The Impact of Membership in Competing Alliance Constellations: Evidence on the Operational Performance of Global Airlines

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Abstract

The global airline industry has witnessed the formation of multiple-partner alliances or "constellations" competing against each other for both clients and members. In this paper I empirically evaluate the proposition that membership in airline constellations allows carriers to capture externalities from other firms in the form of direct or indirect traffic flow, thereby enhancing their operational performance. Analyzing patterns of membership in explicit groups involving formal, multilateral agreements (such as the Star Alliance, Oneworld, SkyTeam, etc.), I find that membership benefits are greatest in constellations involving large aggregate traffic and for carriers contributing with a large portion of the group's capacity. But industry observers have also pointed out the existence of implicit groups comprised of carriers that have more bilateral ties to one another than to firms outside their group. I find that carriers bilaterally linked with key players of such groups are able to increase their operational performance even if they do not belong to any explicit constellation.

Keywords

Constellations, strategic alliances, networks, cooperative strategy, airline industry

INTRODUCTION

Global airlines have aggressively formed alternative groups competing in international markets for both passengers and member airlines through the combination of international routes, joint coordination of operations, and consolidation of marketing tools such as frequent flyer programs (Gomes-Casseres, 1994; Hanlon, 1999; Oum & Yu, 1998). For instance, a traveler wishing to fly from Kansas City in the U.S. to Gothenburg in Sweden can use alternative airline groupings offering connections through distinct intermediate hubs. The traveler can choose the services of the "Star Alliance"—e.g., United Airlines through Chicago and then Lufthansa through Frankfurt—or, alternatively, the services of the "Oneworld" constellation—e.g., American Airlines through Dallas and then British Airways through London (Hanlon, 1999; ter Kuile, 1997). Thus, the global airline industry illustrates a pattern of competition where rivalry shifts, to some degree, from firms to groups of firms involved in joint action. Following Gomes-Casseres (1996), I refer to these competing multiple-partner alliances as *constellations*.

Competing constellations have received sparse attention in the literature on interorganizational collaboration. Although there has been a growing interest in interorganizational networks as sources of competitive advantage (Dyer & Singh, 1998; Gulati, Nohria, & Zaheer, 2000), empirical studies have not paid enough attention to the dynamics of competition in settings involving multiple networks (Gulati, 1998: 310). In other words, empirical research has focused on individual networks in isolation—in general, "ego" networks or the web of alliances surrounding firms (e.g. Dyer & Nobeoka, 2000; Gulati, 1999; McEvily & Zaheer, 1999; Uzzi, 1996)—rather than *competing* networks. Yet, for situations in which competition is shifting from firms to constellations, strategic implications can be profound, as a firm's performance may crucially depend on which group it chooses to join (Gomes-Casseres, 1996; Gulati, 1998). Even though past research has empirically analyzed constellations in several industry contexts (Lorenzoni & Ornati, 1988; Nohria & Garcia-Pont, 1991; Vanhaverbeke & Noorderhaven, 2001; Walker, 1988), the performance implications of constellation membership have not been examined in detail.

In this study, I fill this void by asking whether membership in airline constellations has any impact on carriers' operational performance, and what the drivers of membership benefits are. I focus on operational benefits—namely, the extent to which constellation membership improves carriers' load factors or their ratio of passenger traffic to seat capacity—for two major reasons. First, since I am dealing with carriers from diverse countries, reliable and standardized financial information is unavailable in most cases. Second, benefits from membership in airline constellations are mostly driven by passenger traffic that can be internalized from other carriers. Thus, operational data provide a natural way to directly infer if there is any effect of constellation membership on carriers' traffic. Observing financial data may cloud existing traffic-related effects because carriers may fail to perform due to factors unrelated to their membership in global groups, such as changes in labor contracts or domestic competition. To be sure, the idiosyncratic features of the airline industry (for instance, traffic regulation limiting the full acquisition of foreign carriers) prevent a direct generalization of empirical results to other contexts, but nonetheless provide an appropriate setting to study constellations.

In this sense, the paper begins with background information on the airline industry and an overview of its emerging constellations. Next, I develop hypotheses about how constellation membership can impact the operational performance of firms in the context of the global airline industry. In the subsequent section, data and methods are discussed. I then present and discuss the empirical results. Concluding remarks follow.

