strategic alliances.

Social Network Analysis

Researchers have used various techniques to study strategic alliances. Presently social network analysis (SNA) is one of the pervasive tools to study alliances such that research papers on networks are growing at an exponential rate (Borgatti et al., 2014). SNA has been used by the scholars to study networks in a wide array of industries such as biotechnology (Powell et al., 1996), apparel (Uzzi, 1997), airlines (Lazzarini, 2007), investment (Baum et al., 2004), health care (Provan et al., 2003) and film industry (Baker & Faulkner, 1991).

Defining Networks - In the most basic terms a network consists of a set of actors (nodes) binded by a series of ties (relationships) (Borgatti & Halgin, 2011). Scholars have defined them as “a set of nodes and a set of ties representing some relationship, or lack of relationship, between the nodes” (Brass et al., 2004). Stated more formally, actors are also referred to as ego, and, “alters” are actor’s to which ego is connected in a network. (Zaheer et al., 2010) The ties between actors could be interpersonal (such as friendship), inter-unit ties (where organizational units are nodes having formal and informal ties within an organization), interoganzational (where organizations are nodes interacting with other organizations) (Brass et al., 2004). At interorganizational level, which is the focus of my research, ties could consist of joint ventures, collaborations, strategic alliances, relational contracts and franchising (Podolny & Page, 1998). The relationships between actors yield a particular pattern which is referred as “network structure” (Borgatti & Halgin, 2011). This structure may change or evolve over time. In fact, the interorganizational network structure is not static but dynamic in nature (Powell et al., 2005, Gulati, 1995). It is this characteristic that I aim to investigate over a period. As aforementioned, understanding the evolution of ties can have implications, both, for alliances regarding performance and individual members regarding comprehending how they could effectively manage their relationships.

In the following section I use social network analysis as a tool to study how non-member airline embeddedness in terms of their previous direct or indirect ties with member airline as well as their position in the airline industry impacts their entry into the MPA.

Actor level analysis Entry of Non-member Airlines into MPA

Social Network Analysis at the actor level investigates the ego's networks, its connection to the alters as well the links among its alters (Zaheer et al., 2010). The focus of the analysis here is on the structural properties of the network that the actor is embedded in (Zaheer et al., 2010). Research in the area is concentrated on investigating aspects such as, at what level is an actor involved in the network, does it maintains multiple ties vs. single ties with its alters, does an organization serves as an intermediary linking several other actors which wouldn't be connected otherwise, how has the position of an actor changed in the network over a period (Provan et al., 2007). As far as interorganizational networks are concerned, most of the research at actor level has concerned itself with testing the impact of actor's network membership on various organizational outcomes. One of the manifestation of the above assertion lies in the fact that, centrality, the most commonly researched construct at actor level which concerns itself with identifying members who are prominent in the network due to their ties to other members (Hawe et al., 2004; Zaheer et al., 2010) has been continuously used to test various organizational outcomes such as (but not limited to), firm's growth (Powell et al., 1996), innovation (Powell & Smith, 2004; Ahuja, 2000), competitive vs. cooperative dynamics among firms in a network (Gynawali & Madhavan, 2001). Thus, social network research at actor level has been limited to a great extent to investigate outcomes of network variables. Relatively, less attention has been paid towards examining its evolutionary characteristics. A handful of researchers have used actor level network concepts towards explaining the process of alliance formation over a period. The studies investigating the evolutionary characteristics of actor's networks have mainly utilized the sociological concept of embeddedness (Gulati, 1995; Gulati & Gargiulo, 1999). As stated in the previous sections, it is a phenomenon through which the decision making behaviour of an actor regarding future ties is influenced through its previous and current ties (Gulati, 1995). To repeat, embeddedness is operationalized into different categories such as relational – actors direct ties, structural – actors indirect ties and positional – actors position in the network (Gulati, 1995; Gulati & Gargiulo, 1999). I use these demarcations as the main analytical framework at actor-level for explaining the process of non- member of airline into the MPA

Actor's Relational Embeddedness and Entry of non-member airlines in the MPA

A prominent study encapsulating evolution of alliances was undertaken by Gulati (1995). The article explores the impact of prior direct ties and uses *relational embeddedness* as a tool to explain the process of alliance formation among two given firms in a network. Relational embeddedness aspect comprises of all the previous direct relationships of a firm through which it can obtain firsthand knowledge regarding its partners (Gulati, 1995; Gulati, 1998). Not only firms gain information regarding partner's capabilities but having prior ties also diminishes any uncertainties regarding future partner's opportunistic behavior and fosters greater trust (Gulati & Gargiulo, 1999). Another major reason for two firms who have repeatedly collaborated in the past to ally in future is the development of routines (Gulati, 1995). It is not uncommon for two firms who continuously partner together to come up with common procedures of managing various projects, which in turn could propel them to ally in future as well. (Gulati, 1995).

One could also extrapolate the logic of relational embeddedness onto the airline industry. Many of the member airlines initially shared informal relationships with individual members of the MPAs. Before actually forming a formal alliance most of the members of Star Alliance had implicit ties with most of the other members (Figure 5). Additionally, before becoming a part of multiparner alliance in 1996 Lufthansa had ties with United, SAS, Air Canada and Varig and same goes for other members. Similarly, as shown by Figure 6, before Northwestern airline became a part of SkyTeam in 2005, it had bilateral dyadic ties with two most prominent alliance members – Delta and KLM in 2003.

The pattern of airlines implicitly sharing ties with MPA members before becoming a formal MPA member is still prevalent. EVA , member of Star Alliance since 2013 initially shared implicit ties with many of its members (Airline Business, 2013). It had codesharing agreements with Air Canada since 2000 (one of the founding members of Star Alliance) and with ANA since 2006. Another illustration of such a pattern would entail the admission of China Eastern Airlines into SkyTeam alliance in 2011 (Airline Business, 2013). Thus, drawing from the previous literature as well as observing the pattern of relationships that exists in airline industry, it could be conjectured that prior relationships of non-member airline with member airline are crucial in shaping the current and future relationships and in serving as a channel for the entry of non-member airlines in the MPA.

Hypothesis 1 *–The greater the number of direct ties a non-member airline shares with members of a formal MPA at time T1, the greater the probability of the non-member airline to enter into that MPA at time T2*

Actor's Structural Embeddedness and Entry of non-member airlines in the MPA

In the second component, structural embeddedness, the focus shifts from a direct relationship to indirect ties which comprises of partner's partners (Gualti, 1995; Gulati, 1999). It implies that beyond firm's direct ties, the structure in which the firm is embedded also impacts its future relationships. Common partners influence firm's decisions with regards to the choice of partners for several reasons. Primarily, firms sharing common partners can extract reliable information concerning each other (Gulati, 1995; Gulati & Gargiulo, 1999). Through common ties firms can ensure the required behavior on the part of each other as common links create reputation lock-ins whereby any information regarding the opportunistic behavior on the part of either firm can disseminate quickly in the network (Gulati & Gargiulo; 1999). Thus to reiterate, structural embeddedness incorporates the impact of the structure of common ties on firm's choices and behavior. It provides a source of indirect information regarding a potential partner's behavior, reputation, and capabilities. Previously, researchers have used structural embeddedness concept to explain the phenomena of alliance formation among dyads (Gulati, 1995; Gulati & Gargiulo, 1999).

More specifically, the potential tie formation process among network members through structural embeddedness could also be well explained by the bridging function of the common partner (Granovettor, 1973; Kildulf & Tsai, 2003, p. 54). Consider figure 2, the triadic arrangement consists of a tie between X and Y, Y and Z and a lack of tie between X and Y. X is the common partner between Y and Z or in other words X is the bridge between Y and Z through which information exchange takes place. The information exchanged could be regarding each other's organization capabilities or reputation as potential partners. Thus a network becomes both a pipe through which information flow takes place and as well as a prism to some extent, as it reflects on common partner's reputation (Podolny, 2001).

In the current context, the choices of an MPA regarding admission of a non-member airline may be guided by the fact that that non-members airline shares ties with another non-members who in turn have significant ties with the member airlines of MPA. Referring to Figure 2, non-member airline X serves as bridge between non-member airline Y and MPA member Z, through which reliable information regarding non-member airline Y flows towards the MPA which might influence Y's entry in MPA in subsequent years. Furthermore, in a large network, it might be rare to observe that there is a single path [3] connecting any two given actors in the network (Granovettor, 1973). However, not all paths connecting any two given actors in a large network might be feasible (e.g., some of the paths might be too long). In other words, the number of actors lying on particular paths which connect two given actors might be too many, thus making that path unecnomical (Granovettor, 1973). In this case, the shortest indirect path between any two actors might serve as a bridge locally (Granovettor, 1973). Applying this logic in the context of airline network structure (Figure 3), there are three paths connecting non-member airline 1 with member airline 5, however not all of them serve the purpose of a local bridge. Among the two paths connecting non-member airline 1 and member airline 5, 1-2-5 is the most efficient path considered to the second one (1-4-3-2-5) and apt to be regarded as a local bridge as it is the shortest indirect path, containing only one non-member airline in between.

Hypothesis 2*- The greater the number of indirect ties of path length 2, a non-member airline shares with the alliance members at time T1, the greater the probability of the non-member airline to enter into an MPA at time T2*

Positional Embeddedness and Entry of Non-Member airline in the MPA

The position organizations occupy in a network can influence their ability to have accurate information regarding the potential members, enhance their visibility among other organizations

[3] Path – A path is a sequence of link between any two actors in a given network such that each actor lying on the path is distinct (Jackson, 2008, p. 23).

irrespective of their ties to those organizations, reflect their status, and impact their behavior regarding the formation of future ties. (Gulati & Gargiulo, 1999; Dacin et al., 1999). The concept of positional embeddedness has been used in the past by researchers to discern the process of alliance formation among dyads (Gulati & Gargiulo, 1999). Others have investigated its impact on various outcomes such as performance (Shiplov, 2005) innovation (Hsueh et al., 2010), tie stability (Polidoro Jr. et al., 2011). The most relevant study in the context of my research was carried out by Gulati & Gargiulo (1999), where they study the probability of alliance formation among dyads by analyzing the positional embeddedness (combined alliance network centrality) of both the firms. They conclude that the impact of positional embeddedness increases with time, as and when the entire network evolves (Gulati & Gargiulo, 1999)

Positional embeddedness encapsulates the impact of the position occupied by the firm in the entire network on its decision regarding the choice of new partners. It goes beyond direct and indirect ties and represents the informational benefits that accrue to firm as a result of certain position it occupies in the network (Gualti & Gargiulo, 1999). For instance, organizations that come to occupy the central position, due to their connections to numerous actors, have greater access to fine-grained information as well as have higher visibility as compared to the peripheral members (Zaheer et al., 2010). Thus, central members can readily search for potential partners as well as be more noticeable as future partners as compared to the peripheral members.

Besides the visibility advantages of being positionally embedded in a network, position also bears implications on the status of an actor. Actors comes to occupy a position in the network due to the virtue of their connections and these connections also have an impact on actors status (Gulati & Gargiulo, 1999; Podlony, 1994) Usually ties to high status actors increase the perceived quality of the focal actor whereas ties to low status actor impact focal actor’s status negatively (Podlony, 2001). Thus, the status of an actor becomes a function of who are its partners. The status attained by an actor in a network is vital to its future relationship as in the face of uncertainty regarding the behavior and capabilities of an actor; the status acts as a symbol of certain quality on which other actors in the network base their decisions (Podlony, 1993). Unlike, in case of relational and structural embeddedness where actors have direct or immediate indirect contact (especially in case of single common partner), under positional embeddedness the organizations lack the ways of ascertaining the quality of a particular actor as a potential partner that are not in their immediate network of relationships and thus might tend to use status as a way of determining the actor's potential as a future ally (Podlony, 2001).

As aforementioned, usually high status actors wish to formulate ties with other high status partners as they signal greater quality in term of relationships vs. a low status partner. A prominent measure depicting the status and position of an actor in the network is centrality. Usually, being more central is equated with having more visibility, prestige and higher status (Borgatti et al., 2013). In the present context, the current position of a non- member airline occupies in the entire network in the past might have an impact on it's MPA entry. To elaborate, analysis of positional embeddedness of non- member airline would warrant considering whether the non-member is central or not, which are the other non-member and member airline it is connected to, are these non-members and members themselves central or peripheral? The above mentioned reservations might impact non-member visibility and status as a promising partner and eventually impact its entry in the MPA. To illustrate, consider figure 4. Hypothetically, in an airline network, the bigger circle depicts an MPA, and all the members within the circle are member airlines and those falling outside the boundary are non-member airlines. Actor 11 is a member airline directly connected to non-member airline 3 and 10 as well as indirectly connected to various non-member airlines. Beyond the direct and indirect ties, non-member airline 6 could be considered to be the most central member of the network, as not only it is connected to many other airlines, it is connected to various airlines's that are themselves central in the network. For instance, non-member airline 6 is directly connected to actor 10 which is in turn is connected to various non-member airlines as well as shares a direct tie to the MPA network. Thus, being connected to members that are themselves central in the network, the visibility as well as the status of non-member airline 6 is highlighted and could positively impact its entry in the MPA in the subsequent year.

Hypothesis 3: The greater the centrality of a non-member airline in the entire network at time T1, the higher the probability of the non-member airline to enter into an MPA at time T2

Meso-level Analysis – MPA Structure

As enumerated in the prior sections researchers in past have mainly explored the evolution of strategic alliances in a dyadic context (Provan et al., 2007; Powell et al., 2005). Taking into consideration the potential research directions by prior scholars, my intention here is to explore how MPA network comprising of numerous actors (airlines) has changed regarding its structure over a period. Social network scholars claim that as organizations become a part of the network, it triggers certain structural changes which impact the topology of the entire network. (Powell et al., 2005). Applying the assertion in the context of my research, it interests me to explore how the entry and exit of non-member airlines in the MPA network structure causes changes in the structural pattern of MPA network. More specifically, I aim to explore the evolution of the structure of multipartner alliances regarding changes in its network density and network centralization structural properties. I consider these two specific structural properties as they are highly relevant to the current research context. For instance, airline network has been shown to exhibit hub and spoke network where the network is organized around a lead airline (Lazzarini, 2008). Such a network is analogous to a highly central network (Provan et al., 2007).

Evolution of Network Structure of MPA – Network structure continually evolves as and when the ties are created or dissolved between the nodes (Ahuja et al., 2014). Due to some basic network fundamentals reffered as “micro foundations” such as actor’s motivation to form a beneficial tie and dissolve an unprofitable one , the set of opportunities available to the actors, there is a perpetual formation and dissolution of ties which in turn also modifies the network configuration (Ahuja et al., 2014). It is imperative to analyze and study such structural changes as network provides immense informational (Gulati, 1995), social (Coleman, 1988) and exploitation (Burt, 2000) benefits and such benefits are contingent upon the structure of the network (Ahuja et al., 2012). The value of these benefits also changes as and when the network evolves over time. For example in a network where density is of crucial importance, the density dimension might evolve over a period depending upon how many new actors are admitted in the network, thus, ultimately impacting the density benefits accruing to the network members (Ahuja et al., 2012). Social network scholars have applied various structural variables to study the topology of networks.

Network variables such as density and centralization the have been used to track the changes that network structure undergo over a period (Provan et al., 2007).

Within airline industry itself, scholars have used various social networks measures to study alliance formation. Lazzarini (2008) uses MPA network density and network centralization to explain the process of MPA formation and empirically proves that informal airline alliances which have a network structure that exhibits high network centralization and moderate density are more likely to be formalized into formal Multipartner alliances. However, the above stated study stops short merely at the formation of airline MPA. What happens to the structure of the MPAs over time regarding their evolution is a question yet to be explored. A slightly related study attempting to investigate the evolution of airline MPA network is undertaken by Reggiani et al. (2010). They study Star Alliance and Lufthansa's network and carry out social network analysis to understand how the network has evolved regarding networks degree of concentration and connectivity over a period (for a detailed review, please see Reggiani et al. 2010). However, their study focuses on the flight pattern among various airlines. Also, in a database collected by Saglietto (2009) from 1995 to 2005, there were 829 cooperation agreements which took place within different Airline MPAs. It then becomes pertinent to study the evolution of the network structure of each MPA over an extended period, as the addition of all these new ties and dissolution of the existing one would modify the very structure of MPA which in turn would also alter the benefits accruing to the MPA and the member airlines.

As emphasized above, I aim to map the changes in the network structure of MPAs by exploring how it has evolved regarding its density and centralization. I consider these two specific network variables for the following reasons. Primarily, there are several benefits associated with network density and network centralization , especially in airline context, that accrue to network members as well as the alliance itself which make these network level construct worth mapping over a period. For example, network density could be crucial for connectivity among airlines as in a dense network the time to reach nodes is less as compared to the sparse network. Moreover, when the number of members in an organization range from moderate to high it is preferable for the purpose of network efficiencies that network is highly centralized among one (lead organization) or few network members (network administration organization) (Provan & Kenis, 2008). Secondly, most of the studies in social networks exploring the dimensions of the whole structure have considered them to be central properties of a whole network (Provan et al., 2007). Thirdly, the research focused on the studying the business relationships among airlines has also investigated these two properties while analyzing the formation of multipartner airline alliances (Lazzarini, 2008). More specifically, his research posited that highly central and moderately dense network have a higher probability of being formalized in the subsequent year and found support for his hypothesis. My study could be seen as an extension to Lazzarini (2008) as it explores the changes the MPA network structure has undergone over time since its formalization.

Network Density

It is defined as the degree of connectedness that exists among the network members (Coleman, 1988). It is the ratio of how many connections there actually exist between network members vs. how many connections could probably exist. Sociologists such as Granovetter (1985) and Coleman (1988) argue that dense networks promote trust, as, in dense networks "everyone one knows everyone" (Burt, 2000, p. 351). They facilitate the creation of common norms and sanctions, and, information about opportunistic behavior on the part of any actor would spread quickly as the network is densely connected (Granovettor, 1985). Besides, greater network density promotes greater coordination and facilitates communication among network members (Lazzarini, 2008). These characteristics eventually promote increased cooperation among network members. It could be inferred that network density is an important dimension that has crucial implications both for members as well the network itself. Network density in case of airlines is an important network variable to explore as airlines form alliances with the aim to seek cooperation on "scheduling (convenience), connectivity (joining carriers over nodes) and flow improvement (reducing total travel time between any two nodes in the network)" (Gudmundsson and Lechner, 2006). Hence, a high degree of connectedness in the case of airlines alliances would ensure better connectivity, as well as the total time to reach nodes, would be drastically attenuated. Furthermore, there would be a greater willingness on the part of airlines to co-specialize if they know that most of the actors are connected to each other (Lazzarini, 2008). Alternatively, in sparse networks firms may not comprehend the benefits of collaboration and might be more focussed on cultivating bilateral agreements (Lazzarini, 2008).

However, as aforementioned, the network structure is dynamic and undergoes constant change as and when new actors keep entering and existing members keep exiting the network. This in turn also modifies the benefits and opportunities that accrue to the network members, as these benefits depend on the network structure. It then becomes pertinent to map the structural changes over time that the network goes through. Applying this assertion in the current research context, it could be postulated that the entry and exit of non-member airline within the MPA might trigger changes in network density of MPA network structure. Prior research claims that on an average network density decreases with increase in network size. As network density is the ratio between actual ties that exist in the network and all the potential ties that could exist in the network, with increase in the network size, it becomes difficult for network members to maintain all the possible ties which result in lower network density (Prell, 2012, p. 170). This implies that with the entry of non-member airlines in the MPA, the MPA network size would increase, thus reducing MPA network density and vice versa. Thus, given the significance of network density on alliance member's cooperation, trust and coordination, and the constant changes occurring at actor level regarding entry and exit of non-member and member airlines respectively, I aim to underline changes in network density of the airline MPA's from 1994 to 2007.

Network Centralization

It is the extent to which network is centralized around few actors (Kilduff & Tsai, 2003). In a highly centralized network, a single firm is tied to many others whereas other firms have few connections to each other (Lazzarini, 2007). On the other hand, in a decentralized network ties are more evenly spread among members (Provan et al., 2007). For example, a highly centralized network would be a "star" network, where all the network members are connected to one central organization and no other link exist between non-central actors (Kenis & Knoke, 2002). On the other hand, a highly decentralized network would be a "circle", each organization has a maximum of two partners who in turn are also connected to other different members, thus having a direct contact, and no actor is a central actor (Kenis & Knoke, 2002).

Networks that are centralized around few members have various benefits. The existence of centralization in a network enables network efficiency through joint problem solving (Borgatti et al., 2014). Also, it might be the case that central members coordinate the activities of entire network towards the achievement of the common objective (Lazzarini, 2007). In airline context itself, it might be the case that central airline members may develop a set of regulation and then plan the joint routes of other member airlines thus coordinating the activities of the whole alliance (Lazzarini, 2007). Highly centralized networks can exhibit hub and spoke network (Provan et al., 2007) which is highly relevant in the airline context. In the case of Star Alliance, the hub airline carriers were United Airlines and Lufthansa that led the alliance, whereas in the case of Oneworld, American Airlines and British Airways were the leading carriers (Lazzarini, 2007).

Researchers have used the concept of centralization to gauge at various interorganizational settings. Provan & Milward (1995) showcase that highly centralized networks in mental institutes were greatly effective in enhancing client wellbeing as they allowed for greater coordination, integration and monitoring of services offered across the whole system. In airline context itself, Lazzarinni (2007) puts forwards the idea that informal airline networks that are highly centralized would have a greater tendency to get formalized into Multipartner airline alliances and empirically finds support for the same.

Similar to network density, the actor level changes in the terms of entry of non-member airline in MPA, as well as the exit of member airline from MPA, might impact the overall centralization of the MPA network as well as shift the centrality dynamics of individual MPA members. The overall network centralization[4] is the ratio of actual variation of the centrality of actors to maximum centrality variation of actors (Prell 2012, p. 160). Thus, the maximum possible variation (denominator) is the sum of differences between maximum possible numbers of ties each actor can have and its actual ties (Borgtti et al., 2012, p. 160). The maximum possible number of ties would be equal to n-1, where n is equal to a total number of members in the network (Freeman, 1978). From the above explanation, it could be inferred that any changes at the actor level regarding entry and exit of members from the network would have an impact on the maximum possible number of ties each actor can have in the network ultimately impacting

[4] The MPA network centralization is based on degree centralization. I explain it in further details in the methodology section.

the overall network centralization. Hence, I aim to explore to what extent the Multipartner airline alliance networks have become centralized or decentralized over a period and whether they have been centralized around one or few members and then underline the implications this phenomenon might have on the MPA itself.

Macro-Level Analysis – Small-world of Airline Industry

Prior research has explored the architecture of several, real world, large scale networks from world wide web (Barabasi, 2000) to protein interactions, social networks such as scientific collaboration (Newman, 2001), investment banking networks (Baum et al., 2003), musical artists network (Uzzi & Sapiro, 2005). These networks have exhibited certain similar characteristics such as small worldliness as far as their topology is concerned (Baum et al., 2004). The small worldliness can be characterized as a sparse network consisting of clusters, where actors are densely connected such that it is highly likely that actor's links are also connected to each other and on the other hand, the path connecting actors from one cluster to another remains relatively small as compared to random networks (Baum et al., 2003; Uzzi, 2007; Baum et al., 2004; Kogut & Walker, 2001). Observing and understanding the structure of such networks could have implications for the behavior and performance of the network (Baum et al., 2004) as these networks are very efficient for communication and are very resilient to accidental failures and exogenous shocks (Baum et al., 2004; Barabasi, 2009)

Small-world phenomena was initiated from the seminal work of Miligram (1967) – *six degrees of separation* in which he conducted an experiment, which entailed passing letters from one acquaintance to another, from the east coast of the U.S. to the west coast. The study concluded, that it took on an average only six people for the letter to reach its final destination. What Milgram's experiment emphasized was that even in a large network, it is possible to connect most nodes through short paths (Baum et al., 2004). However, it was Watts & Strogatz (1998) who later formalized the structural properties of small world network – overall clustering coefficient and average path length. The clustering coefficient of individual actor measures the extent to which actors partners are also partners with each other (Uzzi & Sapiro, 2005). It is calculated as "the number of actual links connecting all neighbors of the focal actor with one another, divided by the number of all possible ties among those nodes" (Gulati et al., 2012, p. 450). The clustering coefficient for every actor is similar to the local density of the ego's network and the overall clustering coefficient for the whole network is obtained by averaging each actors clustering coefficient or its local density (Uzzi & Sapiro, 2005). The average path length measures how many nodes on an average exist between all pairs of actors (Uzzi & Sapiro, 2005). In other words, it is the average degree of separation between any two given nodes in the network (Watts & Strogattz, 1998). It is calculated as “the lowest existing number of links between any two actors” (Gulati et al., 2012, p. 450). These two measures are then compared to the path length and clustering coefficient of a random network of the same size. For a network to be a small world network, the average path length should be approximately similar to that of random networks. However, the clustering coefficient should be higher than that of the random network (Watts & Strogatz, 1998; Baum et al., 2004). Specifically, the closer the ratio between actual average path length and random average path length to 1 and greater the ratio between actual clustering coefficient to random clustering coefficient than 1, the more the network resembles a small world characteristics (Uzzi & Sapiro, 2005).

Researchers have used small world as a lens to gauge at the network structures of various industries such as investment banking (Baum et al., 2004), computers (Gulati et al. 2012), music industry (Uzzi & Sapiro, 2005), scientific collaborations (Newman, 2001), network of cross-ownership among German Firms (Kogut &Walker, 2001). Investigation of small world network properties indicated peculiar characteristics about the network structure of these industries. In their research of ownership network of German firms, Kogut and Walker (2001) manifest that irrespective of the increasing globalization pressures, German corporate ownership exhibits a small world pattern. They reveal that even after restructuring 192 ownership relationships, the small world properties of German co-ownership network was still intact, displaying a path length of 5 and actual to random path length ratio of 1.18 (lowest among other small world structures such as film actors, power grid networks, etc.). Also, the actual to random clustering ratio was way higher, 118.57 which made the German companies resilient to external shocks to a greater extent. Moreover, Baum et al., (2004) also showcase small world network features of investment banking network in Canada and empirically prove that the network structure is a small world network exhibiting only two degrees of separation between any two banks, making it apt for transfer of information efficiently among its members.

Observing whether a network is a small world in the present context of the research could impart valuable insights regarding the functioning of the airline industry. For instance, finding out what is the average degree of separation between any two airlines would enable us to know exactly how much time on an average it takes for one airline to reach another airline in the entire industry. Knowing this could have a bearing on the connectivity within the airline industry. Moreover, analyzing who are the central players who hold the entire airline industry, we could become aware of the main hubs in the airline industry. Apart from that, if the airline industry depicts a small world network structure then handful of inferences could be drawn regarding the efficiency, communication effectiveness that exist among airlines, since most of airlines have ties with other airlines either by way of being a part of MPAs or through the implicit bilateral ties they have to the MPA members. Also, interpretations could be made regarding the resilience of the industry to the outside shocks and what impact would it have on the connectivity of the airline industry if we remove the identified hubs in the network.

To summarize, the current research aims to achieve two major goals. The first part of the study intends to carry out a predictive analysis of various social network aspects that affect the entry of non-member airlines in the MPA. More specifically, I hypothesize that prior direct and indirect ties of non-member airlines with MPA members and the position occupied by the non-member airlines in the airline network will impact their entry in the MPA in the subsequent year. The second part of the thesis, which is exploratory in nature seeks to underline the various structural changes airline MPAs, as well as the entire airline industry, have undergone over time due to continuous entry and exit of non-member airlines and member airlines. More precisely, at MPA level, I aim to underline the changes in MPA network density and centralization. At Marco-level, I intend to explore whether or not airline industry exhibits a small world network pattern and if so, I further aim to investigate the changes occurring within the small world pattern of airline industry over time. Ultimately, in the discussion section, I seek to carry out a triangulation[5] between the parts of the study to enrich the understanding of the how the various levels of the analysis (individual airlines, MPAs, and the entire airline industry network) impact each other.

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[5] Triangulation involves using more than one methods to study one phenomena (Jick, 1979). One of the basic triangulation assumption is that the shortcomings of one method will be balanced by the other. In the current context, changes in actor level analysis could be used to provide more holistic conclusions regarding the changes occurring at MPA or whole airline industry network level and vice versa.

Methodology

Overview

The following is a longitudinal study that employs social network analysis for studying the archival data on strategic alliances existing in airline industry from 1995-2007. The secondary data was collected from “Airline Business” magazine’s annual airline alliance survey. The data is comprehensive of all the airlines in the airline industry for the given time period, however, the sample, for each year, only contains those airlines which had at least one alliance with another airline for that given year. The sample was reduced to the airlines sharing at least one tie with other airlines because the analysis entailed calculating social network measures such as density, average path length, overall clustering coefficient which are impacted by the presence of isolates[6]. For instance, presence of isolates would drastically reduce the network density as isolates will reduce the ratio of actual to potential number of ties in the network. On the other hands, the direct and indirect ties are not impacted by the presence and removal of isolates. Keeping this into consideration, all the isolates for every year were removed from the sample. Before conducting social network analysis the data was arranged into n by n matrices for each year, where n is the number of airlines.

Once, the social network variables have been computed, I used times series panel design to restructure my data into panel data, where observations about each airline were repeatedly made over a period of 12 years. I regarded each airline as a panel and recorded observation pertaining to the each airline for 12 years. Further, I employ panel data regression to examine the likelihood of a non-member airlines entry in an MPA based on its previous year direct and indirect ties with member airlines as well as its position in the entire airline industry network. Since the interest was to investigate the impact of present year direct, indirect ties and centrality of non-member airlines on the probability of non-member entry into an MPA in the next year, I led my dependent variable by one year. The unit of analysis are airlines whereas the unit of observation includes all the dyads as well as the MPAs in a particular year.

[6] Actors who are not connected to other actors are called isolates (Hawe et al., 2004)

Dataset and Sample

The model was tested on longitudinal data on multipartner alliances in the airline industry over a time span of 12 years. Information regarding multipartner alliances was obtained from the airlines business alliance survey, airline business from 1994-2007. To my knowledge, this is a comprehensive and reliable data as far as strategic alliances in the airline industry are concerned. The data set includes information on broad fronts. Primarily, it teases out the numerous business ties among 353 passenger airlines and includes nine distinct type of ties- codesharing, blocked space, computer reservation system, insurance and parts pooling, joint services, management contract, baggage handling, joint marketing and equity governance [7]. Data are comprehensive as they are inclusive of any tie that has existed between the airlines. Secondly, it contains information on the formal multipartner alliances that have existed in the airline industry since their inception up until the year 2007. The dataset is explicit on the member airlines within these alliances, their ties to other members as well as non-members. At the initial stage of this phenomena in 1994 only one multipartner alliance existed - Global excellence. In the subsequent years, the number increased to five and eventually scaled down to three alliances. Moreover, the increase in membership of airlines (Figure 7), within a timeframe of 13 years (1994-2007), formally becoming a part of MPA is astounding and warrants the beginning of a new era of a network of relationships moving beyond dyadic ties. Having said that, there is still a huge portion of non-member airlines that share informal ties ranging from code-sharing, baggage handling to joint marketing with member airlines (Figure 8). There has been a very slight drop in non-member airlines in the airline industry from 99% (1994) to 88% (2005).

As mentioned in the overview section, although the dataset is inclusive of all the airlines in the airline industry for the given period, the sample, for each year, only includes those airlines which had atleast one alliance with another airline for a given year. Table 1, illustrates the number of airlines for each year that were included in the sample. In the year 1994, fewer than 50% of the airlines had atleast one alliance with another airline. This percentage increased to 54% in the

[7] For a detailed review on the nature of each type of tie, please review Rhoades & Lush (1997). The current research does not make a distinction between different type of ties and hence it is beyond the scope of the thesis to review each tie in detail

year 1998 and it was highest in 2001. Soon after, in the year 2002, there is a sharp decline in the number of an airline having at least one tie to another airline which gradually decreases to 36% in the year 2007. Moreover, the table also illustrates that in the year 2001 had maximum number of airlines having atleast one tie with another airline.

Variables

Actor Level Variables

Dependent Variable

Dependent variable, MPA entry takes into account the non-member airline entry into the MPA. Using the longitudinal data on various multipartner alliances from 1995-2007, I created an event history for each non-member airline for every year. For each year, I constructed a dichotomous variable for all the airlines coding it as one if a non-member became a member of any alliance in a given year and 0 otherwise. Since I am interested in investigating how current year direct and indirect ties, as well as the centrality of non-members, impacts their odds of entry in an MPA in the subsequent year, I lead my dependent variable by one year.

Independent Variables

To compute my independent variables, I constructed adjacency matrixes[8] for every year and for all the nine different types to ties (i.e. codesharing, baggage handling, etc.) representing the relationships between airlines. Further, using UCINET software, for every year, I added the matrices for different ties to create an overall multiplex matrix for each given year, and then dichotomized it. For each year, I had an n*n (where n equals to the number of airlines which had atleast one tie with another airline in a given year) in which each existing relationship among member and non-member airlines was coded as 1 and 0 respectively. To elaborate, I coded 1 if there existed atleast one or more type of relationship among two airlines and 0 otherwise. Using these matrices, I computed various network measures for the purpose of my operationalizing my independent variables

[8] Adjacency matrix is a square matrix with equal number of rows and columns.

Relational Embeddedness

Relational embeddedness captures the extent to which an organization has shared direct ties with other organizations. When it comes to operationalizing the construct, most of the research has operationalized it as direct ties an organization had with other organizations in the past one year (Gulati, 1995; Staurt, 1998). For the purpose of my research, I operationalize relational embeddedness as any direct tie existing between a non-member and an MPA via the member airlines. For the purpose of calculating direct ties between a member and a non-member airline, I set the ties among the member airlines of a particular MPA to 0. Thus, for measuring the relational embeddedness of a given non-member, I count all the ties it had to members of a given MPA.

Structural Embeddedness

To map the history of the relationship, structural embeddedness takes into consideration the indirect ties that exist between two organizations in the past (Gulati & Gargiulo, 1999). In the context of my research, I regard structural embeddedness as a two-step tie existing between a non-member airline and member airlines of any given MPA in the past one year. For calculating the same, I only take into consideration the geodesic of path length two connecting a given non-member airline with an MPA member. For instance, consider Figure 3, there are two paths connecting non-member 1 and MPA member 5 however, we could say that non-member 1 has only one indirect tie of path-length two with member airline 5. Also, similar to the procedure followed in calculating one step ties, while calculating this variable, I set the ties between the members of an MPA in a particular year to 0 so as to control for the confounding effect where the one step tie between a non-member, and particular member airline, would automatically lead to a two-step tie for the non-member if the given MPA member has a tie with another member airline of the same MPA. To illustrate (Figure 9), if there is a non-member Z and two members airlines X and Y who are connected to each other, then Z's one-step tie with X automatically leads to two-step tie with the Y. To avoid this, I set the among member airlines to 0. To recapture, the structural embeddedness of a non-member airline is the count of all the two-step ties it shares with member's airline of a given MPA.

Positional Embeddedness

It captures the position an organization comes to occupy in the network. Depending upon the position occupied by an organization it could be determined whether it is central in the network or not. One of the important social network measures depicting the position of the firm in the network is centrality. Social network scholars have proposed different measures of centrality[9]. A global property to measure the position of an organization is Bonacich centrality or eigenvector centrality. According to this measure, an organization is said to have a greater centrality if it is linked to those organizations which in turn are linked to many other organizations (Gualti & Gargiulo, 1999). Unlike degree centrality which is based on a count of an ego's direct connections, eigenvector centrality weighs ego's connections according to their centralities (Bonacich, 2007). The centrality of an actor is the "weighted sum of paths connecting other vertices to each position, where longer paths are weighted less" (Bonacich, 1987; Bonacich, 2007). Eigenvector centrality can be expressed as;

$$e_i = \lambda \sum_j x_{ij} \, e_j$$

Where, e is the eigenvector centrality score and λ is the proportionality constant (Borgatti et al., 2013, p. 168).

In the context of my research, it is the most appropriate measure of the position of airlines for the following reasons. Firstly, I am interested in how the entire network structure impacts the formation of ties among airlines and eventually leads to their entry into MPA. Eigenvector centrality takes into account not only the direct ties but indirect ties of any path length, thereby implicitly taking into account the effect of network structure (Bonacich, 2007). Secondly, in my

[9] Degree centrality being the simplest, is the count of the number of ties an actor has. (Zaheer et al. 2010) and thus represents how well connected a node is as far as direct connections are concerned (Jackson, 2010). Although degree centrality has its advantages i.e. of simplicity, it is truly a local measure in the sense that it captures the local structure of ego network and fails to account for global properties of a network (Osphal et al., 2010). The degree centrality measure fails to capture more complex network phenomena such as how well positioned the actor is in the entire network, for examole, it might be the case that an actor has very few connections, however, it might be located in an important position within the network (Jackson, 2008)

hypothesis building section, based on literature, I conjecture that positional embeddedness affects the formation of new ties via status of an actor. Eigenvector centrality is an appropriate measure for gauging into the validity of above relation as it takes into account the status of an actor by way of considering the centrality of actor's partners and their partners and so on.

Control variables and meso-level analysis variables

I included various variables which might impact the MPA entry of a non-member in the alliance but aren't explicitly a part of my research question. These include MPA network level variables -- MPA network density and MPA centralization. Moreover, as enumerated in meso-level literature review, these variables comprise meso-level analysis wherein, I use these variables to explore the changes of MPA network structure over time.

There is an interplay of processes at micro-level and macro-level network constructs (Zaheer et al., 2010). The tie formation process at actor level is motivated by the micro dynamic behavior such as homophily and brokerage, which leads to tie formation, which in turn modifies structural network configurations at the ego and whole-network level. The changes in network structure, in turn, could stimulate a change in the micro dynamic tie formation process (Kenis & Knoke, 2002). Rowley et al., (2000) postulated that there is an interaction of dyadic ties and network density when explaining firm performance and found a significant impact and hypothesized that a firm having strong dyadic ties in a dense network is most likely to have a negative effect on the firm performance. Taking into consideration the enlisted assertions, I controlled for alliance network density and alliance network centralization for each year.

MPA network density

It is the ratio of actual dyadic ties to all the potential ties (Kenis & Knoke, 2002). Usually in high density networks, the average path length between any two actors is shorter, there are multiple paths that link indirectly connected actors vs. a low density network which on an average has a higher path length and a lesser number of multiple paths connecting actors. Network density, thus by way of the path length impacts speed with which information could be diffused in the network (Schilling & Phelps, 2007). This property does seem to have a bearing on the tie formation process at the dyadic level (Kenis & Knoke, 2002).

$$\text{Density} = \frac{T}{n(n-1)}$$

Where T = total number of ties existing in the network
$n(n-1)$ = the total number of possible ties in an undirected graph (Borgatti et al., , 2013, p. 150)

MPA network centralization

As defined in the literature review section, it is the degree to which network is controlled by few actors. I operationalized it using Freeman (1978) measure of degree centralization[10]. To calculate, we take the differences of each actor's degree centrality from that of the most central actor in the network and sum the differences. Then it is divided by the network centralization of a star network (Borgatti et al., 2013, p. 160). Network centralization also has an impact on how information is dispersed in the network. For example, in highly centralized networks, a large chunk of information circulates among few centralized networks as opposed to peripheral actors which in turn has a bearing on the tie formation among actors at the micro level (Kenis & Knoke, 2002). Network centralization based on individual degree centralization is calculated as follows (Prell, 2012, p. 168)

$$\frac{\sum C_D\, max - C_D\,(n_i)}{max \sum C_D\, max - \; C_D\,(n_i)}$$

[10] For detailed review on network centralization and its types please review Freeman (1979). Moreover, I use degree centralization as opposed to Bonacich centralization as network centrality based on bonacich criterion is a more global property which takes into consideration the entire network structure of an actor which goes beyond direct and indirect ties and thus is more appropriate for larger network. Whereas, MPA network structure is small and MPA network centralization based on degree centrality appropriately captures the local network structure of MPA.

Where,

$C_D\, max$ = the highest degree centrality in the network

$C_D\,(n_i)$= degree centrality of actor n_i which is equal to $\frac{d_{n_i}}{n-1}$, where d_{n_i} is the degree of node n_i and n is the number of actors

$max \sum C_D\, max$ = maximum possible degree centrality in a given network

MPA size

It denotes the number of members in each alliance. Bigger alliances have certain advantages like economies of scale and greater market share (Gomes-Casseres, 1994). Having said that, a large alliance size also has its drawbacks regarding increased dependence and coordination problems. On one hand, as and when the number of members increase, it creates complexity regarding coordination, as a greater number of members are involved in decision making processes (Gomes-Casseres, 1994). However, with the increase in the alliance size, the levels of standardization of processes become higher so as to increase effectiveness (Albers, 2010). This could imply that despite increasing size, decision making could still be effective due to standardization of processes, One way or the other, it could be inferred that in the context of the present research, MPA size might impact the decision making process as to the entry of a non-member into a given MPA.

Macro-Level Analysis Variables

Average Path Length

It is defined as the average number of nodes that lie between any two nodes on the shortest path**.** It is calculated as the average of the shortest path existing between all pairs of actors in the network (Watts, 1999)

Clustering Coefficient

The clustering coefficient measure for the whole network can be computed by taking the average of the clustering coefficients of all the actors in the network (Uzzi et al., 2007). As enumerated above, clustering coefficient C is the fraction of a pair of ego's alters which are also connected to each other (Watt and Strogatz, 1998). To explain, given that a node *i* is connected to k_i other nodes. Then the maximum number of links that can exist among them is $k_i\ (k_i - 1)/2$. Thus the clustering coefficient for node *i* is

$$CC_i = \frac{2N_i}{k_i\ (k_i - 1)}$$

Where

$N_i =$ Total number of links connecting the k_i nodes

k_i = total number of nodes that actor *i* is connected to

The clustering coefficient for the whole network is obtained taking the average of all the clustering coefficients for the individual nodes. The variables, along with their probable effects are summarized in Table 2.

Descriptive Statistics

Descriptive statistics are listed in Table 3– mean, standard deviation, minimum, and maximum values as well as correlations for dependent, independent and control variables. A quick descriptive diagnostic indicates that the distribution of the social network variables (i.e. relational, structural, and positional embeddedness) is skewed to the right which violates the basic regression assumption of normality that all the variables should be normally distributed with zero mean and a variance of 1 (Boslaugh and Walters, 2012, p. 47). The positive skewness for all three variables also suggests that the distribution for these variables is highly skewed towards the right (Bulmer, 1979). A similar observation could be made if we look at the corresponding kurtosis. Usual mode to correct the distribution to normal is to log-transform the variables (Boslaugh and Walters, Descriptive 2012, p.72). After the log transformation, the skewness is reduced to some extent (Table 4).

The correlation matrix presented in Table 5 indicates that the relational, structural and positional embeddedness are highly correlated. This could create multicollinearity issue which in turn would result in the inflation of the parameters and deflation of standard errors (Demaris, 2004, p. 226). To tackle this problem and break the common variance among the predicted variables, I employ a two-stage regression model in the subsequent section.

Analytical Model

The following section describes various analytical models that I use to carry out my analysis at different levels. At actor level, I run a panel logistic regression to statistically test my hypothesis. At meso-level, I run an exploratory analysis of the evolution of MPA network structure. Whole network analysis entails using small world network model to underline changes in airline industry network structure overtime.

Actor Level Analysis Model

I modeled MPA entry using random intercept panel logit model. Longitudinal data is problematic as repeated observations over time might not be independent of each other, thus violating the basic assumptions of regression techniques (Fitzmaurice et al., 2011, p. 76; Hilbe 2009, p. 441)[11]. Longitudinal data can be viewed as a collection of clusters or panels, consisting of observations made at different time periods, about same individual, item, organization (Rabe-Hesketh & Skrondal, 2012, p. 73). In the context of present research, I specified my panel as airlines. The observations related to same airlines over a period of several years are assumed to be correlated. Random effect panel model enables us to overcome such problems by taking into account both between and within panel variation. (Hilbe 2009, p. 481). The random effect model allows us to introduce a random intercept for each panel, thus allowing for the airline specific effects or any unobserved heterogeneity to be absorbed by that random intercept. (Rabe-Hesketh & Skrondal, 2012, p. 128)

$$\mathbf{Logit}\ \{\mathbf{Pr}\ (\boldsymbol{Y_{it}} = \mathbf{1} \mid \boldsymbol{x'_{i(t+1)}})\} = \boldsymbol{b_0} + \boldsymbol{\beta x'_{it}} + \boldsymbol{b_i} + \boldsymbol{e_{it}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\mathbf{1}$$

$$\mathbf{Logit}\ \{\mathbf{Pr}\ (\boldsymbol{Y_{it}} = \mathbf{1} \mid \boldsymbol{x'_{i(t+1)}})\} = \boldsymbol{b_0} + \boldsymbol{b_i} + \boldsymbol{b_1 x_{it1}} + \boldsymbol{b_1 x_{it2}} + \boldsymbol{b_1 x_{it3}} + \boldsymbol{e_{it}} \ldots\ldots\mathbf{2}$$

[11] The main source of correlation among observation in longitudinal data is within panel correlation. This could be accounted by introducing random effects in the model by allowing the intercept to be random to incorporate panel specific effect (for a detailed reading please review Rabe-Hesketh &Skrondal, 2012, p. 123 , p. 277)

Where -

- Y_{it} is the lead binary response variable modelling the odds of ith non-member airline entry into a MPA at time t+1;
- b_0 is the intercept term
- x'_{it} is (k*1) vector of covariates and controls for ith non-member airline at time t
- b_i reflects the random intercepts ~ N(0, ψ) , airline specific effects, which are assumed to be independent and identically distributed across all the airlines and independent of the covariates
- e_{it} is the error term which has a cumulative density function ~N (0, $\pi^2/3$)

As mentioned earlier in the descriptive statistics, the independent variables are highly correlated. This could imply that there is a substantial amount of overlap in the variation explained by these variables in predicting the response variable, thus ultimately causing inflated standard errors and reduced regression coefficients (Kellett et al., 2005). One of the several ways to tackle this problem is through residual and sequential regression, wherein, a priori importance is given to one variable (based on theory), and this variable is regressed on less important variables to break the common variation. The less important variable is then replaced by the residual term in the final regression model (Graham, 2003). I modified my initial random effect model wherein, first I regress structural embeddedness on relational embeddedness and I also regress positional embeddedness on relational and structural embeddedness and obtain the residual term for both these regressions respectively. I then use these residual terms in my primary random effect panel logit model.