ALLIANCE CONSTELLATIONS IN THE GLOBAL AIRLINE INDUSTRY

Since the deregulation of the U.S. airline industry and the increasing privatization of carriers in Europe and East Asia, the desire to expand route networks internationally has intensified competition between airline companies (Morrison & Winston, 1995; Pustay, 1992; Taneja, 1988). However, existing regulatory policies that constrain the acquisition and use of foreign resources pose major challenges to international air travel. Although there are instances of companies holding equity stakes in international carriers, most governments disallow complete foreign ownership of domestic airlines and airport facilities (Hanlon, 1999; Pustay, 1992). International air traffic is also heavily regulated. Since the 1944 Chicago Convention on International Civil Aviation, permission to carry out international traffic has been established by agreements between countries mainly on a bilateral basis (Holloway, 1998; Oum & Yu, 1998; Pustay, 1992; Taneja, 1988). In addition, airlines are rarely granted permission to service routes within foreign countries, which is called "cabotage" (Hanlon, 1999; Holloway, 1998). In this context, alliances become a fundamental recourse for airlines to expand internationally (Doganis, 2001; Oum & Yu, 1998; Park & Zhang, 2000; Park & Martin, 2001). Reflecting this fact, the industry has witnessed the formation of several alliances between carriers, especially during the 1990s. Estimates indicate that in 2000 more than 80% of global airline carriers engaged in some form of alliance (Baker, 2001).[1]

The first airline alliances were purely bilateral, involving agreements between two carriers only. The most common type of bilateral alliance is the so-called *codesharing* agreement, by which two carriers combine routes as a single composite product to customers. Usually one firm (the "marketing carrier") sets the price and sells the flight, while the other firm (the "operating carrier") becomes responsible for the connecting routes (Bamberger, Carlton, & Neumann, 2001).[2] Codesharing agreements usually involve substantial efforts to jointly coordinate the flow of passengers and baggage, as well as sharing of airport resources such as gates, lounges, check-in infrastructure, and ground personnel (Chen & Ross, 2000).[3] Carriers also engage in *marketing* agreements, such as the establishment of joint frequent flyer programs (FFP) and combined promotion efforts.

[1] I simplify the analysis by focusing on horizontal transactions only—i.e., networks in the same industry—in order to avoid a distinction between vertical and horizontal ties. Anecdotal evidence suggests that alliances in the airline industry, which are the focus of this paper, are mostly horizontal, i.e., among carriers (Hanlon, 1999: 240-242). The simultaneous consideration of horizontal and vertical ties, however, can be important in other contexts (see e.g. Lazzarini, Chaddad, & Cook, 2001).
[2] Partners receiving antitrust immunity from the U.S. Department of Transportation can also jointly price certain routes involving U.S. cities (Brueckner & Whalen, 2000).
[3] A related type of alliance is the *block space* agreement, through which a marketing carrier buys a block of seats from an operating carrier and then sells those seats to its customers (Hanlon, 1999). Block space agreements can also be used as a mechanism to transfer payments in codesharing alliances (Bamberger *et al.*, 2001).

Broader airline alliances, moving beyond purely bilateral deals and involving several carriers, emerged especially in the late 1990s. Examples include the Star Alliance (with United Airlines, Lufthansa, SAS, etc.), Oneworld (with American Airlines, British Airways, Qantas, etc.), SkyTeam (with Delta and Air France, among others), "Wings" (the unofficial name for the Northwest/KLM alliance), and Qualiflyer (a group of European carriers). These alliances involve full marketing cooperation with respect to FFPs and promotion (including investments in common brand name), besides joint access to airport facilities controlled by individual members. They also offer comprehensive codesharing agreements involving several routes instead of bilateral agreements comprising few routes (Oum & Yu, 1998). Thus, agreements tend to be multilateral, in that they are applicable to all partners and broad in nature.[4] Furthermore, some groups tend to establish committees and common information technology platforms to manage the alliance. I refer to these formal groupings as *explicit* airline constellations: groups of firms pursuing joint action in a formal way through agreements that tend to have a multilateral fashion, supported by organizational mechanisms such as joint decision-making committees and common investment in brand names and technology platforms. Estimates indicate that the five existing explicit airline constellations in 2001 (Star Alliance, Oneworld, SkyTeam, "Wings," and Qualiflyer) made up almost 60% of the global air traffic, representing 203.3 billion dollars in revenues (Baker, 2001). (I present more details on the evolution and composition of these groups later.)

Industry observers, however, have noted the existence of informal airline groupings prior to the emergence of most explicit constellations, corresponding to groups of bilaterally tied firms servicing a web of routes and competing with carriers offering alternative connections (e.g. Doganis, 2001; Whitaker, 1996). These clusters of bilateral associations also appear to be, in some cases, expanded coalitions with key (though not all) members of explicit constellations as

[4] Even though some contractual features of those groups are truly multilateral (such as FFPs), an interviewed airline executive considers that, during the period covered in this study, pair-wise deals within explicit constellations were still common. But there is a perception that agreements are becoming more and more comprehensive. Thus, the results presented here should be properly taken as conservative estimates of the impact of explicit groups.

their core group. For instance, in early 2000 several carriers such as British Midland Airways (bmi), Emirates, Malaysia Airlines, South African Airways and Virgin Atlantic were not members of the Star Alliance but held bilateral ties with members of the group. Given the existence of these multiple-firm linkages through a web of bilateral alliances, it might be possible for a carrier to benefit from traffic coming from other firms even if that carrier is not a member of any explicit group. Thus, observing only the composition of explicit constellations may provide a partial picture of the overall alliance activity in the industry (Doganis, 2001). This idea is consistent with Gomes-Casseres' (1994: 65) view of constellations as "separate companies linked through collaborative agreements," as well as previous studies attempting to demarcate sub-groups of firms taking into account the structure of bilateral ties (alliances or equity stakes) between firms (Burgers, Hill, & Kim, 1993; Nohria & Garcia-Pont, 1991; Vanhaverbeke & Noorderhaven, 2001; Walker, 1988). Since the boundaries of such networks are not readily observable, I propose to analyze informal groups of airline carriers showing relatively more bilateral ties to one another than to firms outside their group (Nohria & Garcia-Pont, 1991: 109), using appropriate quantitative techniques. I refer to these informal groups as *implicit* airline constellations.[5]

While explicit airline constellations can be viewed as broad, multilateral alliances involving several carriers, implicit airline constellations can be viewed as collections of several bilateral alliances (for a general discussion, see Das & Teng, 2002). In this sense, traffic within an implicit constellation should mostly come from direct associations between carriers pursuing joint services on a bilateral basis. Nevertheless, indirect ties through a common partner may also play a role. Consider, for instance, a customer who wants to go from Cape Town to Copenhagen. The customer can possibly go from Cape Town to London using South African Airways, and then from London to Copenhagen in a bmi flight operated by SAS. Even though

[5] Note that bilateral ties in an implicit constellation may be formal, i.e., associated with formal (bilateral) contracts or equity stakes. Implicit constellations are said to be informal because there is no general, formal agreement governing the joint action of firms beyond what is dictated by their bilateral arrangements.

SAS has no direct alliance with South African Airways, it could benefit from traffic coming from the latter due to South African's alliance with bmi, a codesharing partner of SAS. Notice, therefore, that implicit airline constellations do not need to be "cliques" whereby all firms are tied to one another. In fact, the initial groupings in the industry were led by key players—United Airlines and Lufthansa, American Airlines and British Airways, KLM and Northwest, and so on—managing their own bilateral links with other carriers sparsely connected with one another (Whitaker, 1996).

The coexistence of formal, multilateral alliances and informal webs of bilateral associations in the recent history of the airline industry provides the opportunity not only to examine benefits of constellation membership, but also how that effect may vary according to the way the boundaries of competing groups are defined: explicitly or implicitly. I next offer some hypotheses related to drivers of benefits stemming from constellation membership. Since such drivers should differ substantially across markets and activities, I develop hypotheses grounded in the industry under consideration.

AIRLINE CONSTELLATIONS AND FIRM PERFORMANCE

Why should firms expect any benefit associated with constellation membership? Fundamentally, a firm can benefit from joining a constellation when it can capture *positive externalities* emanating from the presence of other firms in the group. Such externalities occur when the benefits that a firm can attain by employing its own resources and targeting its own markets increase when these are articulated, total or partially, with the resources and markets of other firms in the constellation. In the global airline industry, externalities occur mainly through the *traffic* of passengers across carriers, whereby alliances—or, more generally, membership in constellations—serve as conduits for these externalities.[6] For the moment, I make no distinction

[6] Two comments are in order here. First, I disregard cargo and charter operations and focus on scheduled passenger traffic, mainly because the latter has been the major motivation for the formation of airline constellations. Second, although externalities could also be internalized via integration or hierarchy (e.g., mergers or acquisitions among carriers), I focus on the role of alliances. Due to regulatory restrictions to fully acquire foreign carriers, this

between implicit and explicit constellations; I treat them as alternative ways to demarcate the boundaries of multiple-firm alliances, and examine their differential effect on carriers' operational performance in the empirical part of the paper.

Several factors may influence the extent to which a constellation as a whole yields externalities for its members, and the extent to which each member is able to internalize those externalities. Following Gomes-Casseres (1994), I decompose sources of membership benefits into two sets of variables: *constellation-specific* and *member-specific* attributes. Constellation-specific attributes are generic characteristics of a constellation, such as the aggregate traffic of airline carriers. These attributes are equivalent for all firms belonging to the same group, but should be different for firms belonging to different constellations when there is group heterogeneity. Member-specific attributes are individual characteristics of a group member *relative* to other members, such as the extent of a carrier's seat capacity vis-à-vis other firms within the group. These attributes should be different even for firms belonging to the same constellation, provided there is member heterogeneity (Gulati, 1998: 310).