Initially carrying out a random effect panel regression between direct and indirect ties, as well as, Bonacich centrality and direct and indirect ties allows me to tease out the variation caused by each one of them in dependent variable.

$$X_{2it} = b_0 + b_1 X_{1it} + \Upsilon_{1it} \text{ ……….. (2)}$$

Where

X_{1it} = Relational embeddedness, one step ties between member and non-member airlines

X_{2it} = Structural embeddedness, two step ties between member and non-member airlines

$\curlyvee_{1it}$ = Residual term

$$X_{3it} = b_0 + b_1 X_{1it} + b_1 X_{2it} + \curlyvee_{2it} \ldots\ldots\ldots \text{(3)}$$

X_{3it} = Positional embeddedness, centrality of non-members

X_{1it} = Relational embeddedness, one step ties between member and non-member airlines

X_{2it} = Structural embeddedness, two step ties between member and non-member airlines

$\curlyvee_{2it}$ = Residual term

I then substitute the error terms $\curlyvee_{1it}$ and $\curlyvee_{2it}$ from equation 1 and 2 respectively in the initial equation (1). This tackles the problem of high correlations observed among various independent variables (Table 6).

Meso-Level Analysis Model

Meso-level analysis method involves studying the changes in network centralization, density, and size changes of MPAs over time from 1994-2007. Initially, the analysis provides an overall picture of various MPAs network evolution collectively. Further, the study undertakes an in-depth analysis of the structural changes occurring in the MPA network over time.

Macro-Level Analysis Model

The small world network is characterized by two major features – higher clustering and smaller path length when compared with a random network with the same number of ties, k, and nodes, n (Baum et al., 2004). According to prior small world network research average path length of random network is calculated as

$$L_{Random} = log\ (n)/\log(k)$$

and clustering coefficient of random network denoted as C_{Random} is equal to

$$C_{Random} = k/n$$

To statistically examine whether a network is a small world or not, the above two criteria's are compared with the small world network clustering coefficient and path length referred C_{Actual} and L_{Actual} respectively. For a network to be a small world following should be true

$$CC\ Ratio\ =\ C_{Actual}/C_{Random} > 1$$

$$PL\ Ratio = L_{Actual}/L_{Random} \sim 1$$

Moreover, to obtain the small world quotient *Q,* CC Ratio is divided by PL ratio (Davis *et al*., 2003, Uzzi and Spiro, 2005).

$$Q =\ CC\ Ratio/PL\ Ratio$$

$$\mathrm{SW} = \mathrm{Q} > 1$$

For a network to be a small world $Q > 1$ (Davis *et al*., 2003). The greater the *Q,* higher is the small worldliness in a given network

Results

Actor level analysis results

The results presented in Table 8 report the odds of a non-member entering the MPA in the subsequent year based on current direct and indirect ties and centrality of a non-member. To linearize the logistic model, logit or natural log of odds is used and for the ease of interpretation I further convert the parameters from the natural log of odds to odds by exponentiation (Menard, 2010, p. 14). This results in the following equation –

$$\text{Odds}\ (\boldsymbol{Y_{it}} = \mathbf{1}\ |\boldsymbol{x'_{i(t+1)}}) = \boldsymbol{e}^{\boldsymbol{Y_{it}}=\mathbf{1}\ |\boldsymbol{x'_{i(t+1)}})} = \boldsymbol{e}^{\ \boldsymbol{b_0} + \boldsymbol{\beta x'_{it}} + \boldsymbol{b_i} + \boldsymbol{e_{it}}}$$

The intraclass correlation, labeled as rho in the table is the variance of the total random effects in the model (Rodrıguez & Elo, 2003, p .33). A rho greater than 0 showcases that there is within panel variability. Table 8 indicates that rho is 0 meaning that there is no or very little panel variability in the data. In other words, there is little correlation between a non-member airline's odds of entry in the MPA in different years. Model 1 is a base model containing various control variables. Among various controls, MPA network centralization has a significant positive impact on the odds of non-member entry in the MPA. The estimated odds of entry of non-member airline in the subsequent year increase by five times for every one unit increase in the network centralization of an MPA. Network density and alliance size do not seem to significantly impact the non-member entry into MPA. Model 2 supports hypothesis 1 and indicates that greater number of direct ties between the non-member and an MPA member in the present year increases the odds of non-member entry in the MPA in the subsequent year. Model 2 reports that for every additional direct tie between the non-member and a member of MPA, the odds of entry of non-member into the MPA increase by 1.40 times compared to not having that additional tie. Similar to model 1, among the control variables present, network centralization of the MPA has a significant positive impact on the entry of non-member in the MPA in future. Moreover, the introduction of direct ties improves the chi-square statistics by four times as well makes it significant at .001 level. Model 3 introduces the effect of indirect ties after controlling for direct ties and supports hypothesis 2, that greater number of indirect ties in the present year would increase the probability of a non-member entry into the MPA in the next year. The model depicts that after controlling for the effect of direct ties, for every one additional indirect tie between a non-member airline and a member airline the odds of entry of member into MPA increase by 3.59 times. Model 4 adds the residual effect of Bonacich centrality of non-member airline, once the effect of direct and the indirect ties of non-member airlines have been accounted for. The model shows support for hypothesis 3 indicating that greater the centrality of a non-member in the present year, higher are the chances of non-member becoming a member in the subsequent year. This indicates that as the non-members become more central, prestigious and of high status, their odds of entering into the MPA also increase. The odds of non-member becoming a member of MPA in the subsequent year increase by 63 times with each unit increase in the Bonacich centrality of a non-member airline. The high exponentiated coefficient showcases the substantial impact the boncich centrality of a non-member exhibits in explaining the variation in the dependent variable. This is further the illustration of the underlying phenomena that Bonacich centrality takes into account not only the immediate network of the ego but considers the global network of an actor. Bonacich centrality takes into account not only egos direct connection but also the centrality of egos connections, and is a weighted sum of all the ego's connections and their connections and thus, also indirectly includes the effect of the entire network structure of an actor. Moreover, with the introduction of Bonacich centrality, the MPA size becomes significant. For each additional member in the MPA in the present year, the odds of non-member becoming a member in the next year increase by 1.11 times. Bonacich centrality is an indication an actor's status and prestige. The significant positive effect of MPA size after the effect of Bonacich centrality on non-member MPA entry is accounted for indicates that the MPA size only seems to matters for members that are not central or of low status. The larger size of the MPA attracts non-members that are peripheral vs. non-members that are more central or of high status. Also, chi-square statistics improve by 41% with the introduction of Bonacich centrality.

Probable Moderating effects

The sample depicted that in a given year, some of the non-members shared both direct and indirect ties with MPA member airlines, plus had a Bonacich centrality of greater than 0. Although not hypothesized in the original model, the presence of these three variables might create interacting effects on the MPA entry of the non-members. Direct ties between a non-member and a member airline might moderate the relationship of indirect ties and non-member entry in the MPA. Moreover, the direct and indirect ties between non-member and an MPA member might moderate the impact of Bonacich centrality of non-member on non-member entry in the MPA. I ran panel logistic regression with interactions to examine this effect. Before running the model with interactions I mean centered three variables. Table 10 illustrates the interaction effects between direct, indirect ties and Bonacich centrality. Model 1, showcases the individual effect of direct and indirect ties as well as the effect of their interaction. The positive significant interaction coefficient indicates that the effect of indirect ties on the MPA entry might be dependent on varying levels of direct ties a non-member maintains with the MPA. Similarly, as depicted in model 2 and 3, the interaction effect of direct ties and Bonacich centrality, as well as indirect ties and Bonacich centrality, is positive and significant on the non-member entry in the MPA. These significant interactions signal that the effect of non-member airline centrality on MPA entry is dependent on the varying levels of direct and indirect ties of non-members.

In general, the interaction term showcases that the slope of the independent variable varies across various levels of the moderating variable in its impact on the response variables (Demaris, 2004, p. 104). Moreover, when the interaction term involves two continuous variables, then it becomes informative to tease out the effect of one continuous variable at various levels of other continuous variables. This is best illustrated in Figure 10, which showcases the probability of entry of non-member airline into the MPA depending on indirect ties of non-member airline with member airline, holding direct ties at various levels. For example, given that a non-member has a single one-step tie, prior two-step ties will lead to a 60% probability of the entry of non- member in the MPA. As depicted in the figure, the effect of two-step ties gradually decreases with the increase in one step ties. Similarly, Figure 11 and Figure 12 show that the impact of non-member's Bonacich centrality on the probability of entry in an MPA is moderated by direct and indirect ties. Figure 11 illustrates that when a non-member has one direct tie Bonacich centrality will lead to more than 90% chance of entry into MPA. On the other hand, the impact of Bonacich centrality of non-member decreases to 20% when a non-member has ten direct ties.

Furthermore, since both direct and indirect ties are count variables, illustrating the effects of direct and indirect ties at their minimum and maximum levels would further showcase the subtle effects of interaction between direct and indirect ties more clearly. This is clearly depicted in Figure 13. The Figure showcases that the impact of a non-member having a high number of indirect ties (i.e. four indirect ties) on the MPA entry varies with the different number of direct ties a non-member has with the MPA members. The effect of having four indirect ties on the probability of non-member MPA entry is .02, when a non-member has two direct ties. On the other hand, the likelihood of MPA entry based on four indirect ties increases by 50%, when a non-member has two direct ties instead of 4 direct ties. Thus, the impact of having greater indirect ties on non-member entry increases at lower levels of direct ties and decreases at higher levels of direct ties.

Meso-Level Analysis results-Airline MPA

Meso-Level analysis is focussed on exploring structural changes that MPA network structure has undergone over a period. More specifically, meso-level analysis underlines the evolution of network structure of MPA's density and centralization. For reasons enumerated in the introductory sections, evolution of these characteristics is worth exploring as network density, and centralization are vital in the context of airline MPA, because these features have a bearing on connectivity and scheduling of the member airlines as well as the governance of the MPA itself.

Overall MPA Network Density and Centralization

Table 11 illustrates the evolution of overall network Density and Centralization of MPA network. Similarly, a trend line for the overall MPA network characteristics is depicted by Figure 14 and 15. In the inception year 1995, the overall density of the MPA member network was 1. The reason being that there was only one MPA namely, Global Excellence with three member airline and all three were connected among themselves. Consequently, since network centralization is inversely related to network density, network centralization was 0. In 1997, two other MPAs, namely, Atlantic Excellence and Star Alliance came into existence. The number of member airlines rose from 3 to 11 members and the density of the MPA network was reduced by 10%. Consequently, the centralization of the network increased to 13%. After 1997, on average the MPA network density gradually decreases and by 2001 MPA network on average was 40% less dense than before. In the subsequent years, the density increased gradually. As with the majority of network structures, a drop in network density is associated with an increase in the network centralization and vice versa. Similarly, the MPA centralization moved in opposite direction to MPA density. MPA networks first became increasingly centralized until 2001 and then gradually became decentralized overtime until 2007. The decrease in density and increase in centralization until 2001 could be attributed to two factors. Primarily, the network size of most of the MPAs grew from 1994 to 2001, and as network density decreases with increase in network size, it resulted in lower MPA network density. However, after 2001, despite the growth in size, the number of ties formed within the MPA increased substantially which led to increase in MPA density. For instance (see Table 11), the total average degree, that is an average number of ties per member in 1998 was 1 per member. However, the average degree increased substantially after 2000 indicating that on average each MPA member had a greater number of ties which eventually made the MPA denser.

MPA network density and network centralization

This section underlines the network evolution of various MPAs with respect to their network density and network centralization. More specifically, I underline the structural changes that Star Alliance, Oneworld, and SkyTeam have undergone since their inception up until 2007. I consider these MPAs for three major reasons. Primarily, these MPAs are still present while most of the other MPAs dissolved by 2003. Secondly, they have been in existence for a greater number of years as compared to other MPAs which provides for ample data points to study the network change longitudinally. Lastly, these MPAs have undergone more structural changes regarding non-member entry in the MPAs which in turn makes the network structure of these MPAs more dynamic. Beyond the analysis of network evolution of these three MPAs, evolution of network characteristics of other MPAs is presented in Table 12.

Star Alliance Network Evolution

Star Alliance came into existence in 1997 and still presently exists. I discuss at length the network evolution of Star Alliance for the year 1997, 2000 and 2006[12]. A bird's eye view of Figure 16 provides an overview of the star alliance network density and network centralization. While over the number of years Star Alliance density has decreased sharply and then gradually increased, the network centralization on the other hand has moved in opposite direction.

The year 1997 - Star Alliance came into existence in 1997 and had six founding members among which Lufthansa and United Airlines were the most central members whereas Air Canada seems to be a peripheral one. Table 12 shows that the network density of .733 indicated there existed a 73.3 % probability that a tie would exist between any two randomly chosen actors in the MPA. Moreover, quickly examining Figure 19 allows us to visualize that out of 15 possible ties

[12] I chose these three particular years because 1997 was the inception year and the year 2000 provides a mid-point for my data and year 2006 is the ending year of my dataset. For the detailed network analysis of all the years please refer to table 12

between 6 airlines, there are 11 actual ties among star alliance members. On the other hand, centralization index of .40 indicates that the network is centralized up to some extent. Figure 19 illustrates that star alliance network is highly centralized around Lufthansa and United Airlines as these two members' airlines have connections to all other MPA members, including the connections among themselves.

The year 2000 - The number of members was more than twice (13 members) as compared to its inception year, and the network density decreased to .45 from .733 (Table 12). On the other hand, centralization of the network increased to .65. Figure 20 shows that United is the most central member with connections to all other members in the network, followed by Lufthansa whereas Varig, Mexicana and SAS are the peripheral members.

The year 2006 – There has been an addition of 3 new members in the star alliance since the year 2000. The network density has increased to .667 whereas there has been a substantial reduction in the network centralization (Table 12). The increased density and reduced centralization could be attributed to increasing network size as well increasing average degree in the network. The average number of ties per member in 2006 is ten ties per member in the network and is twice as compared to the year 2000. Figure 21 also shows that the network has grown larger and has become more complex.

Oneworld Network Evolution

Oneworld, one of the three major MPAs, came into existence in 2000. Figure 17 illustrates that the density and centralization move in opposite directions over the number of years. While the density first increases from .60 to .9 eventually reducing back to .65, the centralization on the other hand first decreases to from .60 to .20 and then increases back to 0.5. Regarding, the number of members Oneworld hasn't gone through much of a structural shift. During its inception it had seven members, Quantas and Lan Chile Airlines entered the MPA in 2000. Beyond that Japan Airlines and Swiss Airways entered the alliance in 2001 and 2004 respectively, however, ended their membership within one year of admission. I below discuss

Oneworld's network structure in the year 1999 (inception year), 2003 and 2006. Table 12 provides the detailed evolution of OneWorld network for all the years.

The year 1999 – At the time of inception Oneworld had seven members, out of which British Airways and American Airlines were the central members and Cathay Pacific was the peripheral one. A quick look at figure 22 illustrates that British Airways is connected to all the members of the MPA and serves as the only connection between Cathay Pacific and rest of the MPA members. Table 12 shows that the density of OneWorld is .57, indicating that there was 57% probability that a tie existed between any two randomly chosen nodes in the MPA network. Also, network centralization of .6 indicates that the network was fairly centralized around central players

The year 2003 – Figure 23 shows that OneWorld network structure has evolved from a fairly simple to somewhat complex network. Most of the MPA airlines are connected to each other. On an average, most of the airlines atleast have four ties in MPA. British Airways and Aer Lingus are the most central ones with having connections with all the MPA members including connection among themselves. Also, Cathay Pacific which was a peripheral member at the time of inception of the MPA has become quite central. In the year 2003, it maintained ties with four other members of the MPA including British Airways and Aer Lingus. On the whole, it has become a dense network with a density of .75 and is less centralized (Table 12).

The year 2006 – OneWorld hasn't undergone changes regarding entry of new members. However, there are some changes as far as structural changes within the MPA are concerned. Primarily, Aer Lingus one of the central members up until this year has shifted to the network periphery. Moreover, British Airways and American Airlines have consistently maintained their status as central members (Figure 24). Also, it has become denser than 2003 with a density of .803 (Table 12).

Sky Team Network Evolution

SkyTeam was formed in the year 2000 with four founding members. The number of members rose to six in the year 2002 with the admission of CSA Czech and Alitalia airlines finally rising to 9 members in the year 2006. It was a relatively dense network at the beginning with a density above 0.5. In the following years, the network became even denser with density rising to .90 in the year 2004 and then eventually decreasing in the year 2006. On the other hand, it started as a centralized network with network centralization of 0.6, however, network centralization, consistently decreased until the year 2005 and then rose to 0.4 in the year 2006 (Table 12). Moreover, Figure 18 illustrates the drastic changes SkyTeam network has undergone regarding its centralization and density.

The year 2000 - In its inception year, it had four members namely Aeromexico, Delta, Air France and Koren Airline. Figure 25 illustrates that Air France and Delta Airlines were the most central members and were connected to all MPA members. While the network was relatively dense with most of the actors having connections to the other MPA members, however, it was also highly centralized.

The year 2003 - Two new members were admitted in SkyTeam in the year 2002. The network became denser with a network density of 0.86 and less centralized with a network centralization of .2 (Table 12). Delta Airlines was the most central member sharing ties with all other members. Rest of the members were also fairly well connected as they all had ties to three other member airlines (Figure 26).

The year 2006 – SkyTeam went through some structural changes with regards to the admission of three new members namely Continental, KLM and Northwest in the preceding year (2005). Consequently, as illustrated in Figure 27, the network became somewhat complex as compared to prior years. A quick glance at the figure enables us to decipher that Continental, Alitalia, Delta and Air France are the most central members each having atleast ties to 7 other members. Rest of the MPA members are also fairly well-connected except Northwest Airlines, which is 50% less connected as compared to the most central member (Continental Airline). Overall, the SkyTeam had a density of .80 and it’s network centralization was 0.25 (Table 12).

In conclusion, the number of MPAs have been reduced to three major MPAs – Star Alliance, Oneworld, and SkyTeam. However, there has been a tremendous increase in the number of non-member airlines which have become part of MPAs in the airline industry. Moreover, over the number of years the overall MPA network has become less dense and more centralized. Further talking about the network dimensions of the three major MPAs, Star Alliance appears to the be the largest MPA out of the three in terms of members, however, SkyTeam has the most dense network whereas Oneworld seems to be the most centralized out of three The entry and exit of non-member airlines in the MPA impacts the network structure of the MPA, thus making it dynamic and more complex . These changes in turn might impact the actor level tie formation process among airlines and in addition, impact the non-member entry into the MPA

Macro-Level Analysis Results – Small Worldliness of Airline Industry

The main premise behind small world network is that they have a smaller average path length and high clustering as compared to the random network. Table 13 illustrates the dynamics of the small world in airline industry from the year 1995-2007. Each row represents the number of ties existing in the network, a total number of airline that atleast had a tie in the network[13], actual path length and clustering coefficient of the small world network as well as the random network. Each row also includes the CC ratio and PL ratio as well the small world quotient *Q*.

Overall, Figure 28 clearly depicts that the average path length of the small world network of airline industry shows a downward trend whereas the clustering coefficient increases overtime. Similarly, figure 29 indicates the trendline for small world quotient, *Q* from 1994-2007 and indicates that overall, the small worldliness of airline network has decreased from 1994-2007. Moreover, Table 13 indicates that the actual clustering coefficient has been consistently greater that the clustering coefficient of the random network. The CC ratio indicates that in the initial years the clustering coefficient within the airline industry is nine times larger than that of a random network. Although, during later years the CC ratio decreases, it is still 6:1 for actual vs. random clustering coefficients. As far as the actual and random path length are concerned, they are more or less the same. While, in the initial years the actual path length of the small world network is somewhat greater than that of a random network, towards the later years they converge to be almost same. Besides, to reinforce the small world results statistically, Table 13 indicates that the small world quotient *Q* is consistently above 1 for all the years. Below I discuss the evolution of two major small world network components – Average Path Length, Clustering coefficient.

[13] As the original sample only includes the airline which had atleast one tie with other airline in a given year, all the isolates are excluded from the network for calculating the small world characteristics

Clustering Coefficient

Table 13 depicts that throughout the period the actual clustering coefficient of airline industry network is fairly high when compared to the random clustering coefficient. Additionally, it gradually increases over time and is .3 by the year 2006. This indicates that over the number of years the airline network has become more and more cliquish. In other words, since the clustering coefficient indicate the probability that two nodes are adjacent to each other in a network (Barabási et al., 2000) it tells us that in the year 2006, on average there was a 30% probability that any two airlines in the network would collaborate. Over a period of 13 years, the likelihood of two airlines collaborating with each other has increased by 33.33%. The overall trend of the clustering coefficient is depicted in Figure 28.

Average Path Length

The actual average path length of the network is more or less similar to the random path length for most of the years. This is clearly depicted by the PL ratio in Table 13 which for most of the years is approximately 1. Figure 28 illustrates the pattern of path length for years 1994-2007. Initially, the average path length of the network was 3.5. It reflects the average separation of the network. It could be said that if any given airline wanted to reach another airline in the network, it would have to pass through three intermediate airlines. Over time, the actual average path length has gradually decreased and by 2007 it was 2.67 indicating that any two airlines in the network were on an average separated by two airlines.

Discussion

The key message that I intend to reinforce is twofold. Primarily, the formation of new ties and entry of non-members in a network is contingent upon their past relationships and how well they are embedded in the network. (Gulati & Gargiulo, 1999).The results demonstrate that entry of non-members in the airline MPA could be attributed to their previous direct and indirect relationships as well as to how well they are positioned in the network. Secondly, network in which the organizations are embedded is dynamic in nature and is under constant change due to the formation and dissolution of ties at the actor-level. I demonstrated this by analyzing the evolution of MPA and entire airline industry network structure over a period of 13 years. Various levels of a network coevolve. As aforementioned, in prior sections, the structural changes at different levels of network impact each other. Although not empirically explored, I intend to discuss the coevolution of airline network structure below with the aid of results obtained at all three levels of my analysis. In the context of present research, the changes in the relationship among airlines, more specifically, entry of non-member airline in the industry would affect the changes in the MPA structure as well as the whole-network. Conversely, the changes in the MPA structure and the whole-network structure could also impact the tie formation process and eventually non-member MPA entry in the MPA.

As such, the discussion section is organized into two major parts. Initial subsection discusses the results obtained from actor-level analysis and the subsequent sub-sections discuss the changes airline industry has undergone at the meso-level and whole-network level and link these changes to the entry and exit of non-member airline in the MPA. In other words, the subsections explore the coevolution of network of airline industry by studying the intricacies involved among actor, meso and whole-network levels.

Actor- Level - Non-Member entry into the MPA

Actor-level analysis reinforces the premise that formation of new alliances between organizations is impacted by the web of relationships the organizations are embedded in (Granovettor, 1985). The results of this study confirm to this central principle of social network research. The study examined the impact of various levels of embeddedness on airlines future tie formation behavior. More specifically, the study investigated whether or not prior non-member airline embeddedness would impact their entry into the MPAs. The results of the study provides evidence that prior direct ties and indirect existing between a non-member and member airline impact the entry of non-member airline in the MPA in the subsequent year. The results obtained in the current study are similar to those obtained by prior studies (Gulati, 1995; Gualti & Gargiulo, 1999). Prior ties between two organizations acquaint each other regarding the behavior and increase cooperation between partners whereas prior indirect ties between organizations serve as information conduits regarding the reputation and behavior of future partners (Gulati, 1995). Above mentioned reasoning justifies that actors who have entered into alliances in the past or have had a common partner demonstrate high tendency to ally in future. These results confirm to the propositions concerning airline alliance underlined in the theory building section. Prior research suggests that various non-member airlines had bilateral ties to existing member airlines before formally becoming an MPA member. Beyond the immediate structure of an airline (i.e. direct and indirect ties), the study indicates that there is a significant positive impact of the position occupied by a non-member airline in the network on its entry in the MPA. Again, the results of the present research confirm the results of prior studies (Gulati & Gargiulo, 1999). I measured the position of a non-member airline using Bonacich Centrality. Being a more global property of ego's network the Bonacich centrality takes into consideration all of actor's direct and indirect connections in the network and thus exhibits a stronger impact on MPA entry of a non-member airline when compared with direct and indirect ties.

Beyond investigating the individual impact of various types of embeddedness, the study also explored the interacting effects of different levels of embeddedness. Although not hypothesized initially in the model, it seemed practical to explore the combined effect of direct and indirect ties and the position occupied by a non-member airline in the network, as the sample indicated that a given non-member airline has both direct and indirect ties and also occupies a particular position in the network. Although the interaction among these variables has seldom been discovered as an explanatory variable in the network research and less so in explaining the future tie formation behavior among actors, Rowley et al. (2000) claim that interaction among these comprise an important explanatory variable which warrants due attention. The results showcase significant interaction coefficients for all three types of embeddedness and indicate that the relationship between indirect ties of a non-member airline and its MPA entry could depend on varying levels of direct ties. Specifically, the indirect ties have a greater impact on MPA entry when a given non-member has no or lower level of direct ties. Similarly, the effect of the position held by a non-member airline on its future MPA entry is impacted by the number of direct and indirect ties it has with the member airlines. This could be explained through the concept of "tie strength." Granovettor (1973) defines it as a function of the amount of time, emotional involvement and reciprocity among the actors. Stronger ties have been operationalized as immediate connections whereas weaker ties have been operationalized as actor's indirect ties (Lin et al., 1981). In other words, as the distance between two actors increases, the strength of the relationship decreases (Borgatti et al., 2013, p. 112) and moreover stronger ties have been associated with greater trust formation and are known to be more efficient for knowledge transfer (Uzzi, 1997; Levin & Cross, 2004). Thus in the presence of direct ties which are more stronger as compared to indirect ties and positional embeddedness, the impact of the latter two variables on MPA entry is lessened.

Triangulation Analysis - Coevolution of Non -member airline entry, MPA structure, and airline industry whole network

This section aims to triangulate the two broad sections of the thesis – predictive and exploratory to draw more meaningful and holistic conclusions regarding the structural dynamics of actor-level (non-member airlines), meso-level (MPA structure) and whole-network level (airline industry). In doing so, I intend to explore how these three levels co-evolve. In other words, I am interested in studying how changes at actor-levels entry and exit of non-member and member airlines in MPA effect the MPA and airline industry network structure and vice versa.

The term coevolution has been primarily coined by biology researchers wherein they examined the coevolution of butterflies and their food plants (Ehrlich and Raven, 1964). The premise behind the coevolution concept existing in biology is "mutual adaptation" and being interdependent wherein species are impacted by their environment, and the environment itself is affected by the species (Potter, 2006). Extrapolating it to organizations would indicate that coevolution would occur in a context where a set of organizations interact and change occurs not only due to direct relationships of interacting organizations but also through the entire structure of these interacting organizations (Baum & Singh, 1994).

Although a pervasive concept in biology, coevolution is a relatively new concept in management science (Potter, 2006). Up until 2000, there had been merely 52 articles on coevolution since its inception (Potter, 2006). Nevertheless, coevolution is an intriguing concept which could provide some meaningful insights about how organizations are affected by the systems that they are embedded in and vice versa. This approach is pertinent especially when studying organizations is fairly complex and involves a feedback loop between organizations and systems which is a primary reason for the existence of dynamic behavior (Baum & Singh 1994). In the past, the coevolution concept has been extensively applied in various management theories such as ecology theory, open system theory, and complexity theory (Porter, 2006), but its limited presence in social networks research is surprising. Several social network scholars have advocated the exploration of the interactions among various levels of the network. For instance, the guidelines provided by social network literature, as far as, future directions are concerned, encompass exploring the ideas such as, but not limited to, how does changes at the actor-level impact the whole network stability (Provan et al., 2007) or how would the density impact the dyadic relationships (Zaheer et al., 2010). Indeed, there are few scholars who have initiated the exploration of how does network coevolve at different levels. Gulati et al. (2012) carried out an analysis of micro-macro dynamics of small world network in computer industry and demonstrated how micro-level dynamics, the formation of cohesive as well as bridging ties initially contributes to the formation as well as expansion of small world, however, eventually also becomes a cause of its decline over a period.

The coevolutionary approach within social networks would be useful in exploring the intricate relationships that exist among various levels of a network. To illustrate, while actor-level relationships together determine the structure of the network, network properties guide the behavior and the opportunities for the actors, whichin turn, impacts the tie formation at the actor-level (Ahuja et al., 2012). In other words, presence or absence of ties at the actor-level determines network structure attributes such as density, centralization, connectivity which subsequently impact actor-level ties (Kenis & Knoke, 2002). In short, there exists a constant feedback loop which explains the dynamic nature of the networks. There is a continuous interplay between the actor, dyadic and whole network in a way that coevolution occurs at all levels.

Below I explore the coevolution of the airline industry network structure at three levels - actor, meso and macro. My analysis is not confirmatory in nature but intended at exploring the coevolution of airline dyadic relationships, MPA structure, and whole-network structure of airline industry. More specifically, I observe the following -

- Impact of entry and exit of non-member airlines in the MPA on
    - the MPA structure regarding centralization and density of the MPA networks
    - the small worldliness of the whole airline networks - the average path length and the overall clustering in the whole airline network
- The MPA structure impact on
    - tie formation between member and non-member airlines; MPA entry of non-member airlines

Co-evolution of non-member entry and exit in MPA and MPA structure

Meso-level analysis results indicate the overall MPA network gradually evolved from being a highly dense network to a somewhat sparse eventually resuming its density to some extent over a period of 13 years. Conversely, in initial years the network was less centralized while in the latter years it transitioned into a relatively centralized network. At the inception of MPAs in 1994, there was only one MPA namely Global Excellence with three airline members and all of them had direct ties with each other, thus maintaining a network which was 100% dense with no centralization (Alliance Business, 1994). In 1997 the total number of MPAs increased to 3 and on an average had 4 MPA members. Thus, an increase in one MPA member resulted in a decrease in overall MPA density by 10% and an increase in network centralization of 13%. Prior research suggests that an increase in network size leads to decrease in network density, as when the total number of actors in a network increase, it becomes difficult for an ego to maintain all the possible ties in the network (Donald, 2005). This could also be explained in terms of time constraints the ego faces while maintaining various relationships. It is generally argued that actors need to invest time and resources, which are often limited, in maintaining different relationships (Scott, 2013, p. 74). With the increase in the network size, the number of potential relationships also increases, thus making it difficult for the actors to maintain all the possible ties, which eventually decreases the overall network density (Prell, 2012, p. 170). In the context of the present research, the relationship between the entry of new members in MPA and a decrease in overall MPA density could be explained as follows. Density is the ratio of actual ties in a network over a total number of possible ties that could exist in the network. In 1994, the ties that existed in the MPA network were three which is equal to the total number of possible ties that could exist in the network and hence the network was 100% dense. On the other hand in 1997, the average number of members per MPA was four approx while on an average the total number of ties in an MPA was ten, whereas the total possible ties were twelve{n* (n-1)}, thus bringing down the MPA density by 10%. As the average number of MPA member grew from four members per MPA in 1997 to seven members per MPA in 2001, the overall MPA density decreased by one 40%. However, after 2001, the overall MPA density started to increase despite increase in MPA size. As noted in the result sections, this could be attributed to increase in average degree (number of ties per member on average) of each member on an average.

The above subsection underlined the evolution of network density of MPA network structure with respect to changing MPA size in term of its members. However, to get more in-depth insight into the dynamics of the network structure of MPAs, it becomes critical to observe the coevolution of non-member entry and exit into specific MPAs and their network structure. Since in the analysis section, I analyzed the network structure of three major MPA's Star Alliance, Oneworld and SkyTeam, accordingly, for consistency, I will limit my co-evolution discussion to these MPAs. Star Alliance came into existence in 1997. During its inception year, it had six members and a network density of .733 and a network centralization of 0.4. In 1999, two new members became part of Star Alliance, and it’s network density dropped by 85%. This can be explained by the increase in network size. Consequently, in the year 2001, one member exited the MPA, and this resulted in an increase of MPA density by 50% (approx.). However, in the subsequent years after 2001, the number of non-member airlines entering the MPA gradually increased and so did the network density. This is counterintuitive to the logic stated above that network density usually decreases with increase in size and vice versa. However, the increasing star alliance network density with increase in network size could be well explained by bringing in the concept of degree centralization, another MPA level attribute analyzed in the meso analysis section. High degree centralization of the network would indicate that the network is centralized around few actors. Few actors have a high number of ties, while most of the actors might have fewer ties on average. This in turn is also driving high network density, as network density takes into account the actual number of ties present in the network .For example, in the year 2004 Star Alliance had more than double the MPA members as compared to the year 1998 or 1999, yet, its network density increased threefold. This could be attributed to the fact that in 2004, out of fourteen members, the network was highly centralized around three major airlines - Air Canada, Lufthansa and United Airlines, which had more than double the ties as compared to other members. The same phenomenon was observed among other two major MPA – SkyTeam and Oneworld. Thus, analyzing the two constructs MPA network density and MPA network centralization together enables to decipher the true dynamics of network structure. Viewing these two constructs together allows to deduct that networks displaying high density index might not be actually dense due to the presence of few highly central actors which drive up the network density.

Having considered the impact of entry and exit of MPA members on MPA structure, I below discuss the potential implications of a change in MPA network structure density and centralization on MPA entry. As far as MPA network density is concerned the actor-level predictive analysis indicated that it did not significantly impact the non-member entry into the MPA. One major reason behind this result could be that as density of a given network is associated with greater trust and efficient information transfer between the network it might eventually lead to increased tie formation in future (Granovettor, 1985, Kenis & Knoke, 2002). However, It could be extrapolated that for actors to reap the benefits of future tie formation in a dense network, they have to be part of that network. However, in the present context, non-members airlines weren't part of given MPA network unless they were formally admitted in the MPA. On the other hand, the actor-level analysis suggested that MPA network centralization has a significant positive impact on the non-member MPA entry. As mentioned earlier, network centralization is associated with increased coordination where few centralized actors may coordinate the activities of entire network on behalf of all network members (Lazzarini, 2008).

On the other hand, if a network is decentralized and also large it might experience difficulty in efficiently operating as a single entity (Provan & Milard, 1995). Similarly, a study undertaken on the formation of MPAs in airline industry the results indicated that having networks that are highly centralized have greater chances of being formalized into MPAs (Lazzarini, 2008). In the present context, a highly centralized MPA network could indicate effective coordination and greater consensus regarding the entry of a non-member in the MPA. A quick look at Table 11 shows that over the years as the number of members per MPA (on average) goes up, the MPA network centralization has also gone up. Beside the Random Panel Logistic results (Table 8) indicate that the impact of MPA network centralization is significant and positive in all four models.

To summarize, change in the network structure at actor-level seems to impact the meso-level structure of MPAs. More specifically, the increase in non-member airline entry in the MPA might decrease the overall network density of the MPAs. However, when examining the specific cohesive groups within the overall MPA network, the specific MPA density and centralization seems to be increasing with the addition of the non-members in the MPA. This indicates that as the network density of the MPA increases even when the MPA network size increases, the network density of a specific MPA is driven by highly centralized members in the network

Co-evolution of non- member MPA entry, MPA network structure and Small worldliness of Airline Network

Small world analysis of airline industry network indicate a decline in small worldliness of airline network structure over time. The small worldliness pattern of airline network structure is triggered by the actor-level tie formation (Gulati et al., 2012). More specifically, at actor-level two key tie formation patterns – tie formation among prior direct and indirect partners and formation of bridging ties with new actors triggers the development of small world network pattern at the whole network level (Gulati et al., 2012). As explained previously in the theory section, due to information uncertainty regarding the behavior of actors as potential partners in the network, a given actor is inclined to forge ties with its previous partners or with their partners (Gulati, 1995, Gulati & Gargiulo, 1999). The tie formation pattern with prior direct and indirect partners tends to create densely connected clusters in the network. This often leads to information redundancy in these dense clusters as most of the actors are connected to each other which leads to the flow of similar information within the network. To overcome the problem of information redundancy and have access to new resources few actors will be inclined to form ties across these clusters (Burt, 2000). Tie formation tendency of few actors across these clusters create bridges in whole-network providing the clusters and actors with new information regarding the emergent opportunities (Burt, 2001). Moreover, the bridging ties have been associated with improved performance (Zaheer & Bell, 2005), higher competitive capabilities (McEvily & Zaheer, 1999), innovation (Hargadon and Sutton, 1997). Thus, actors in search of new opportunities will be motivated to form bridging ties which in turn will improve the overall network connectivity.

Consequently, the two actor-level tie formation process of forming local as well as bridging ties would impact the small world characteristics of the whole-network. As more and more actors form ties locally, the emergence of dense clusters will lead to overall high clustering in the network (Gulati, 2013). On the other hand bridging behavior |of actors will impact the overall small world path length. As these bridges connect otherwise unconnected actors these ties will shorten the average path length of the entire network (Gulati, 2013). Thus in the initial phases of network development, two key actor-level actions of local and bridging tie formations, together enables a network structure that is highly clustered and has a short reachability.

In the airline industry context, the declining small worldliness pattern can be explained with the help of transformations happening at the actor and meso-level. The network structure of airline industry has been significantly impacted by the emergence and development of MPAs. MPAs in airline industry created dense clusters of airlines that are tightly knit to each other. Beyond MPAs, the non-member airlines share dyadic ties to member airlines also indirectly form part of these dense clusters, in the whole-network. Thus, each MPA could be viewed as the core around which a dense cluster of relationship emerges between various MPA members and between MPA members and non-members. Beyond being a part of dense clusters non-member airlines also perform the bridging tie formation actions within the airline network. This is because MPA airline members are restricted from forming ties with member airlines of another MPA but they can enter into unrestricted ties with non-member airlines. Thus, various MPA clusters are connected to each other via common ties to non-member airlines. To illustrate (Figure 30), the red nodes represent different MPA members who are part of three different MPAs whereas blue nodes represent non-member airlines. Star Alliance member airlines Lufthansa, Air Canada, SAS, Swissair, Vraig, Thai Airways form a single MPA cluster while other two MPA clusters Atlantic Excellence and Global Excellence are formed by Sabena, Austrian Airlines and Delta, Singapore Airlines respectively. The member airline within one MPA are densely connected to each other as well as to some non-member airlines. However, they are only indirectly connected to members of other MPA via non-member airlines that serve as bridges between them and other MPA member airlines. The figure clearly depicts that various non-member airlines British, KLM Royal Dutch and American Airlines act as bridges between the three MPA clusters. The bridging function of non-member airlines shortens the overall path length in the network. Thus, it could be implied that increasing size of dense clusters formed around various MPA networks and their tendency to form ties locally within the MPA as well as the bridging function of non-member airlines contributes to the overall small worldliness of the network structure.

As more and more non-member airlines enter in the MPA, intuitively it would imply that there will be fewer bridges connecting various clusters formed around different MPAs. This is because once non-member airlines become a member of specific MPAs, they are required to dissolve their prior ties with member airlines of other MPAs. This would impact the small-world network characteristics in two ways. Primarily, it would increase the overall path length of the network as there would be fewer bridges connecting dense MPA clusters. On the other hand, as non-members formally become part of an MPA, they would increasingly partner with other member airlines of that MPA. This could be deducted from the fact the overall density of MPA networks is much higher than that of the whole industry network structure. For instance, in 2002, the average MPA density was 80% for an MPA size of 8 members per MPA while the density of whole airline industry network was 3.8% and the total number of actors was 164. This would, in turn, increase the overall network clustering in the network. Thus, as more and more non-member airlines enter into MPAs, the whole network structure would become highly clustered with an increasing reachability. On the other hand, I restrict from inferring implications of actor-level actions of member airline regarding existing of member airlines from the MPA on whole network industry structure for the following reasons. Primarily, there have been very few exits of

MPA members' overtime. For instance, in Star Alliance, there has been merely one exit of Ansett Australia whereas no member airline exited SkyTeam overtime. As such, there aren't enough data points to draw a probable relation between the exit of MPA members and whole-network of the airline industry. Moreover, the data seems to suggest that usually MPA airlines exit one MPA and enter another MPA instead of transitioning back to non-members. As such the exit of MPA members would seem to have no impactions on the whole network characteristics.

The small world statistics (Table 13) and overall MPA network statistics (Table 11) suggests that over time the total number of MPA members have increased tremendously. In other words, non-member airlines have become members of various MPAs at an increasing rate. On the other hand over a number of years, the small world quotient has also decreased tremendously. This finding, when corroborated with the mico-macro network structure dynamic theory explained above, seems to suggest that MPA entry of non-members overtime could be possibly linked to the decline of the small worldliness of airline industry network structure. As more and more non-members enter into the MPA, they increase the size of dense clusters surrounding MPAs and reduce the number of bridges connecting those clusters.

Contribution

The present study contributes to growing literature on interorganizational networks in many ways. Primarily, the study contributes to the vast literature on embeddedness. By using embeddedness as a lens to explain the phenomena of actor's tie formation process and actor's entry into alliances at the micro-level, the study corroborates the central premise of social network that actions and behaviors of actors are impacted by the web of relationships that they are embedded in (Granovettor, 1985). Not only does the current research describes how various levels of embeddedness – relational, structural and positional embeddedness impact the tie formation behavior among actors, it also illustrates that these levels of embeddedness interact and exert a combined effect on actor's tie formation action. Secondly, the thesis contributes to growing research on dynamics of interorganizational networks (Gulati & Gargilo, 1999, Powell et al., 2005, Gulati et al., 2013). This body of research advocates that a network structure is not static but dynamic in nature and is under constant change due to the actions of individual actors. It necessitates that before using networks as explanatory variables, it is imperative to study their evolution, as, change in network structure also leads to the changes in opportunities and restraints existing in the network (Gulati & Gargilo, 1999; Ahuja et al., 2014).The thesis showcases the dynamics of interorganizational networks by illustrating that the network structure of airline multipartner alliances as well the network structure of entire airline industry is constantly changing regarding its network attributes such as density, centralization, overall clustering and average path length. Thirdly, the current study contributes to the scant literature on whole-networks analysis (Powell et al. 2005; Gulati et al. 2013; Provan et al, 2007). Studying whole networks is imperative as it is only through their analysis, that a holistic picture of their evolution can be depicted (Provan et al., 2007). The thesis adds to the whole-network literature by analyzing the developments in the entire airline industry structure regarding its small worldliness and underlining its decline over time. As such, the study also contributes to the small world network literature (Baum et al., 2003, 2004; Uzzi and Sapiro, 2005; Gulati et al., 2013). Lastly, the current thesis makes an effort at contributing to the research of co-evolaution of network structure at various levels. Increasingly, social network scholars are advocating that different levels of network impact each other (Zaher et al., 2010; Ahuja et al., 2014, Gulati et al., 2012). They posit that at actor-level formation and dissolution of ties changes the structural dimensions of the whole network structure and the modifications at the whole-network level in turn shapes the actor's tie formation and dissolution action (Gulati et al., 2012; Ahuja et al., 2014). The study showcases in the multilevel coevolution of airline network structure at different levels in three ways. Primarily, the current research underlines the possible effects of entry and exit of member airlines on MPA network structure evolution and conversely the impact of changing MPA structure on MPA entry. Secondly, the thesis underlines how the existence of MPA and the dense clusters formed around them impact the small-world network structure of airline industry. Lastly the study explores the micro-macro linkages regarding relating the bridging behavior of non-member airlines and its impact on the whole-network of airline industry.

Limitations and Future Research

In any research, there are gaps which serve as opportunities for future research. The present study is limited in the following ways. Primarily, the study is limited to airline industry which might limit the generalizability of results in numerous ways. Unlike other industries, multipartner alliances in the airline industry are highly formalized and governed. The member airlines of MPAs are restricted from entering into alliances with member- airlines from other MPAs which as seen in the discussion section, impact the overall network structure of airline industry. Moreover, the major motivation behind alliance formation in airline industry is to seek better connectivity, scheduling and reduction in total travel time (Gudmundsson and Lechner, 2006) as opposed to knowledge intensive industry such as technology (Gulati et al., 2013), biotechnology (Powell, 1995) where major motive is knowledge exploitation and exploration. Another major reason for the formation of alliances in airlines industry is the strict regulatory environment. Often airlines face restriction on foreign ownership and control of airlines (Agusdinata & Klien, 2002). As such formation of large and formally governed multipartner alliances is a common norm in airline industry. The differences in industry environment might limit the inference of results of the current study to different contexts. However, the results of the current research provide a framework for replicating the study in other similar industries which are heavily regulated and where alliances are formally governed.

Secondly, the actor-level study investigating the impact of previous direct and indirect ties between member and non-member airline on MPA entry of non-members treats various types of ties such as codesharing agreements, joint marketing, equity governance, baggage handling, etc. as similar. These ties differ regarding resource commitment and complexity (Rhodes and Lush, 1997). As the aim of the study was to achieve a more holistic picture of dynamics of the network structure of airline industry; the different ties were aggregated when analyzing the direct and prior indirect member and non-member airline ties. Future research can look at the various types of ties individually and investigate if they exert a different impact on MPA entry of non-members.