I argue below that while constellation-specific attributes determine the total externalities generated by the group, member-specific attributes determine how those externalities are distributed among members. Since traffic is a key element in the airline industry, I focus specifically on the effect of constellation membership on the operational performance of carriers: the extent to which they are able to attract traffic, given their existing seat capacity. In this sense, my approach to analyzing the implications of airline constellation membership is to outline key constellation- and member-specific attributes that might influence the extent of traffic that a member can capture, and then to observe whether these variables explain inter-firm performance differences. More specifically, if constellation membership has an impact on the internalization of traffic, then, other things being equal, the operational performance of carriers should differ in two ways (Figure 1). First, in situations where groups are heterogeneous,

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analytical simplification is appropriate in the airline industry, though not necessarily so in other industries. I provide more comments on this important issue in the conclusion section of this paper.

constellations with distinct constellation-specific attributes should yield differential performance for carriers belonging to different constellations. Second, in situations where members are heterogeneous, distinct member-specific attributes should induce differential performance for carriers belonging to the *same* constellation. In other words, some firms will attain superior membership benefits even if they belong to the same group.

<Figure 1 around here>

More formally, suppose that the formation of constellations causes a partition of a set S of firms within the industry into several disjoint subsets denoted by $C_j \subseteq S, j = 1, \ldots, J$. I consider that the performance of a carrier i belonging to a constellation C_j is given by

(1) $y_i = \pi(\boldsymbol{x}(C_j), \boldsymbol{z}_i(C_j)) + f_i$,

where $\pi(.)$ indicates the benefits (traffic) that firm i attains by being a member of C_j; $\boldsymbol{x}(C_j)$ represents a vector of generic characteristics of group C_j, i.e., constellation-specific attributes; $\boldsymbol{z}_i(C_j)$, represents a vector of firm i's individual characteristics relative to other constellation members, i.e., its member-specific attributes; and f_i denotes firm-specific effects independent of constellation membership. I next discuss constellation- and member-specific attributes that might be important in the airline industry, and how they might create inter-firm performance differences.

Constellation-specific attributes

The *size* of the aggregate customer base brought by group members may be an important attribute influencing the extent of inter-firm externalities generated by a constellation. A large aggregate customer base can attract more customers in a context of network externalities, which occurs when the benefits that individuals attain by consuming the products of a constellation increase with the expected number of users (Economides, 1996; Farrell & Saloner, 1985; Katz & Shapiro, 1985, 1994) This effect is particularly prominent when customers face switching costs to pursue alternative products supplied by other firms, thus implying that the attraction of new customers to a particular constellation requires, to a large extent, that customers' individual suppliers become members. In the airline industry, joint frequent flyer programs (FFPs) largely induce switching costs. Since FFPs reward customers who purchase tickets from the same carrier, "customers who switch between different companies are penalized relative to those who remain with a single firm" (Klemperer, 1987: 376). Thus, by establishing joint FFPs, airlines can benefit from the captive demand of other firms. FFPs can also be considered a particular type of industry standard since, once multiple carriers form a group involving large aggregate traffic, customers will have increasing benefits if they continue using a particular FFP instead of programs offered by competitors. As an executive from an airline member of a certain explicit constellation once affirmed, the combined FFP "is the glue to hold the alliance together" (quoted in Hanlon, 1999: 57).

Furthermore, unit costs may decrease and services may improve under jointly coordinated operations. The presence of such increasing returns to scale is another factor that makes the benefits of a constellation's product increase with the extent of its demand (Tirole, 1988: 409). When airline routes are jointly coordinated, as in the case of codesharing alliances, the quality of customer service will tend to increase as the constellation resembles a "single-carrier" service with respect to check-in and baggage handling (Bamberger *et al.*, 2001; Brueckner & Whalen, 2000; Youssef & Hansen, 1994). Joint operations and marketing activities are also expected to reduce unit costs due to economies of scale (Bamberger *et al.*, 2001; Oum & Yu, 1998; Park & Zhang, 2000). As a result, improved service and lower costs will tend to increase demand for coordinated services.[7] Collectively, these arguments imply that the size of the aggregate traffic of the constellation is an important constellation-specific attributing influencing the benefits of membership, thereby leading to:

[7] Even if allying carriers monopolize connections on a route, prices may be lower than in the case of independent sale and pricing of such connections, which will also contribute to an increase in demand. This is because when a single airline sets the price for the total route or partners jointly do so (in cases where they are granted antitrust immunity), "double marginalization" is eliminated. The so-called Cournot double marginalization problem occurs when a monopolist pricing a downstream product introduces a mark-up over the mark-up of the monopolist offering a complementary, upstream product (see e.g. Economides & Salop, 1992). The reduction in prices from the elimination of double marginalization when one firm or both firms price the *whole* nexus of products is expected to prompt demand. Empirical evidence in the airline industry is corroborative (Bamberger *et al.*, 2001; Brueckner & Whalen, 2000).