Thirdly, when analyzing the impact of member and non-member ties at actor-level, the current research does not conducts an in-depth analysis of characteristics of member airlines. For instance, having a connection with central members within the airline vs. a peripheral airline might impact the MPA entry of non-members in different ways. The future research can consider the benefits of maintaining ties with central vs. non-central members of the given network on the entry of non-members.

Fourthly, actor-level analysis tests the impact of prior direct and indirect ties of non-member airline entry into the MPA. Another dependent variable worth exploring is member exit from the MPA. The exit of members from the dense clique is equally important as the entry of members for comprehending the network dynamics (Rowley et al., 2005). One could explore the impact of member airline ties to other MPA members as well as non-member's, airlines on its MPA exit. Beyond investigating the impact of member airline's immediate network future research could also explore the impact of member airline position in the MPA on member airline exit from the MPA.

Moreover, at the actor-level, the predictive analysis purely views the tie formation process from a network perspective. Although the network of an actor impacts its future ties, the strategic interdependence between the actors might also shape the tie formation behavior among actors (Gulati and Gargiulo, 1999). For instance, a study conducted concerning the formation of multipartner alliances in airline industry took into consideration the multimarket contact between airlines as a means of interdependencies among airline. Future research could incorporate this dimension while investigating the tie formation process at actor-level.

Lastly, at multilevel coevolution analysis the current research performs an exploratory analysis of how MPA entry and exit changes the structural configurations of the MPA network structure and whole network and in turn how the network structure might impact the tie formation behavior at actor-level. To further enrich our understanding regarding the evolutionary dynamics of various levels of network structure future research can statistically explore these propositions.

Conclusion

The study has outlined the evolution of airline network structure over a period of 13 years at airline, MPA and whole airline industry level. Beyond that, a genuine effort has been made towards understanding how tie formation among airlines modifies the MPA network and whole industry network structure and in turn how the whole industry network and MPA network structure impacts the tie formation process at actor-level.

What now? An actor's immediate network, as well as its position, determines it's the opportunities, and outcome. In the present context, that translates into non-member entry within the MPA. Thus, non-member airlines can strategically orchestrate their network so as to achieve desirable outcome rather than passively following the path. Moreover, as stated above, another generic network premise dictates the existence micro-macro linkages within a network. Thus, whatever actions member and non-member airlines undertake not only impacts them but affects the entire network. This becomes more imperative in case of multipartner airline alliances as they are collective entities comprising of a large number of airlines and as such their actions as a group would have a much stronger bearing on the whole network as well individual airlines within the airline industry.

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APPENDICES

Tables

Table 1: Sample size for each year - total number of airlines having at least one tie

Year	Airlines (n)
1994	170
1995	156
1996	172
1997	177
1998	190
1999	202
2000	184
2001	219
2002	164
2003	156
2004	118
2005	124
2006	128
2007	159

Table 2: Summary of variables

Variable	Nature	Network Level	Definition	Hypothetical effect on the Response Variable
MPA Entry	Binary	Actor Level	Entry of a non-member airline into the variable	Response Variable
Relational Embeddedness - Direct ties	Continuous	Actor	Direct ties between a non-member airline and a MPA member airline	+
Structural Embeddedness - Indirect ties	Continuous	Actor	Indirect ties between a non-member airline and a MPA member airline of path length two	+
Positional Embeddedness - Bonacich Centrality	Continuous	Actor	Bonacich centrality of each member is a function of its connections centralities	+
MPA Size	Continuous	Meso	No of Members in the multipartner Alliance	No prediction
MPA Network Density	Continuous	Meso	Ratio between actual dyadic ties to all the potential ties existing in a given network	No prediction
MPA Network Centralization	Continuous	Meso	Degree to which network is centralized around few members	No prediction
Network Average Path Length	Continuous	Whole Network	Average degree of seperation between any two given nodes in the network	No prediction
Network Clustering Coefficient	Continuous	Whole Network	It is obtained by averaging individual actors clustering coefficient where it is the degree to which an actor's connections are also linked to each other	No prediction

Table 3: Descriptive statistics

Variables	Mean	SD	Skewness	Kurtosis	Min	Max
MPA Entry	0.00	0.06	16.45	271.50	0.00	1.00
Direct Ties	1.26	1.44	1.62	5.42	0.00	4.41
Indirect Ties	0.48	0.75	2.40	8.99	0.00	2.83
Bonacich Centrality	0.20	0.33	0.30	0.60	0.00	1.84
Size	2.13	0.49	0.63	2.45	1.10	2.89
MPA Network Centralization	0.27	0.17	-0.50	2.77	0.00	0.69
MPA Network Density	0.48	0.17	0.50	3.33	0.00	0.69
Average Path Length	0.26	0.32	-0.40	1.76	2.64	3.55
Clustering Coefficient	0.26	0.05	0.08	1.82	0.20	0.34

Table 4: Descriptive Statistics of log-transformed variables

Variables	Skewness	Kurtosis
Log_Direct Ties	0.41	1.41
Log_Indirect Ties	1.27	3.24
Log_Bonacich Centrality	1.90	1.90

Table 5: Correlation Matrix

	MPA Entry	Direct Ties	Indirect Ties	Bonacich Centrality	MPA Size	MPA Network Density	MPA Network Centralization
MPA Entry	1						
Direct Ties	0.034***	1					
Indirect Ties	0.061***	0.70***	1				
Bonacich Centrality	0.13***	0.50***	0.66***	1			
MPA Size	0.017	0.067***	0.16***	-0.043***	1		
MPA Network Density	-0.014	-0.088***	-0.030***	-0.035***	-0.19***	1	
MPA Network Centralization	0.025**	0.092***	0.079***	0.0051	0.26***	-0.43***	1

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 6: Correlation Matrix – residual independent and other variables

	MPA Entry	Direct Ties	Res_Indirect Ties	Res_Bonacich Centrality	MPA Size	MPA Network Density	MPA Network Centralization
MPA Entry	1						
Direct Ties	0.034***	1					
Res_Indirect Ties	0.053***	-0.000000055	1				
Res_Bonacich Centrality	0.12***	-0.000000055	0	1			
MPA Size	0.017	0.067***	0.15***	-0.16***	1		
MPA Network Density	-0.014	-0.088***	0.046***	-0.030**	-0.19***	1	
MPA Network Centralization	0.025**	0.092***	0.018	-0.051***	0.26***	-0.43***	1

* p<0.05 ** p<0.01 *** p<0.001

Table 7: Two-step residual random effect panel logistic regression

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-6.47***	-6.97***	-6.45***	-8.45***
	(-8.70)	(-8.91)	(-8.39)	(-9.35)
Direct_Ties		0.34**	0.23	0.13
		(3.16)	(1.80)	(0.89)
Res_Indirect_Ties			1.28***	0.79*
			(4.15)	(2.49)
Res_Bonacich				4.16***
				(9.43)
MPA_Size	0.050	0.037	-0.0061	0.11**
	(1.51)	(1.08)	(-0.16)	(2.70)
MPA_Network_Density	-0.33	-0.18	-0.52	0.27
	(-0.44)	(-0.23)	(-0.67)	(0.35)
MPA_Network_Centralization	1.58*	1.49*	1.48*	1.53*
	(2.22)	(2.06)	(2.02)	(2.05)
N	12034	12034	12034	12034
rho	0.00	0.00	0.00	0.00
chi2	8.45	18.9	43.1	133.3

t statistics in parentheses; t statistics in parentheses
* p<0.05   ** p<0.01   *** p<0.001

Table 8: Two-step residual random effect panel logistic regression, odds ratio

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Direct_Ties		1.40**	1.26	1.14
		(3.16)	(1.80)	(0.89)
Res_Indirect_Ties			3.59***	2.20*
			(4.15)	(2.49)
Res_Bonacich				63.9***
				(9.43)
MPA_Size	1.05	1.04	0.99	1.11**
	(1.51)	(1.08)	(-0.16)	(2.70)
MPA_Network_Density	0.72	0.84	0.60	1.32
	(-0.44)	(-0.23)	(-0.67)	(0.35)
MPA_Network_Centralization	4.84*	4.44*	4.38*	4.60*
	(2.22)	(2.06)	(2.02)	(2.05)
N	12034	12034	12034	12034
rho	0.00	0.00	0.00	0.00
chi2	8.45	18.9	43.1	133.3

Exponentiated coefficients ; t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 9: Random effect panel logistic model with interactions

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	-6.21***	-8.50***	-8.26***	-8.89***
	(-8.08)	(-7.51)	(-9.10)	(-7.12)
Direct_Ties	-0.042	-0.0088		-0.067*
	(-1.91)	(-0.64)		(-1.98)
Indirect_Ties	0.40***		0.17**	0.37***
	(6.50)		(3.02)	(3.55)
Bonachich		1.49***	1.73***	1.76***
		(9.12)	(10.30)	(7.54)
Direct Ties × Indirect ties	-0.0085*			-0.0037
	(-2.19)			(-0.76)
Bonachich × Direct ties		-0.059***		-0.014
		(-3.55)		(-0.52)
Bonachich × Indirect ties			-0.21***	-0.22**
			(-4.73)	(-2.99)
MPA_Size	0.030	0.16***	0.12**	0.17***
	(0.70)	(3.67)	(2.68)	(3.36)
MPA_Network_Density	-0.44	0.36	0.23	0.36
	(-0.56)	(0.45)	(0.29)	(0.44)
MPA_Network_Centralization	1.18	1.37	1.69*	1.43
	(1.54)	(1.84)	(2.31)	(1.84)
N	12034	12034	12034	12034
rho	0.00	0.00	0.00	0.00
chi2	63.1	86.3	126.8	81.7

t statistics in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 10: Random effect panel logistic regression with interactions, odds ratio

Variables	Model 1	Model 2	Model 3	Model 4
Intercept	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Direct_Ties	0.96 (-1.91)	0.99 (-0.64)		0.93* (-1.98)
Indirect_Ties	1.49*** (6.50)		1.18** (3.02)	1.45*** (3.55)
Bonachich		4.43*** (9.12)	5.65*** (10.30)	5.81*** (7.54)
Direct Ties × Indirect ties	0.99* (-2.19)			1.00 (-0.76)
Bonachich × Direct ties		0.94*** (-3.55)		0.99 (-0.52)
Bonachich × Indirect ties			0.81*** (-4.73)	0.80** (-2.99)
MPA_Size	1.03 (0.70)	1.17*** (3.67)	1.13** (2.68)	1.19*** (3.36)
MPA_Network_Density	0.65 (-0.56)	1.43 (0.45)	1.26 (0.29)	1.43 (0.44)
MPA_Network_Centralization	3.24 (1.54)	3.95 (1.84)	5.41* (2.31)	4.16 (1.84)
N	12034	12034	12034	12034
rho	0.00	0.00	0.00	0.00
chi2	63.1	86.3	126.8	81.7

Exponentiated coefficients ; t statistics in parentheses

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 11: Overall MPA network density and centralization (1994-2007)

Year	No. of MPAs	No. Of Members per MPA	Total number of No. of ties	No of ties per MPA	Average degree	Centralization	Density
1994	1	4	6.00	6.00	2.00	0.00	1.00
1995	1	3	6.00	6.00	2.00	0.00	1.00
1996	1	3	6.00	6.00	2.00	0.00	1.00
1997	3	4	10.00	3.33	2.22	0.13	0.91
1998	3	5	6.00	2.00	1.39	0.24	0.43
1999	4	5	10.00	2.50	1.65	0.39	0.53
2000	5	8	26.00	5.20	3.13	0.46	0.60
2001	5	7	27.00	5.40	3.01	0.62	0.53
2002	4	8	43.50	10.88	4.75	0.27	0.80
2003	3	10	58.67	19.56	5.59	0.25	0.71
2004	3	11	112.00	37.33	8.04	0.33	0.67
2005	3	11	74.00	24.67	6.44	0.27	0.69
2006	3	11	86.00	28.67	7.15	0.31	0.73
2007	3	11	86.00	28.67	6.86	0.34	0.68

Table 12: Meso-Level Analysis - MPA Density and network centralization

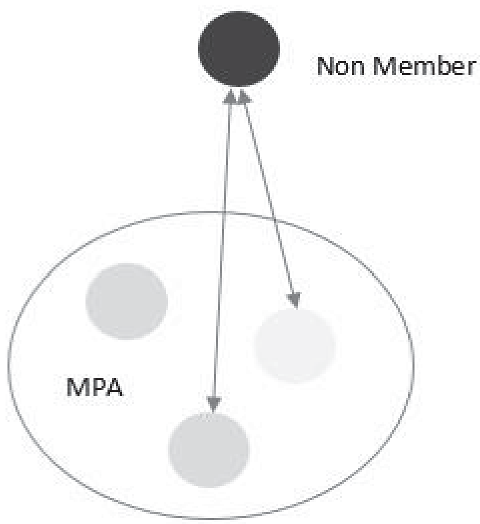
Year	Alliance	No. Of Members	Density	No. of ties	Av degree	Centralization
1997	Atlantic Excellence	2	1.00	2.00	1.00	0.00
1998	Atlantic Excellence	4	1.00	12.00	3.00	0.00
1994	Global Excellence	4	1.00	6.00	2.00	0.00
1995	Global Excellence	3	1.00	6.00	2.00	0.00
1996	Global Excellence	3	1.00	6.00	2.00	0.00
1997	Global Excellence	3	1.00	6.00	2.00	0.00
1999	One World	7	0.57	24.00	3.43	0.60
2000	One World	8	0.54	30.00	3.75	0.62
2001	One World	9	0.46	33.00	3.67	0.21
2002	One World	8	0.71	40.00	5.00	0.38
2003	One World	8	0.75	42.00	5.25	0.14
2004	One World	9	0.89	64.00	7.11	0.14
2005	One World	8	0.89	50.00	6.25	0.14
2006	One World	8	0.71	40.00	5.00	0.38
2007	One World	8	0.64	36.00	4.50	0.48
1998	Qualiflyer	4	0.17	2.00	0.50	0.33
1999	Qualiflyer	3	0.33	2.00	0.67	0.50
2000	Qualiflyer	11	0.53	16.00	2.67	0.70
2001	Qualiflyer	6	0.53	16.00	2.67	0.70
2000	Skyteam	4	0.83	10.00	2.50	0.33
2001	Skyteam	5	0.60	12.00	2.40	0.67
2002	Skyteam	6	0.80	24.00	4.00	0.30
2003	Skyteam	6	0.87	26.00	4.33	0.20
2004	Skyteam	6	0.57	136.00	8.50	0.42
2005	Skyteam	9	0.67	48.00	5.33	0.27
2006	Skyteam	9	0.81	58.00	6.44	0.25
2007	Skyteam	9	0.81	58.00	6.44	0.25
1997	Star Alliance	6	0.73	22.00	3.67	0.40
1998	Star Alliance	6	0.13	4.00	0.67	0.40
1999	Star Alliance	8	0.21	12.00	1.50	0.48
2000	Star Alliance	13	0.45	70.00	5.39	0.65
2001	Star Alliance	14	0.39	70.00	5.00	0.54
2002	Star Alliance	13	0.67	104.00	8.00	0.39
2003	Star Alliance	15	0.51	108.00	7.20	0.40
2004	Star Alliance	17	0.57	136.00	8.50	0.42
2005	Star Alliance	17	0.52	124.00	7.75	0.40
2006	Star Alliance	17	0.67	160.00	10.00	0.31

2007	Star Alliance	17	0.60	164.00	9.65	0.31
1999	Wings	2	1.00	2.00	1.00	0.00
2000	Wings	2	0.67	4.00	1.33	0.00
2001	Wings	3	0.67	4.00	1.33	1.00
2002	Wings	3	1.00	6.00	2.00	0.00

Table 13: Small World Statistics of Airline Industry (1994-2007)

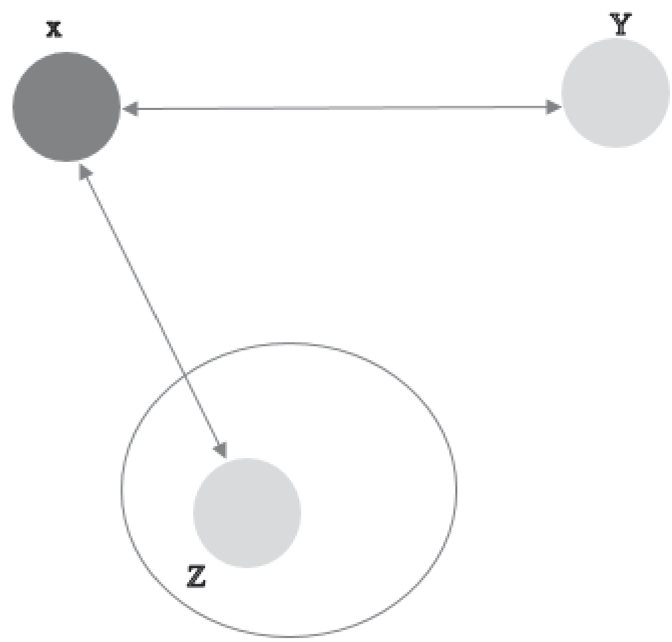
Year	Ties	Airlines (n)	Ties/Airlines (k)	C_{ACTUAL}	C_{RANDOM} k/n	CA/CR	L_{ACTUAL}	In(n)	In(k)	l_{RANDOM} In(n)/In(k)	LA/LR	Small world $\frac{CA/CR}{LA/LR}$
1994	530	170	3.12	0.20	0.02	11.01	3.55	2.23	0.49	4.52	0.78	14.03
1995	644	156	4.13	0.21	0.03	7.82	3.45	2.19	0.62	3.56	0.97	8.07
1996	768	172	4.47	0.26	0.03	10.09	3.44	2.24	0.65	3.44	1.00	10.10
1997	876	177	4.95	0.27	0.03	9.66	3.27	2.25	0.69	3.24	1.01	9.57
1998	940	190	4.95	0.25	0.03	9.41	3.50	2.28	0.69	3.28	1.07	8.83
1999	1052	202	5.21	0.24	0.03	9.39	3.23	2.31	0.72	3.22	1.00	9.34
2000	1186	184	6.45	0.21	0.04	6.02	3.27	2.26	0.81	2.80	1.17	5.16
2001	891	219	4.07	0.21	0.02	11.20	3.17	2.34	0.61	3.84	0.83	13.56
2002	1012	164	6.17	0.30	0.04	7.97	3.15	2.21	0.79	2.80	1.12	7.10
2003	1052	156	6.74	0.34	0.04	7.84	3.05	2.19	0.83	2.65	1.15	6.81
2004	952	118	8.07	0.29	0.07	4.23	2.67	2.07	0.91	2.28	1.17	3.62
2005	1010	124	8.15	0.33	0.07	5.02	2.67	2.09	0.91	2.30	1.16	4.33
2006	1090	128	8.52	0.30	0.07	4.43	2.64	2.11	0.93	2.27	1.17	3.80
2007	1196	159	7.52	0.29	0.05	6.09	2.76	2.20	0.88	2.51	1.10	5.53

Figure 1: One step ties



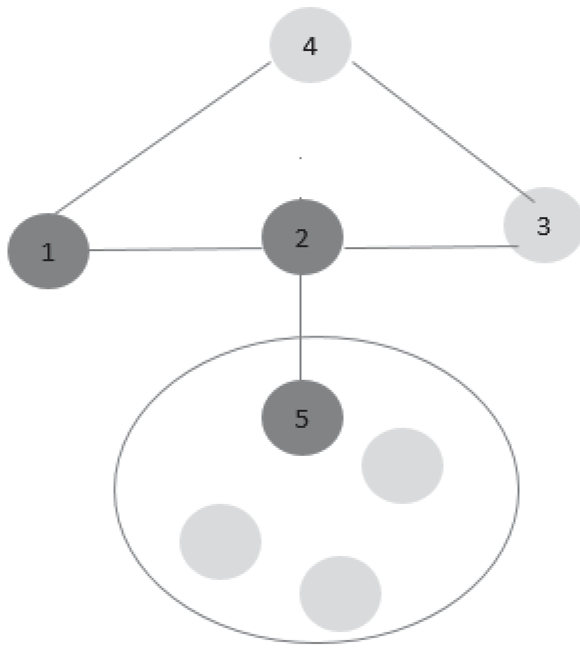
The circle represents the MPA

Figure 2: Indirect ties of non-member and member airlines



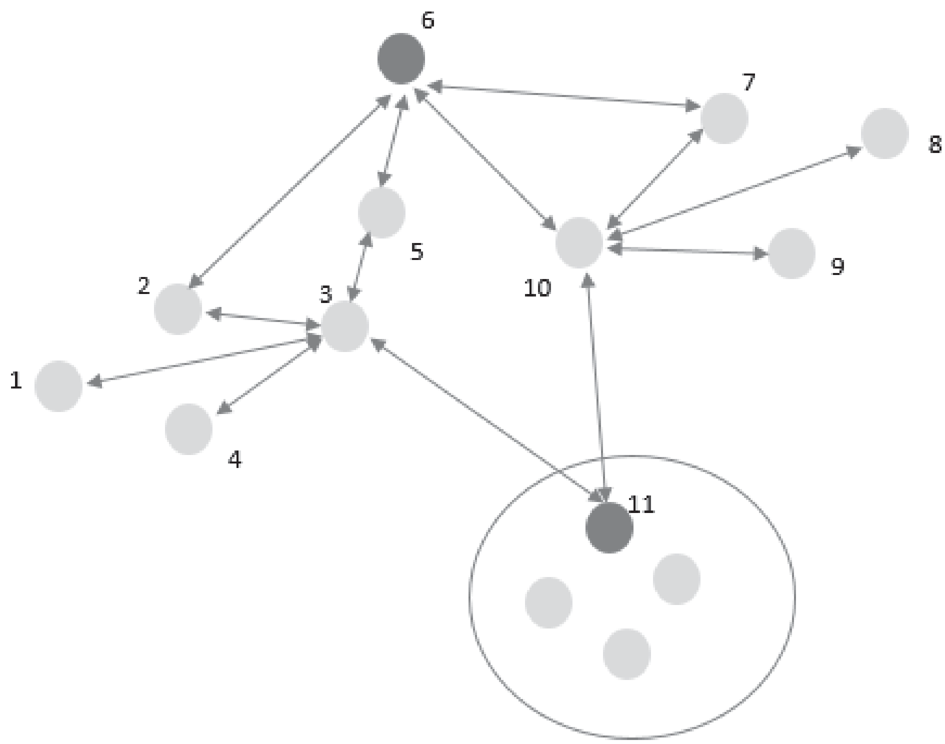
The circle represents the MPA

Figure 3: Two-step indirect tie between member and non-member airlines



The circle represents the MPA

Figure 4: Bonacich/ Eigenvector Centrality



The circle represents the MPA

Figure 5: Star Alliance member network prior to the alliance formation (1996)

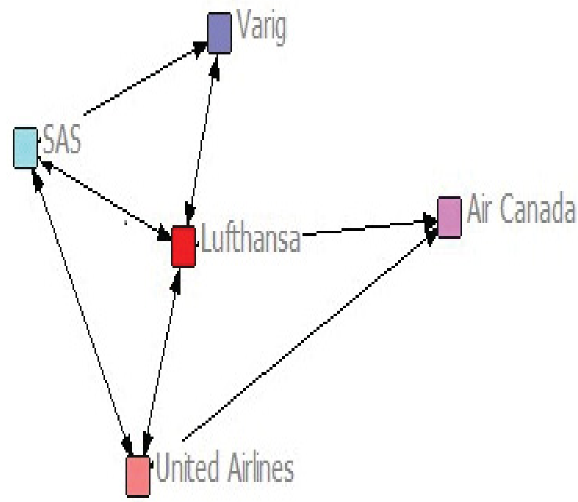


Figure 6: Northwestern Airline network, 2003

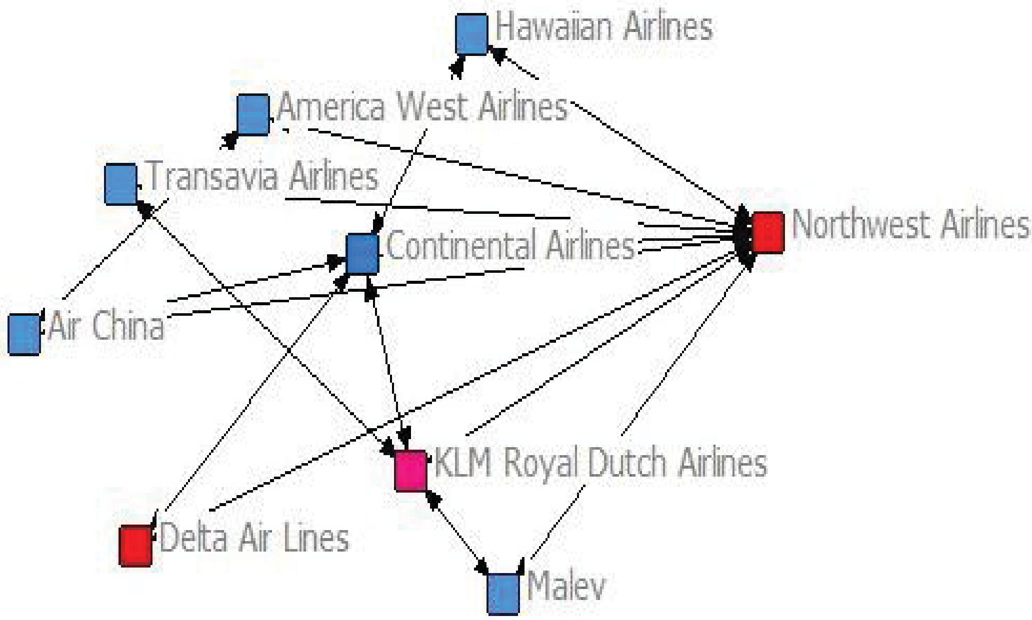


Figure 7: Membership in MPA 1994-2007

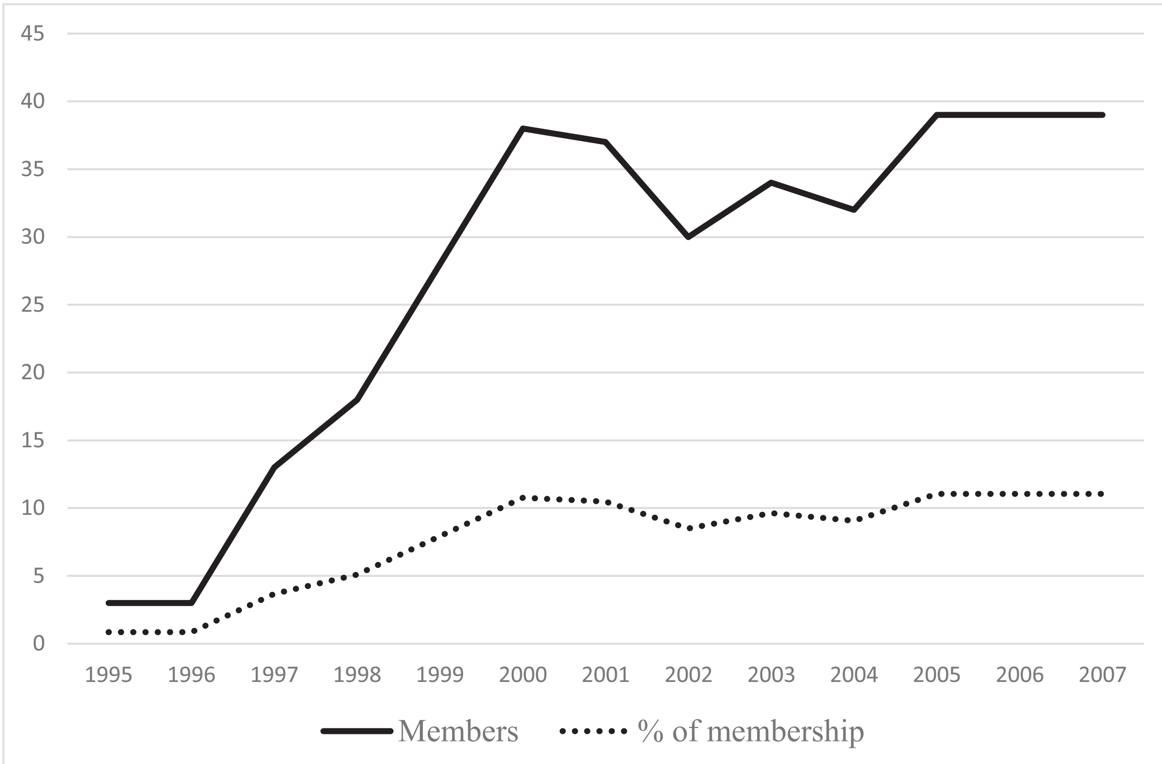


Figure 8: Non-member airline 1994-2007

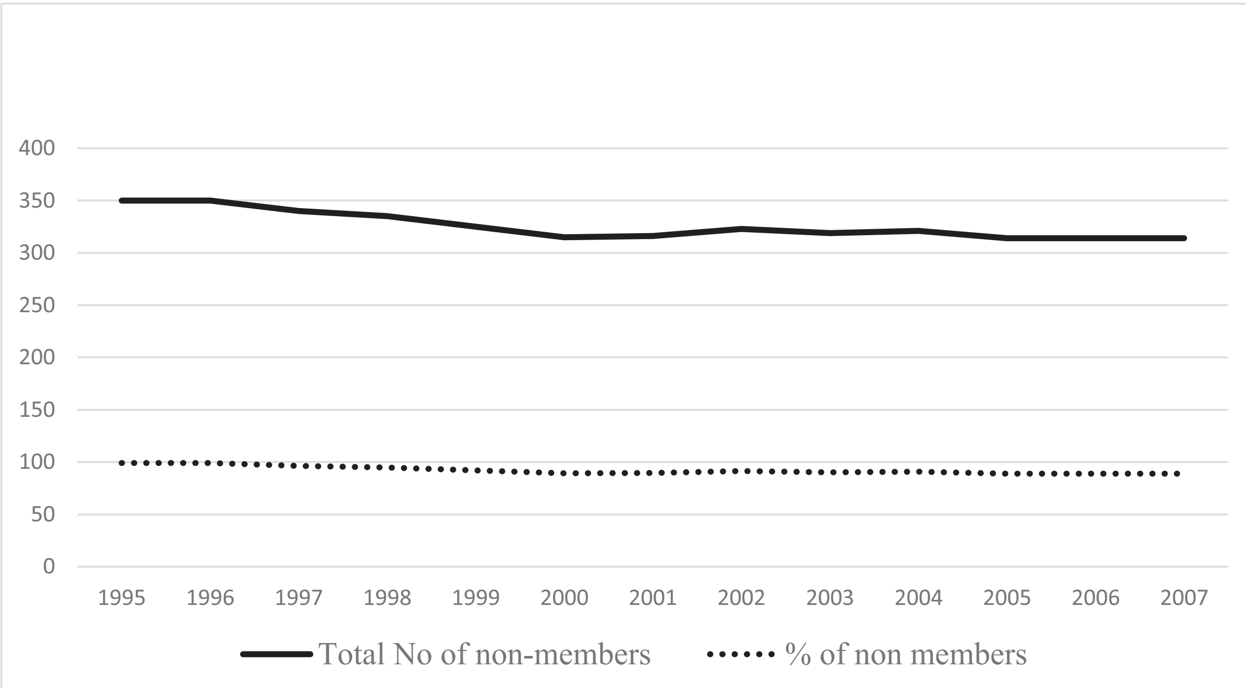


Figure 9: Non-member – member ties

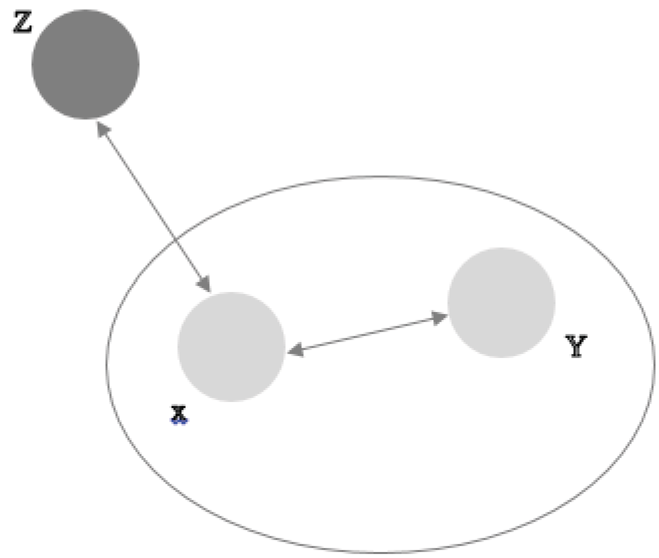


Figure 10: Impact of indirect ties on MPA entry at various levels of direct ties

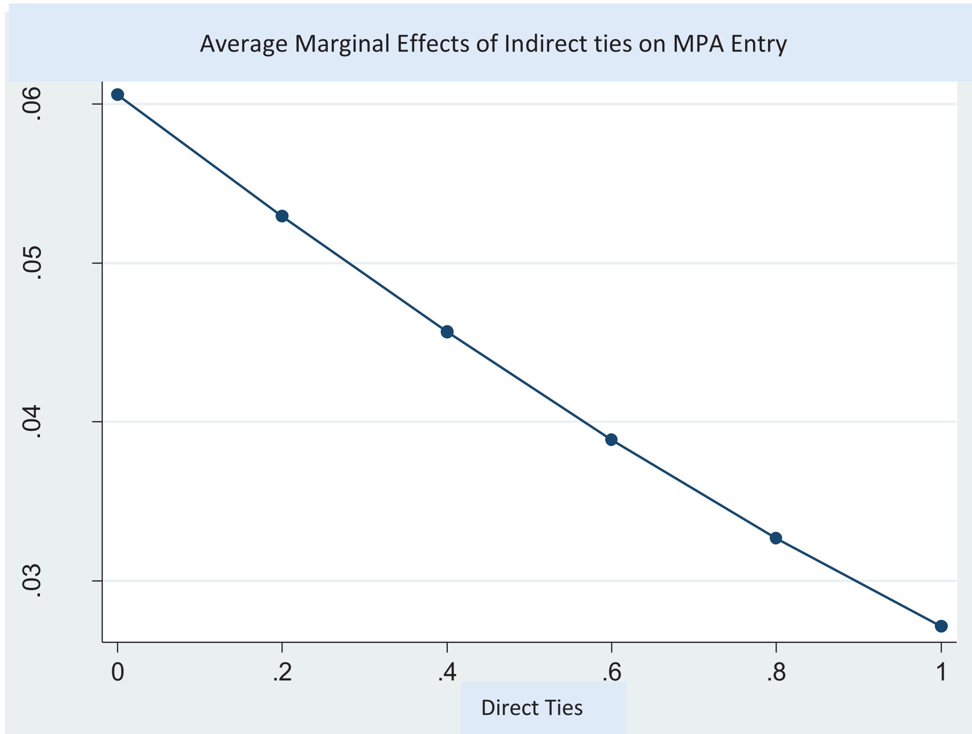


Figure 11: Impact of Bonacich centrality on non-member entry at various levels of direct ties

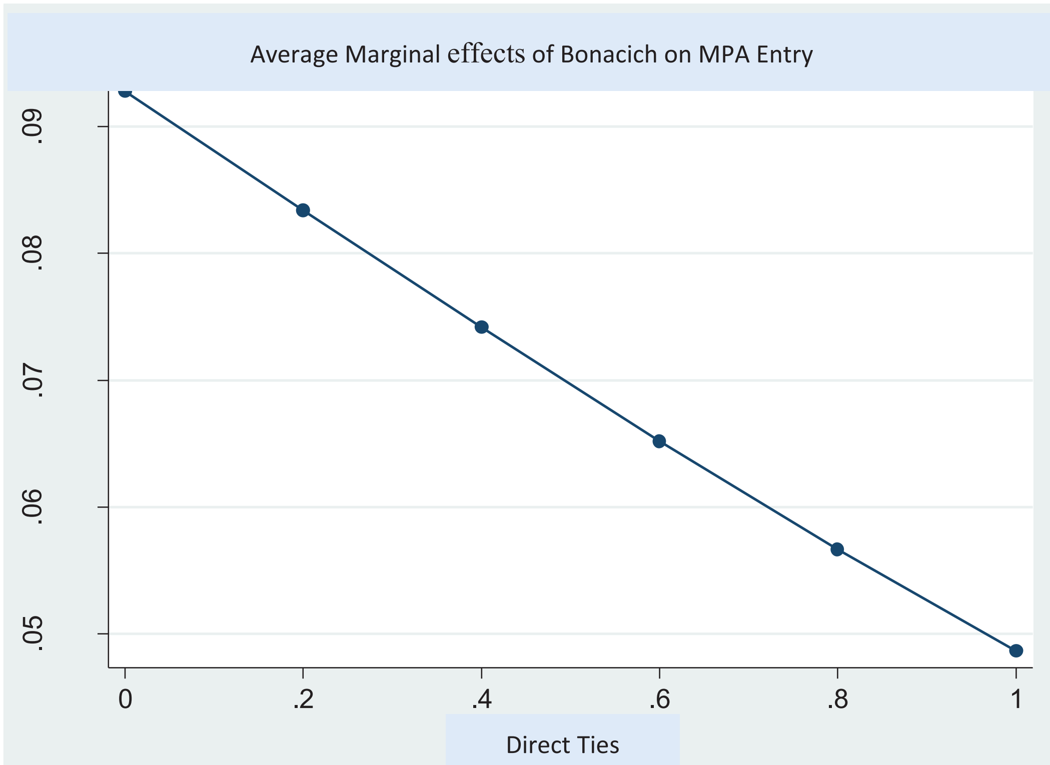


Figure 12: Impact of Bonacich centrality on MPA entry at various levels of indirect ties

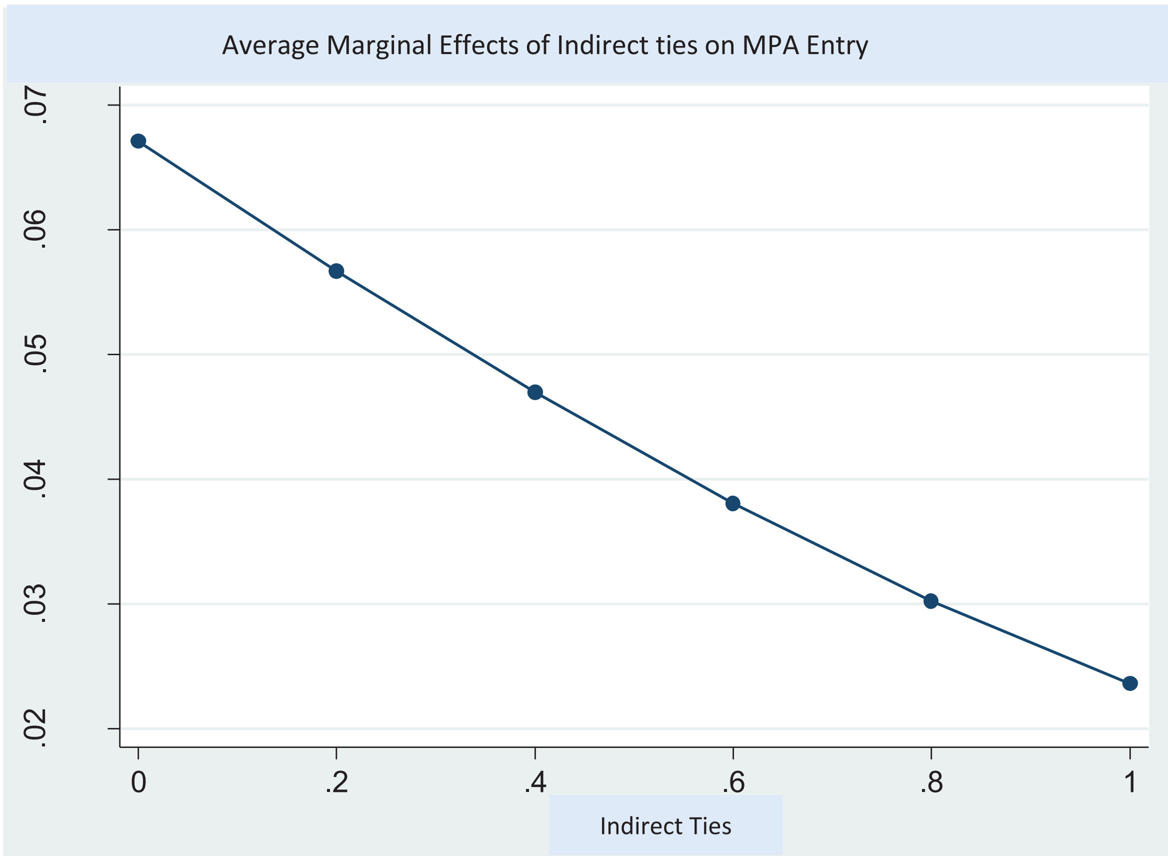
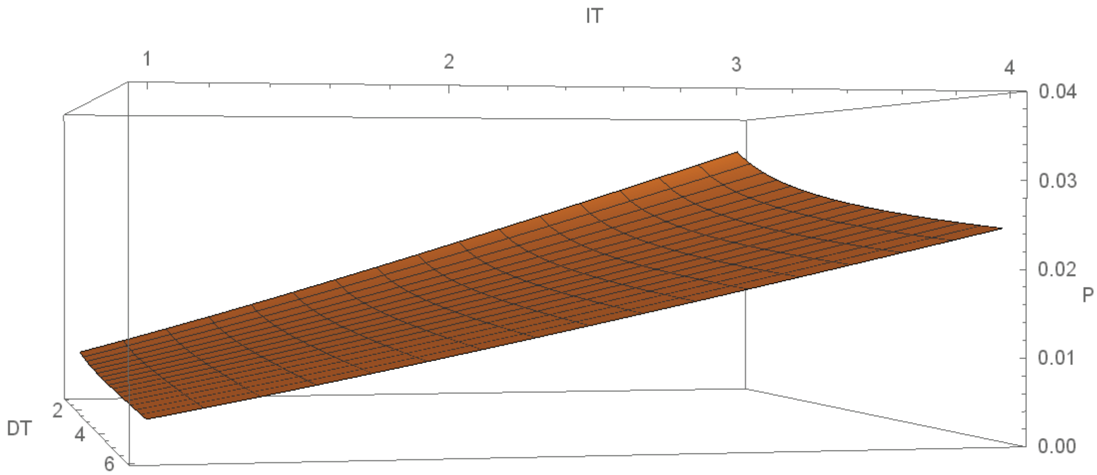


Figure 13: Marginal effect of indirect ties on the MPA entry at varying level of direct ties



DT = direct ties

IT= Indirect ties|

P = Probability of entry in the MPA

Figure 14: MPA Density and Centralization (1994-2007)

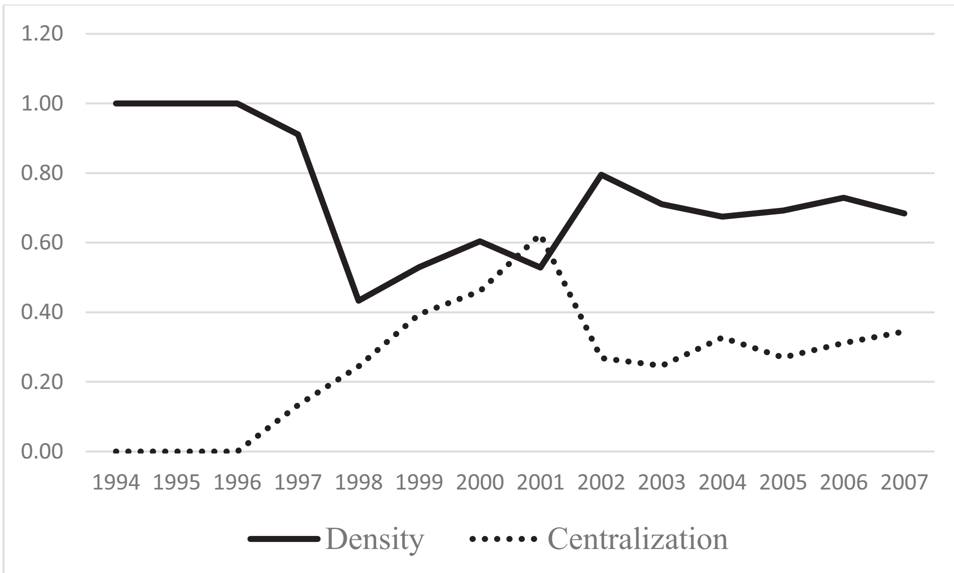


Figure 15: Average number of members per MPA and their average degree (1994-2007)

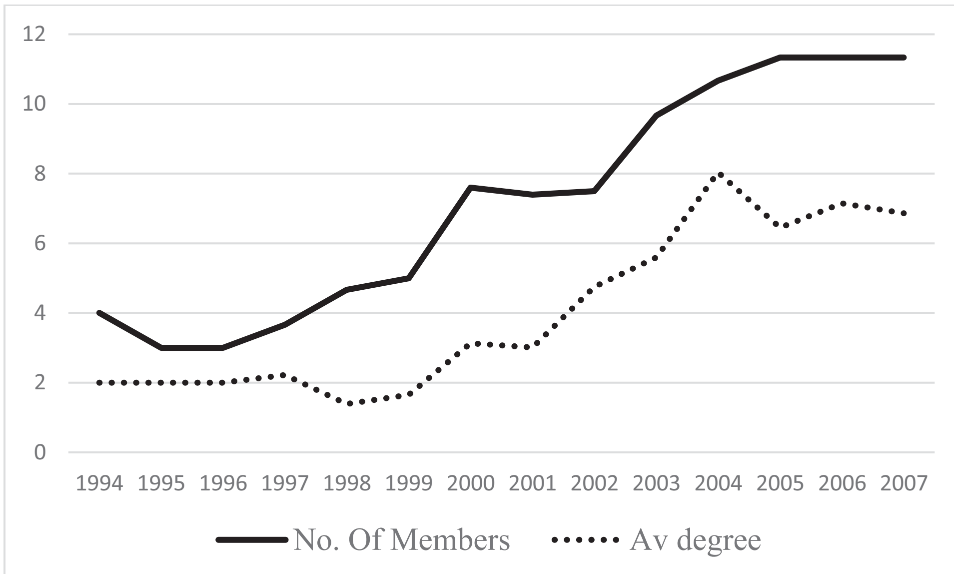


Figure 16: Star Alliance- Density and Centralization (1994-2007)