Hypothesis 1. Members of an airline constellation with large aggregate passenger traffic will outperform members of an airline constellation with small aggregate passenger traffic.

Besides the size of a constellation's aggregate market, another constellation-specific attribute that may influence the extent of inter-firm externalities within the group is the *diversity of the resources* brought by members. Inter-firm externalities increase when members hold complementary resources, i.e., when the benefits to use of a resource increase as it is joined with other resources supplied by partners (Grandori & Soda, 1995; Lorenzoni & Ornati, 1988; Richardson, 1972; Teece, 1992). The existence of complementary resources tends to occur when firms contribute to a constellation with diverse resources that can be combined in several ways. For instance, in a one-stop flight connecting two cities, "the two legs of the journey are two complementary components of the complete flight" (Encaoua, Moreaux, & Perrot, 1996: 703). To create this composite route, two or more carriers will need to coordinate the joint use of their local resources in origin, stop points, and destination. Since regulatory restrictions prevent global carriers from acquiring domestic feeders within foreign countries, they must ally with other airlines controlling local facilities, which in turn act as local hubs and thus help to bring local customers to the global network (Doganis, 2001; Hanlon, 1999; Youssef & Hansen, 1994).[8]

In addition, resource diversity should allow members to avoid or reduce within-group competition (Axelrod, Mitchell, Thomas, Bennett, & Bruderer, 1995; Gomes-Casseres, 1994; Lawless & Anderson, 1996). Firms holding similar resources tend to engage in direct competition since they are able to offer substitute products and thus undercut one another (Chen, 1996; Gimeno & Woo, 1996). Thus, airline carriers positioned in similar or proximate hubs will have both the local knowledge and infrastructure to offer competing connections for customers; they may simply be competing for traffic instead of creating new traffic opportunities. In

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[8] Unlike size-related externalities, which presuppose gains from an increase in the size of the network and its customer base, resource-related externalities are based on gains from *traffic density* (Brueckner & Spiller, 1994; Caves, Christensen, & Tretheway, 1984), which allow airlines to schedule flights from or to different points and thus offer more options to customers. To be sure, traffic density also enhances the flow of passengers and creates economies—e.g., more efficient utilization of aircraft and crew—which are akin to size-related externalities. However, traffic density presupposes the combination of qualitatively complementary routes, which are largely dependent on the resources available in the network rather than its size.

contrast, carriers positioned in different hubs should have more incentives to collaborate on the development of new routes and on the improvement of existing ones, consequently leading to an increase in the constellation's overall traffic flow. Therefore, another key constellation-specific attribute in the airline industry should be the diversity of international hubs within the constellation, which leads to:

Hypothesis 2. Members of an airline constellation with high diversity of international hubs will outperform members of an airline constellation with low diversity of such hubs.

Member-specific attributes

While constellation-specific attributes determine the total externalities generated by a group, member-specific attributes define how those externalities are captured by individual members. Heterogeneity of member-specific attributes within a constellation should induce differential membership benefits even for firms belonging to the same group. In airline constellations, an obvious source of heterogeneity is the *size* of individual members in terms of their passenger base. At first glance, one might propose that smaller carriers will be able to benefit more from their association in an airline constellation than larger carriers because they would capture substantial traffic flow coming from the latter. But this will happen only if constellation members agree to restructure existing route networks or develop new routes in such a way to increase traffic to small members. The opposite, however, is likely to be true: large members will tend to redesign route networks jointly with other large carriers, which will be able to bring a substantially greater customer base to the constellation relative to small firms. For instance, most explicit airline constellations are led by large US and European firms, with routes designed to exploit transatlantic traffic (Odell & Spiegel, 2002).

At the most fundamental level, the general mechanism that may enable large firms to benefit more from the constellation's traffic than smaller firms is, to use Hirschman's (1970) terminology, the threat of *exit*. To understand the nature of exit tactics, denote $\Pi(C_j) = \sum_{i \in Cj} \pi(\boldsymbol{x}(C_j), \boldsymbol{z}_i(C_j))$ as the collective benefits (e.g., passenger traffic) that firms can achieve by being members of constellation C_j, and assume for simplicity that members exhaust all possibilities of value creation within the group. Then define the variable

(2) $\Delta_k(C_j) = \Pi(C_j) - \Pi(C_j \backslash \{k\})$,

which is simply the change in the aggregate benefits of constellation C_j if member k departs the group; in the language of cooperative game theory, $\Delta_k(C_j)$ is the *marginal contribution* of k to coalition C_j (e.g. Osborne & Rubinstein, 1994: 291). If the marginal contribution of firm k is large, then it will be able to threaten departure from the group unless it obtains sufficient membership benefits. As a result, members with a large marginal contribution will tend to capture a larger portion of the group's collective benefits (Brandenburger & Nalebuff, 1996).