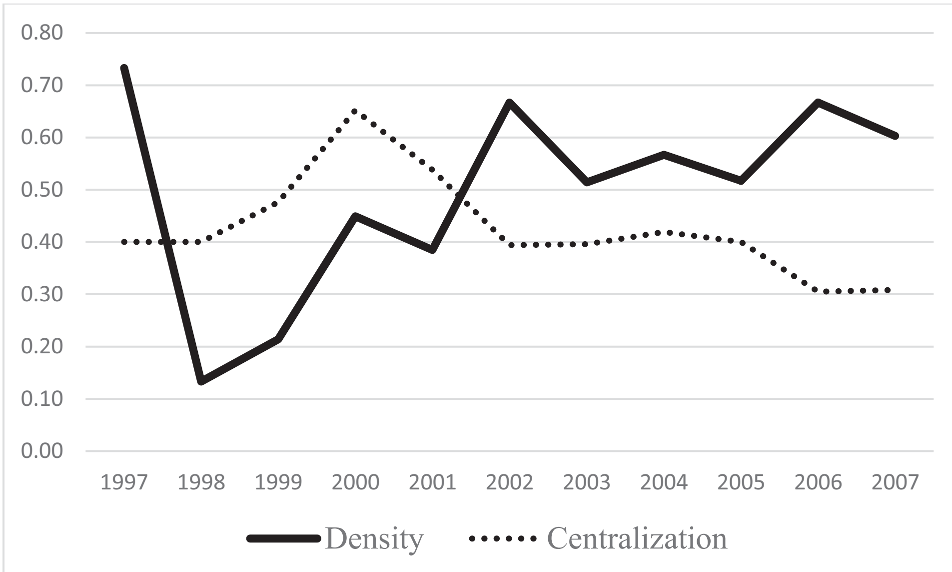


Figure 17: OneWorld- Density and Centralization (1994-2007)

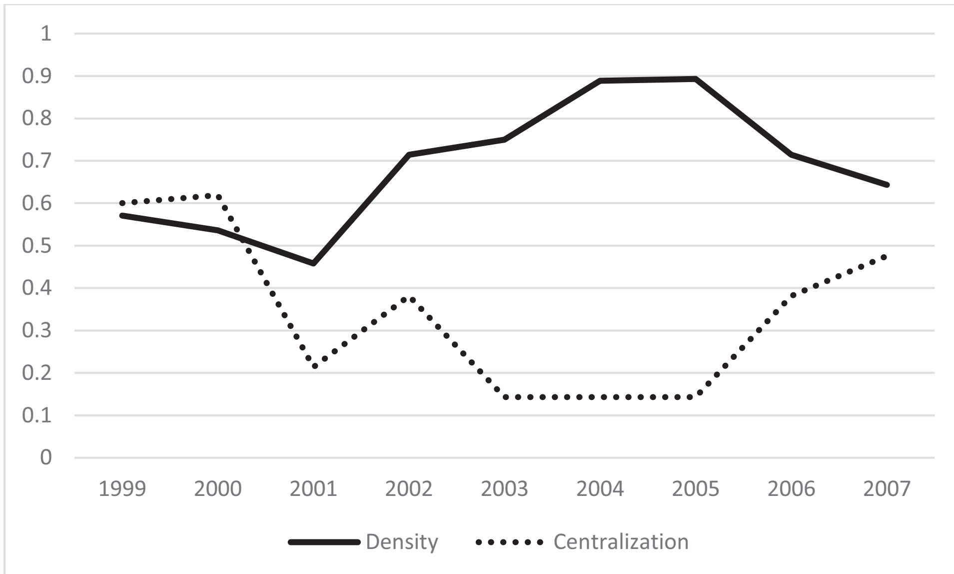


Figure 18: Sky Team- Density and Centralization, (1994-2007)