In airline constellations, the extent of a carrier's marginal contribution should be directly related to the extent of its customer base. Such carriers will tend to be in the deposition to threaten their departure from the group or simply operate alone, which would cause a substantial loss to small members in terms of foregone traffic flow (for a general discussion, see Economides & Flyer, 1997; Katz & Shapiro, 1985). The exit of small carriers, in contrast, should cause a lower reduction in the aggregate traffic of the constellation. Therefore, the restructuring of existing route networks or the development of new routes will tend to favor large members of the group. This logic leads to:

Hypothesis 3. A member with a large seat capacity relative to the aggregate seat capacity of its airline constellation will outperform another constellation member with a relatively small capacity.

The marginal contribution of a constellation member should also depend on whether the firm controls or not *critical resources* within the constellation, i.e., resources whose withdrawal from the group substantially reduces the benefits from the articulation of the remaining resources (Harrigan, 1988; Pfeffer & Salancik, 1978). For instance, hubs that are natural points of traffic aggregation—e.g., connecting cities in Continental Europe, such as Paris and Frankfurt, or in East Asia, such as Singapore (Hanlon, 1999)—will be critical to the establishment of an international route network serviced by constellation members. Similarly to the effect of relative capacity, the control of critical hubs should improve a carrier's ability to benefit from the constellation because the design of members' route networks will tend to emphasize use of those hubs. Consequently:

Hypothesis 4. A member controlling critical international hubs within its airline constellation will outperform another constellation member without control of such critical hubs.

Another crucial member-specific attribute in the context of airline constellations is the extent to which firms establish *bilateral ties* to key members of the group. Holding bilateral codesharing and marketing agreements with key constellation members allows a carrier to benefit directly from passenger traffic that comes from those other firms. But it is also reasonable to suppose that those ties represent conduits of information and influence beyond their own particular terms (Burgers *et al.*, 1993; Powell, Koput, & Smith-Doerr, 1996: 120). Still using Hirschman's (1970) terminology, the establishment of extensive bilateral ties to constellation members may also be an attempt to increase membership benefits through *voice*: "dialog, persuasion, and sustained organizational effort" (Williamson, 1985: 257). Notice that, differently from firms, constellations do not have strict hierarchical relations where certain agents are responsible for most decisions. Thus, members that are "more centrally located than others, in the sense that they are directly connected to many members" (Gomes-Casseres, 1996: 56) will have an improved ability to exercise voice. Such members will be more able to lead joint efforts and influence collective strategies in their favor (Barley, Freeman, & Hybels, 1992; Gnyawali & Madhavan, 2001; Money, 1998). For instance, a carrier may be able to influence the creation of codesharing agreements that enhances the use of its major hubs. In any case, it is reasonable to suppose that the benefits of establishing bilateral ties will be larger when such ties are directed to firms contributing with large traffic flow. The level of externalities (traffic) that a firm can capture through direct agreements with other members should be directly related to the extent of traffic handled by those members. This leads to the last hypothesis:

Hypothesis 5. A member holding several bilateral ties to other constellation members with large passenger traffic will outperform another constellation member holding few bilateral ties or ties to members with small passenger traffic.

DATA AND METHODS

Data

This study uses information about the operations of 75 global airlines as well as their alliances and patterns of membership in constellations between 1995 and 2000. The carriers in the sample represent about 81% of the total world passenger traffic in 2000, and 54 distinct countries (Table 1).[9] The data come from multiple sources. Carriers' operational information, such as traffic and capacity, is obtained from the *World Air Transport Statistics* compiled by the International Air Transport Association (IATA). Data on airline alliances and the evolution of constellations are taken from several issues of the magazine *Airline Business*, which conducts annual surveys on the alliance activity of the industry, including equity stakes. Since it is based on annual surveys, an advantage of this alliance database is that it provides a picture of alliances in place at a particular time.[10] Finally, I collect information on international routes from the International Civil Aviation Organization's (ICAO) digest of statistics *Traffic by Flight Stage*.

<Table 1 around here>

[9] The estimate of world passenger traffic used here is taken from Baker (2001). Individually, these databases contain information on more than 75 carriers, but I had to reduce the sample size due to missing data on certain variables of interest for certain carriers. Whenever feasible, I supplemented missing data with information obtained through Nexis-Lexis. I excluded carriers that, over the *whole* period, were fully owned by another airline carrier. However, some mergers and full acquisitions occurred especially in the last year of the sample. Thus, in 2000 TWA was acquired by American Airlines, Canadian Airlines by Air Canada, and European carriers AOM and Air Liberte (jointly with Air Littoral) merged.

[10] I disregard agreements that were pending in a given year, and focus on passenger agreements only (i.e., exclusive cargo and charter agreements are not included in the sample.) Sometimes, a survey at year t indicates that an alliance resumed in year $t - n$, but there is no reference to that alliance in the $t - n$ survey. Unless the latter indicates that the alliance is pending at $t - n$, I consider that the alliance was already in place in that period. I also ignore ties based exclusively on common computer reservation systems, which are considered to be regional in nature (Hanlon, 1999; Pustay, 1992). Finally, I take the structure of bilateral partnering in the industry as given. For an analysis of how alliances are formed in the global airline industry, see Gimeno (2003).

The database includes information on individual carriers observed through time; thus, the data have a panel structure. Besides the fact that alliances in the airline industry are prevalent and there is substantial heterogeneity in terms of routes serviced, countries of origin, dominance of local resources (such as airport facilities), performance, and composition of airline groups, the database has several other attractive features to assess the performance implications of constellation membership. First, although there is heterogeneity in terms of markets and resources of individual airlines, air transportation technology is fairly standardized, which facilitates comparisons (Oum & Yu, 1998; Park & Martin, 2001). Second, in the period under analysis, several explicit constellations were formed and the pattern of bilateral linkages suggests several implicit groups, which allows for their comparative assessment.

Assessing constellation boundaries: implicit vs. explicit constellations

As discussed earlier, explicit constellations are broad, formal multilateral alliances involving several carriers, while implicit constellations are collections of bilateral alliances such that members have more ties to one another than to carriers outside the group. Membership in explicit airline constellations is easily observable. In this study, it is simply based on public announcements of carriers' membership in airline constellations, as well as (if this is the case) their departure from those groups, as recorded in the magazine *Airline Business* and other sources obtained through Nexis-Lexis.[11] The boundaries of implicit constellations, however, are more difficult to demarcate. Since implicit constellations are collections of bilateral ties between firms, a natural way to proceed is to use an algorithm that yields a pattern of grouping based on the matrix of bilateral ties among carriers in the sample.

Following previous work (Burgers *et al.*, 1993; Nohria & Garcia-Pont, 1991; Vanhaverbeke & Noorderhaven, 2001; Walker, 1988), I adopt a clustering approach to demarcating the boundaries of implicit constellations. More specifically, I employ a clustering algorithm based

[11] I assume that a carrier is a member of an explicit constellation in a given year if it announced its association with the group in the first half of that year, i.e., between January and June. If an explicit constellation is dissolved in a given year, I assume that the group is in place in that year if the termination occurs in the second half of that year.

on *tabu search* optimization (Glover, 1989), which is available in the software *UCINET 5.0* (Borgatti, Everett, & Freeman, 1999). An advantage of this algorithm is that it finds groups given a certain pre-specified number of partitions, independent of the clustering configurations found with fewer partitions. Thus, it does not present the critical shortcoming of conventional hierarchical clustering algorithms (such as *CONCOR*), where a partition "made at one of the early stages of the analysis cannot be undone at a later stage" (Wasserman & Faust, 1994: 385). This is a restriction imposed by hierarchical clustering algorithms, rather than necessarily a feature of the data.[12] Basically, the tabu search algorithm maximizes a fit function based on the average "proximity" of group members defined in terms of the existence of bilateral ties to one another, given a pre-specified number of groups or partitions. Thus, the algorithm has a clear rule for optimizing the composition of groups, which is somewhat obscure in other clustering methods (Lawless & Anderson, 1996).

To create a matrix of inter-firm links, I simply consider that there is a link between two firms (coded 1) when they have either a bilateral alliance or an ownership relation (i.e., when at least one of the carriers has an equity stake in the other carrier). Otherwise, I consider that there is no link (coded 0).[13] Such a matrix is constructed for every year in the sample. Before applying the optimization algorithm, I first perform a visual inspection of the overall network, to identify carriers that either do not have ties to the carriers in the sample or that have only isolated, pair-wise ties. I drop such carriers from the sample prior to the clustering analysis (e.g. Vanhaverbeke & Noorderhaven, 2001). I then run the algorithm several times to locate carriers that are classified into particular groups, but that do not show ties to any member of such groups. Since this suggests that such actors do not have a clear pattern of membership, I also drop them

[12] The hierarchical clustering algorithm *CONCOR* has still another major drawback: it promotes successive splits of existing sets into exactly two new subsets. Again, such binary partitions may not be a feature of the data at hand (Wasserman & Faust, 1994: 380).