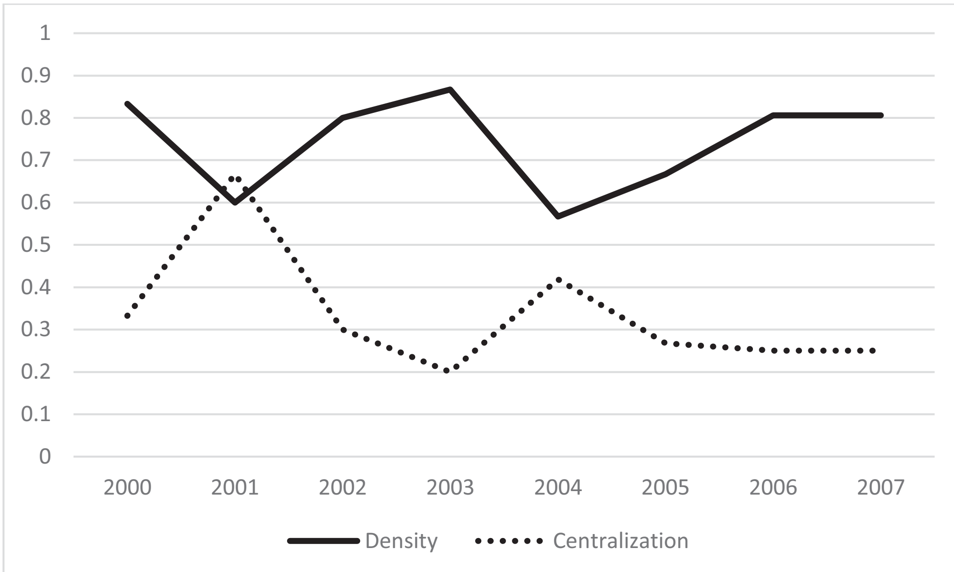


Figure 19: Star Alliance network, 1997

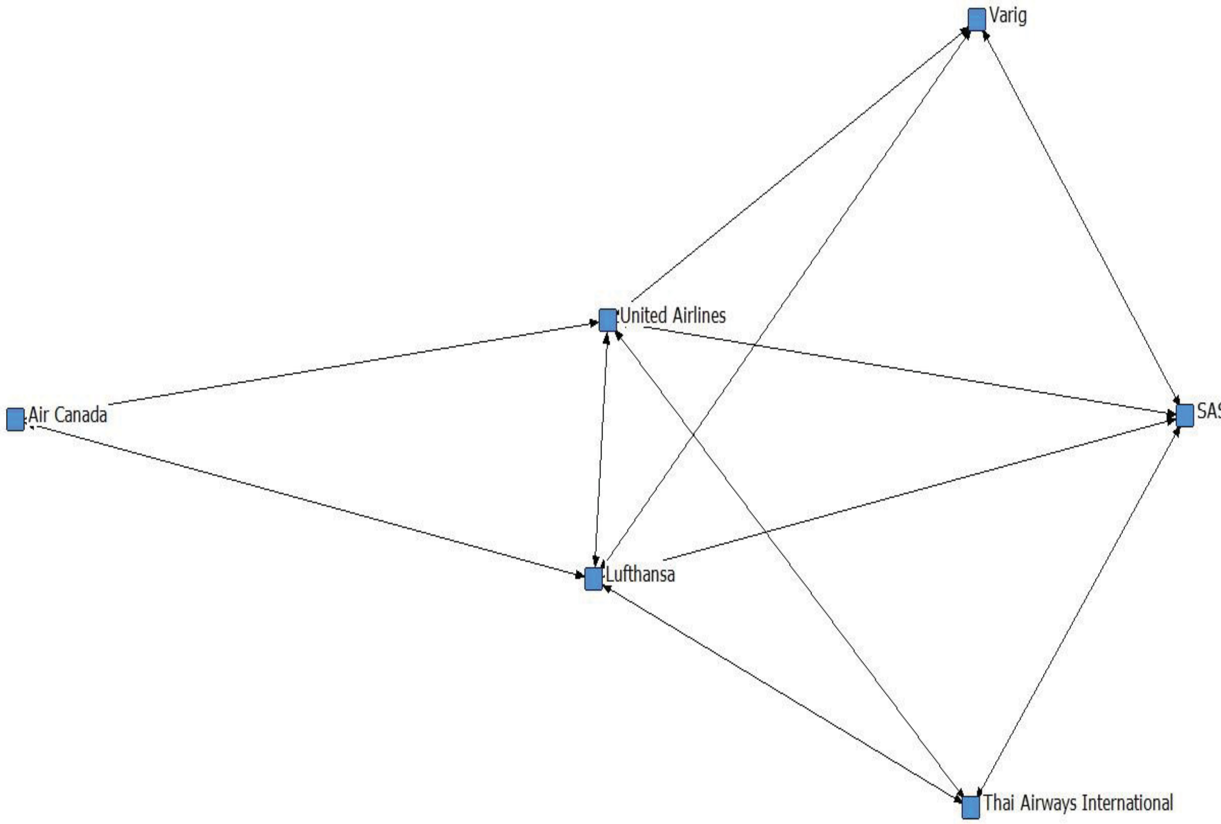


Figure 20: Star Alliance network, 2000

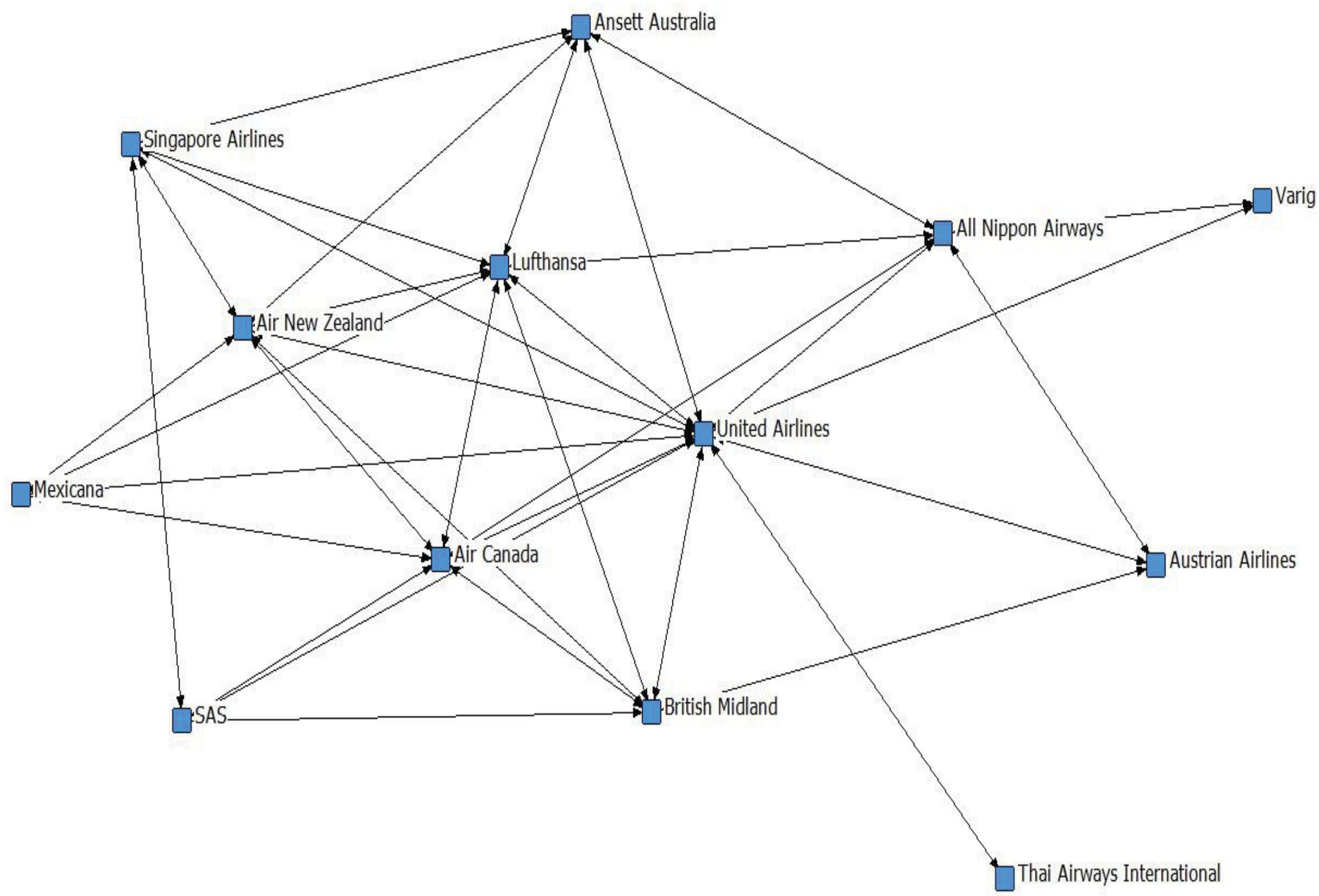


Figure 21: Star Alliance network, 2006

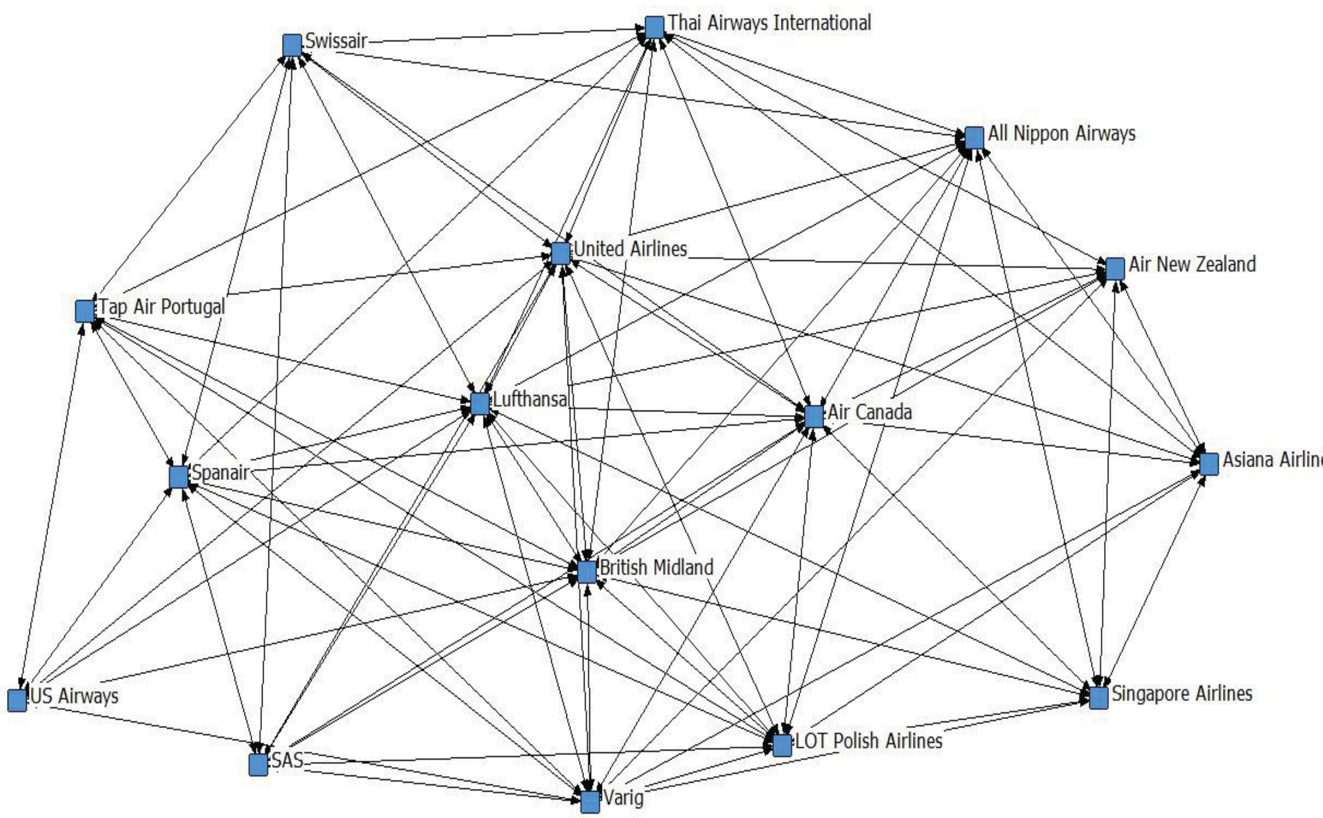


Figure 22: Oneworld network, 1999

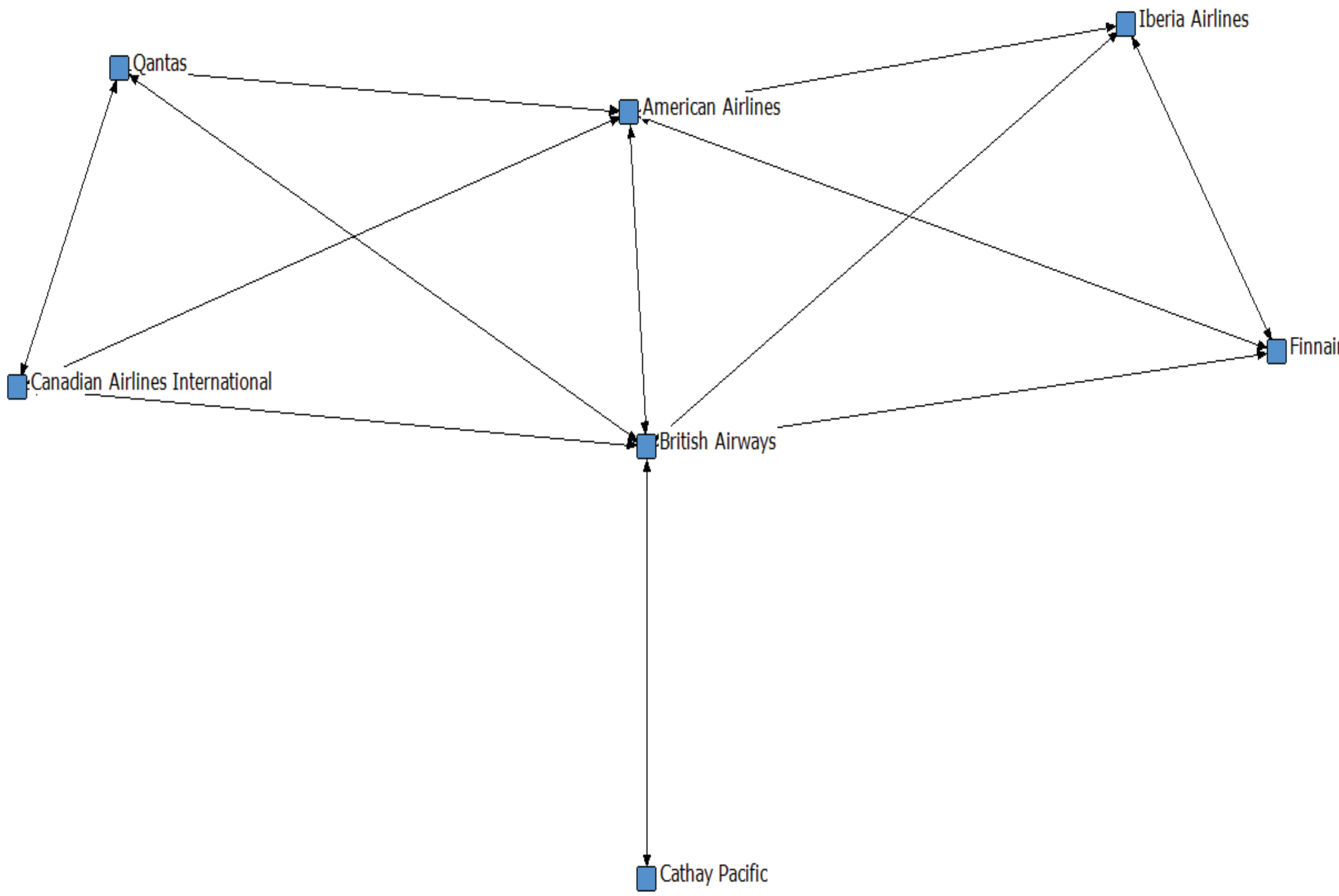


Figure 23: Oneworld network, 2003

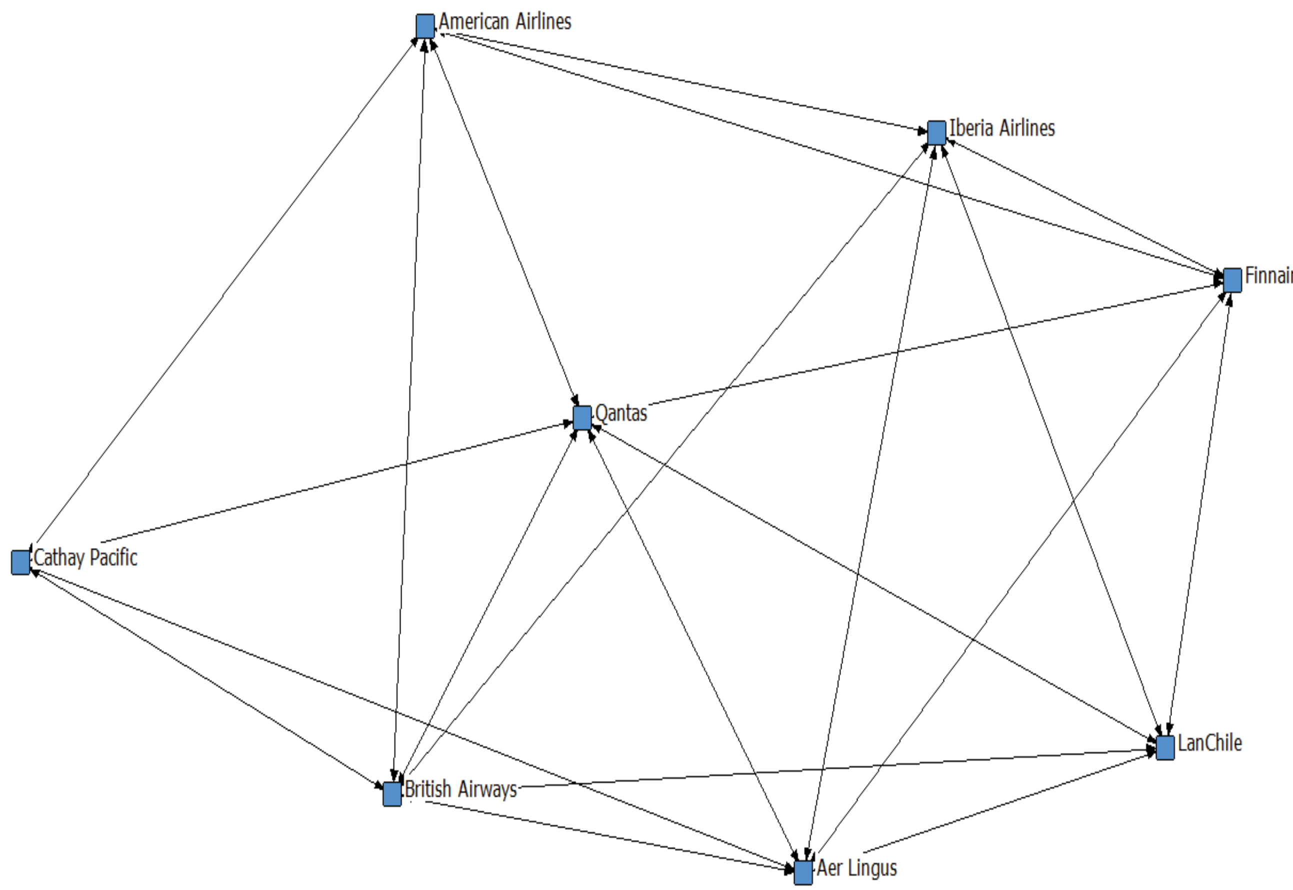


Figure 24: Oneworld network, 2006

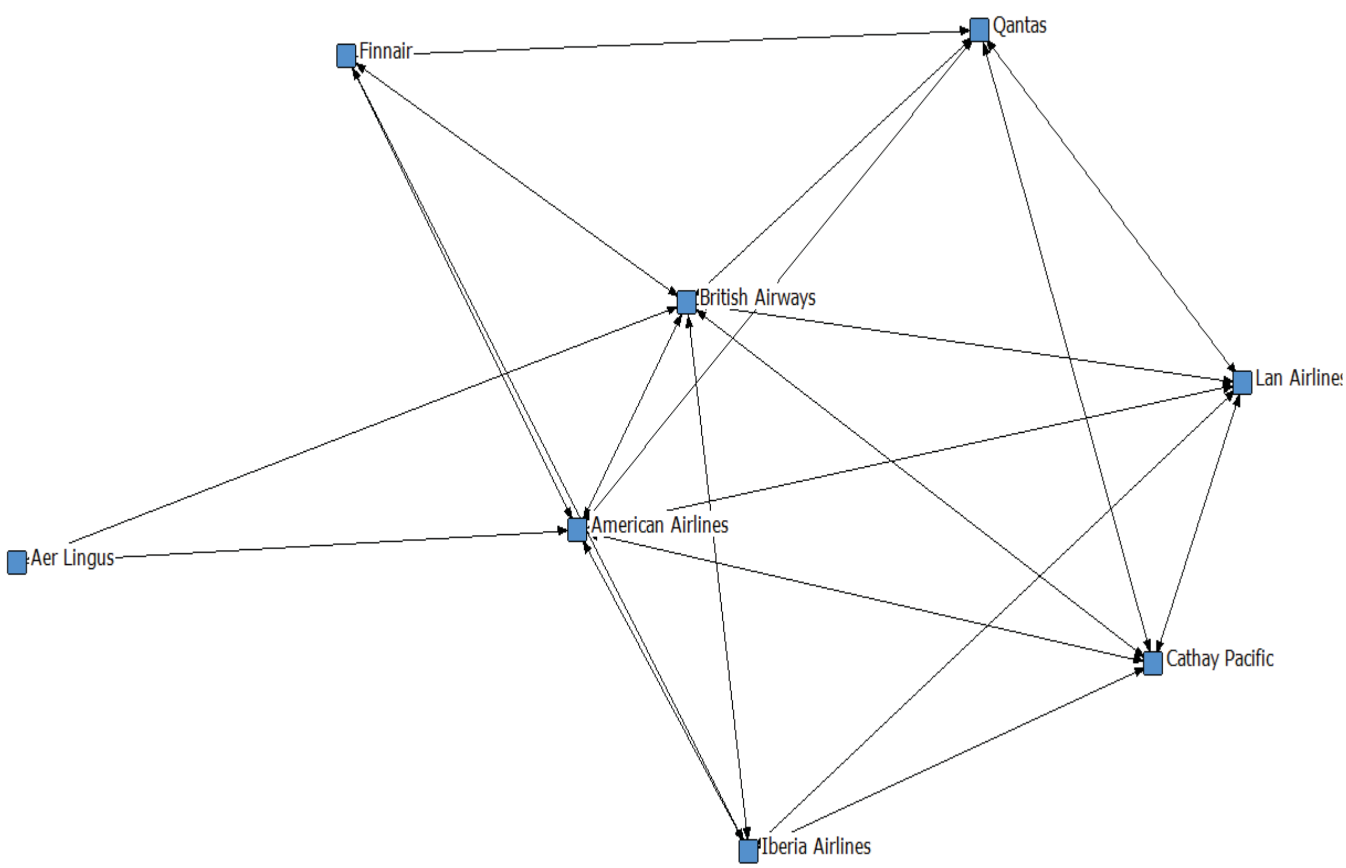


Figure 25: SkyTeam network, 2000

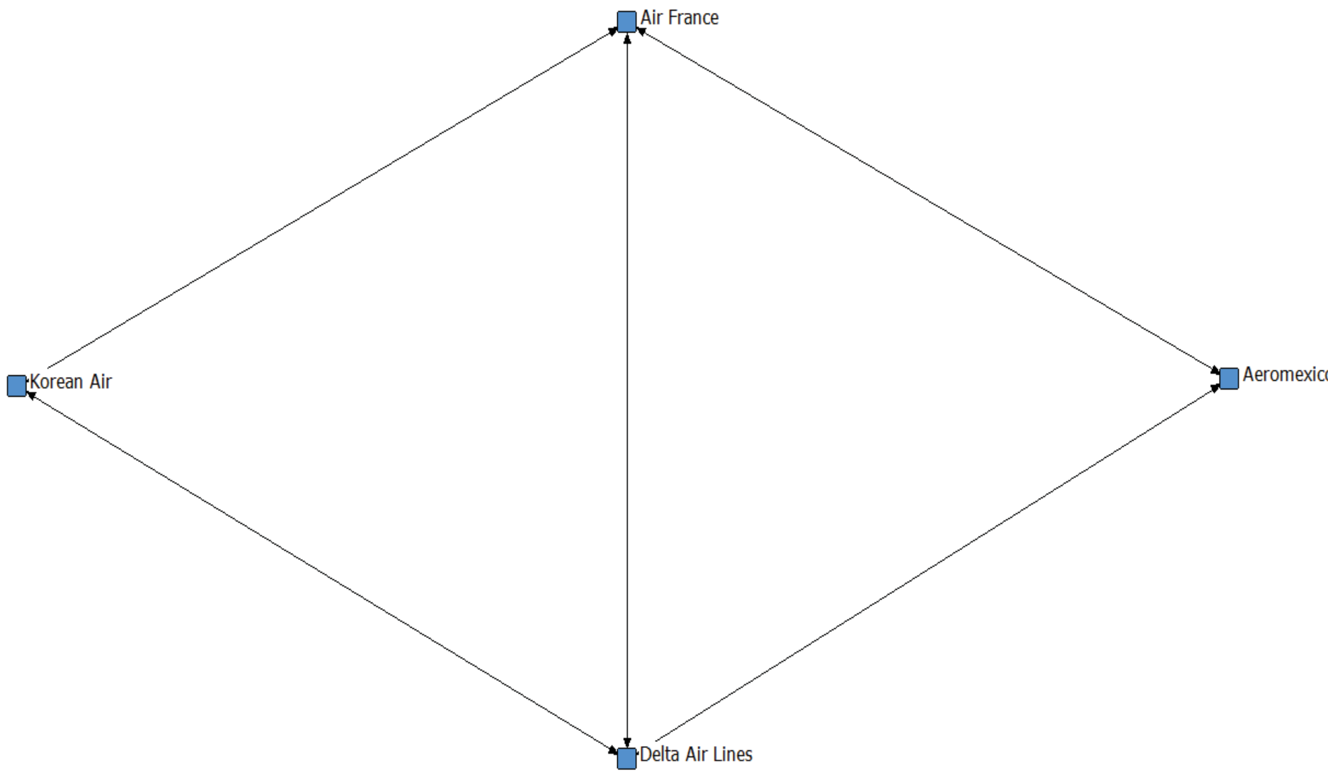


Figure 26: SkyTeam network 2003

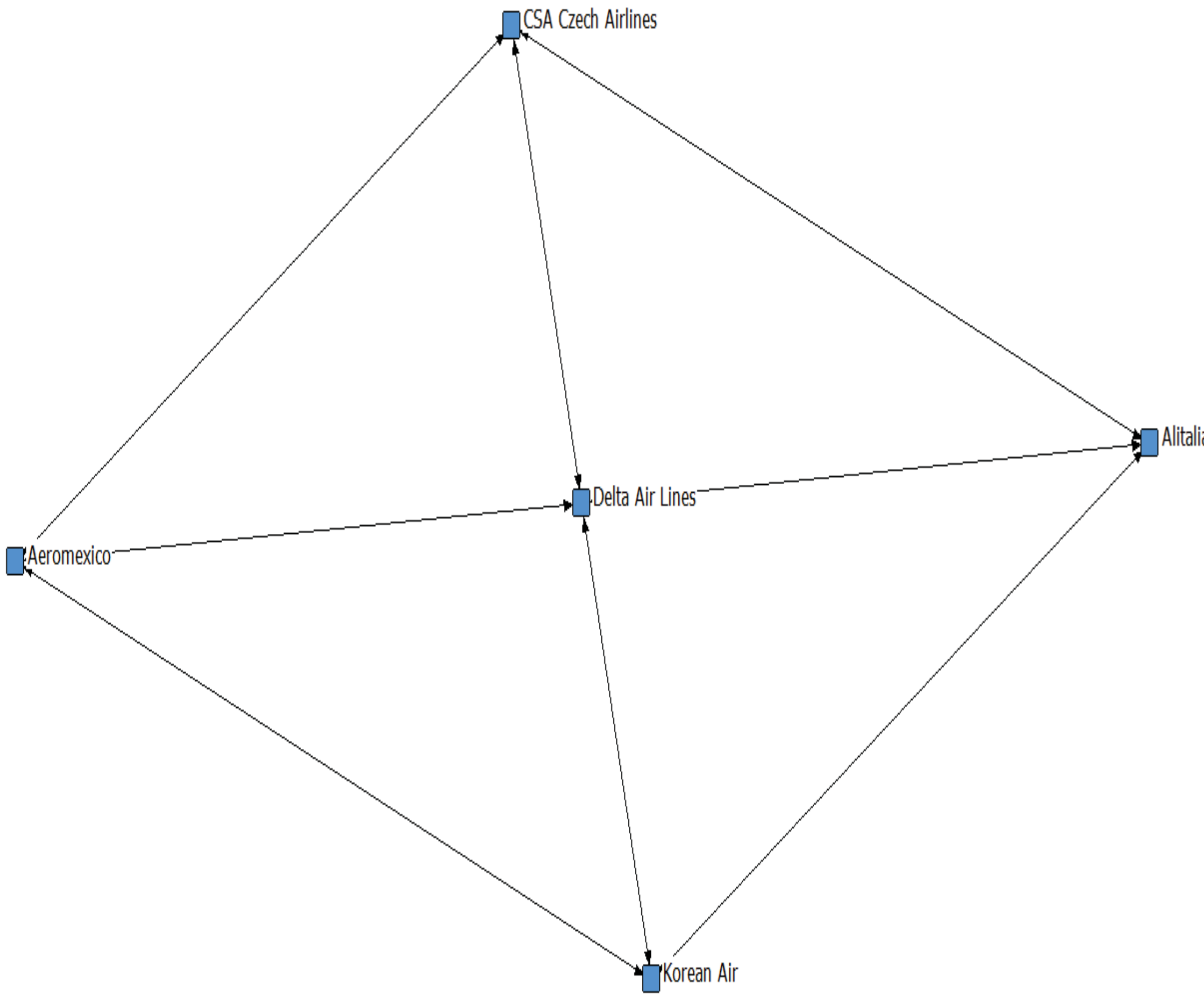


Figure 27: SkyTeam network 2006

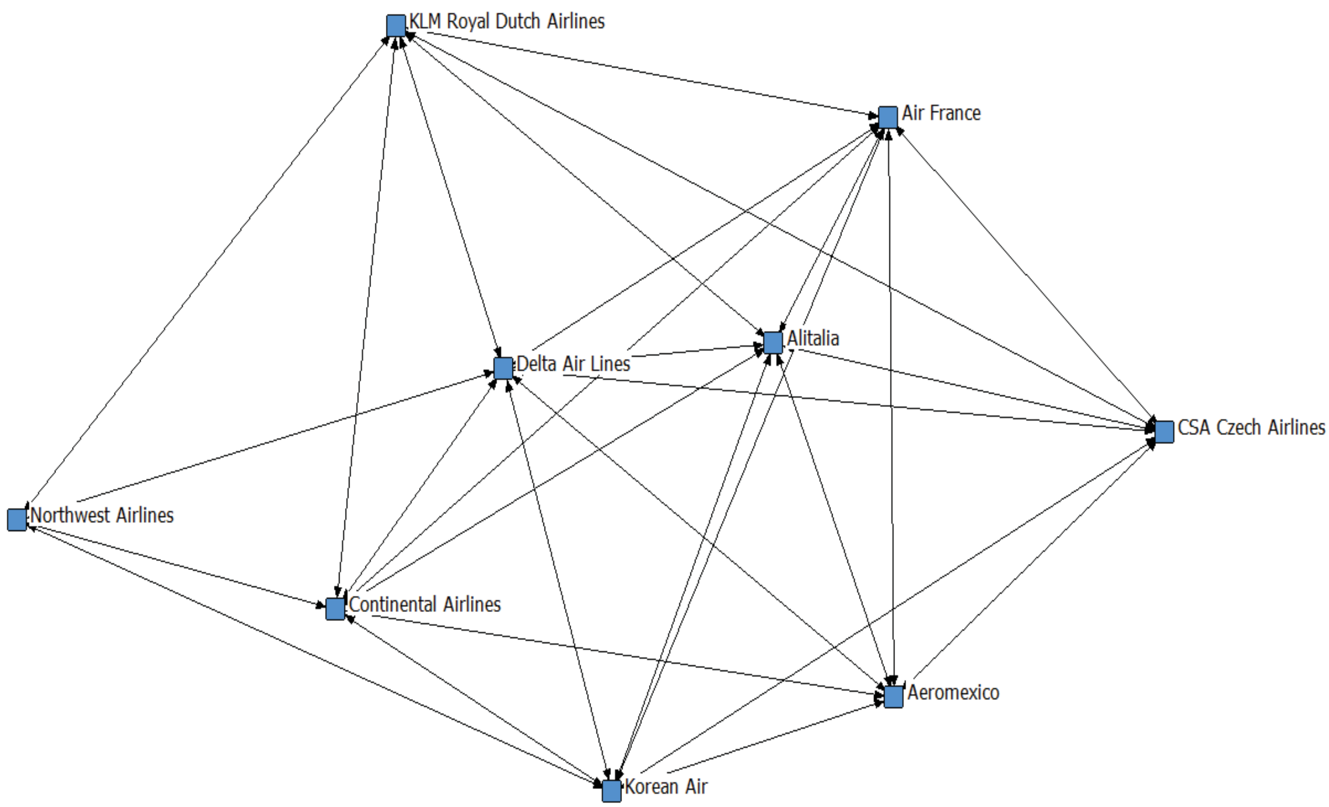


Figure 28: Average path length and clustering coefficient of airline industry from 1994-2007

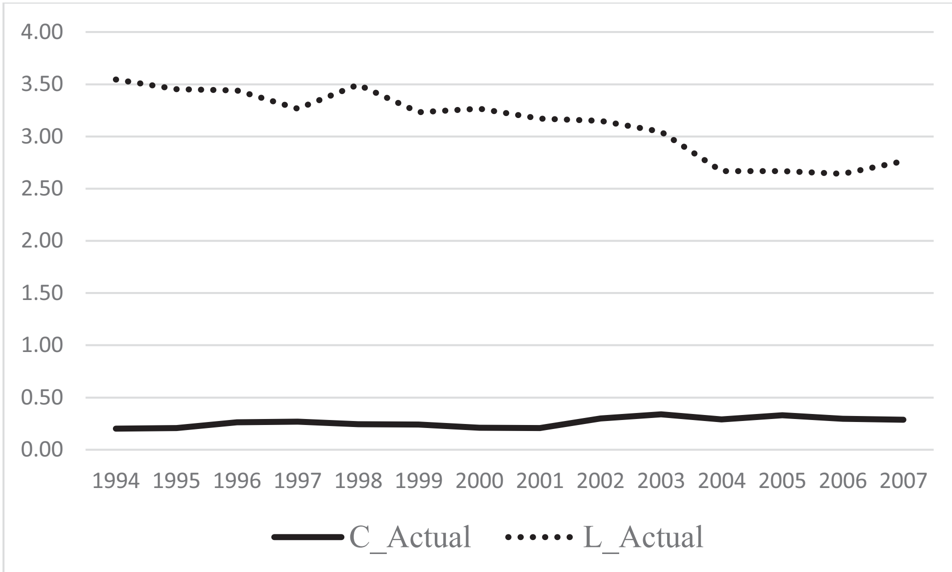


Figure 29: Small world quotient – Q of airline industry from 1994-2007

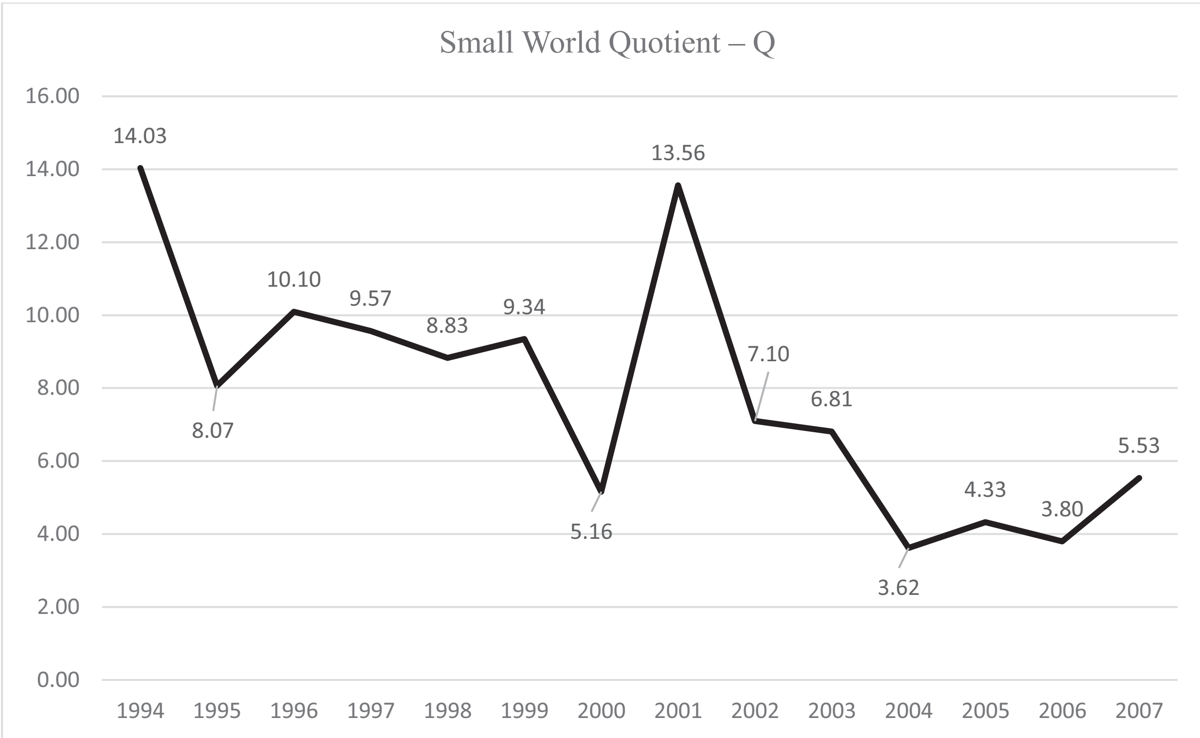
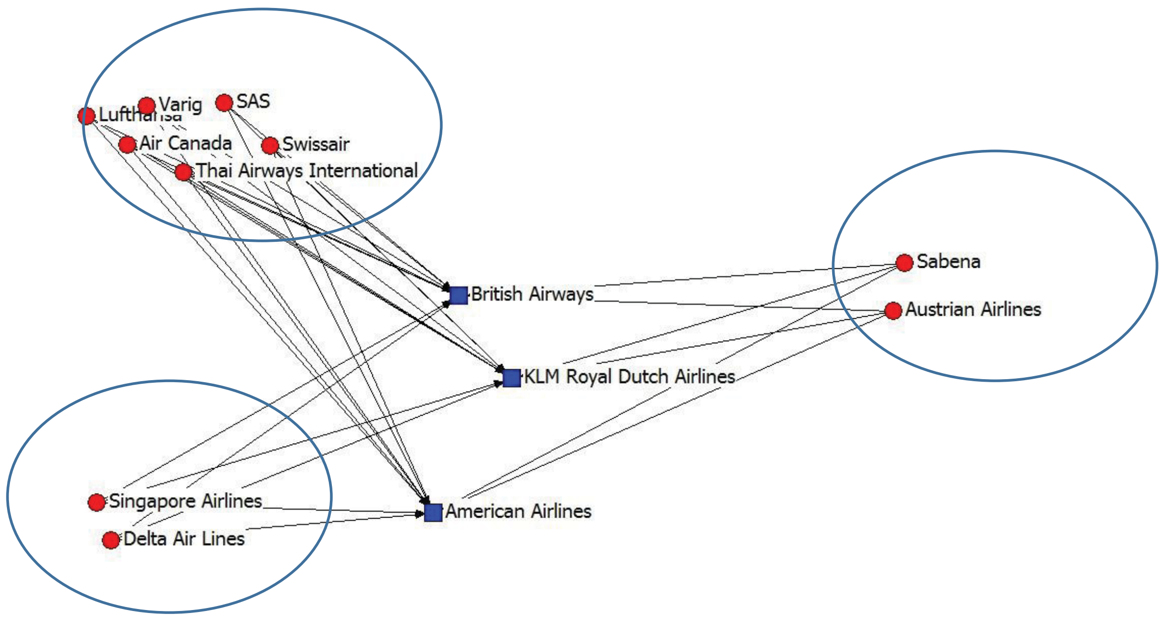


Figure 30: Bridging actions of non-member airlines, 1997



Blue Nodes represent Non-Members

Red nodes represent members

Circles represent MPAs