[13] Alternatively, I could consider the "strength" of a tie between two carriers based on the nature of their relationship; for instance, I could attach a higher score to links involving an ownership relation (e.g. Nohria & Garcia-Pont, 1991; Rowley, Behrens, & Krackhardt, 2000). In the present context, this procedure is problematic since in some cases carriers have equity stakes in other firms but there is no publicly announced bilateral alliance involving, for instance, codesharing. To avoid unjustified assumptions guiding differential coding schemes, I opt for the simple criterion described above. See, however, footnote 33.

from the sample prior to the final analysis. Although tabu search greatly increases the likelihood that a global maximum will be found (Lawless & Anderson, 1996), the procedure may in some cases get trapped into a local maximum or stop before the attainment of superior solutions. In an attempt to avoid this problem, I run the algorithm five times and choose the clustering configuration that yields the highest value of the "fit" function.[14]

Any cluster algorithm, however, has an important drawback: there is a lot of subjectivity in choosing the "ideal" number of partitions (Barney & Hoskisson, 1990; Wasserman & Faust, 1994). In the present study, I choose five partitions for two main reasons. First, in the last year of the sample (2000), there were five explicit constellations in place. Thus, if I follow the supposition discussed earlier, that implicit constellations may be either precursors of explicit groups or "expanded" versions of such groups when they are in place, then it makes sense to find a clustering pattern that has some correspondence to the eventual configuration of explicit constellations. Second, transatlantic routes between Europe and the United States are considered to be a key target for global airline alliances.[15] Thus, it is natural to assume that key competing U.S. carriers will be central players in each group. In my sample, four U.S. carriers can be considered key international players: American Airlines, Delta, Northwest Airlines, and United Airlines, thus suggesting at least four constellations.[16] Adding an apparent cluster of European carriers led by Swissair results in five groupings.

Dependent variable

I employ carriers' *passenger load factor* as a measure of operational performance, which serves as the dependent variable in this study. The load factor is a measure of aircraft capacity utilization. More precisely, it is the ratio of carrier i's total traffic, measured in revenue

[14] In some cases, even after eliminating some carriers prior to the actual optimization runs, the procedure groups together some carriers that do not have direct ties, or that show only pair-wise, isolated ties. I again drop such carriers from the composition of the final groups.
[15] As mentioned by an airline executive, "some 80 per cent of the benefits from any of the global alliances come on the transatlantic" (quoted in Odell & Spiegel, 2002).
[16] The other carriers in the sample are less significant international players. Alaska Airlines, America West, and US Airways are mostly domestic carriers. TWA was acquired by American Airlines in 2000. Continental Airlines, in turn, has an extensive agreement with Northwest Airlines.

passenger kilometers (RPK), to its overall seat capacity, measured in available seat kilometers (ASK), at year *t* (%). This corresponds to the variable $LoadFactor_{it}$.

This measure's main advantage is that it is a simple and standard industry metric of airline performance. Moreover, it is directly related to the previous theoretical discussion, which argues that inter-firm externalities in the airline industry involve mostly passenger traffic flow. The main disadvantage of the load factor measure is that it is purely operational. Thus, it ignores the role of non-passenger sources of revenue and operational inputs besides aircraft capacity, such as labor (Schefczyk, 1993). An alternative approach would be to use financial measures such as operational margins or information from stock markets (e.g. Park & Martin, 2001). A potential problem in the case of global constellations is that not all foreign carriers are publicly traded, and in several cases not even reliable and standardized accounting information is available. Another more fundamental problem is that carriers may fail to perform due to factors unrelated to their membership in global groups, such as changes in labor contracts or domestic competition, which are more difficult to observe and control for. Thus, it might be desirable to focus on performance aspects that are directly related to membership externalities (e.g., traffic). Using overall financial results should add error to the assessment of certain resources or strategies (e.g. Ray, Barney, & Muhanna, 2004). Fortunately, previous research has found that, controlling for other variables, a carrier's load factor is significantly related to its financial performance (e.g. Behn & Riley Jr., 1999; Morrison & Winston, 1995). Thus, instead of restricting the sample to carriers with reliable financial information, I opt for expanding the sample and adopting passenger load factor as an operational performance measure, which is a widely used metric in the airline industry.[17]

Independent variables

[17] Arguably, load factors may capture two sorts of effects associated with constellation membership: an increase in traffic (which is the basis of my theoretical arguments) or a reduction in seat capacity (which would imply some sort of coordinated effort to reorganize available services). I thank an anonymous referee for raising this point. As a way to confirm the first effect, I used carriers' passenger traffic as an alternative dependent variable, adding its seat capacity as a control. Results are similar to those reported in the empirical part of the paper using load factors as a dependent variable.

Constellation-specific attributes

Aggregate passenger traffic. I measure the size of a constellation's aggregate traffic using the variable $TotTraffic_t(C_j)$, which corresponds to the total scheduled passenger traffic (sum of individual billion RPKs) of constellation C_j at year t. To avoid a spurious correlation between this variable and the size of a carrier's *individual* customer base, for each carrier I exclude from this variable the carrier's total passenger traffic.[18]

Diversity of international hubs. As previously discussed, the constellation will exhibit high diversity in international hubs when members are positioned in distant cities/hubs, which expands the possibilities for connections (e.g. Doganis, 2001). In contrast, similar or proximate hubs will tend to be substitutes rather than complements. Based on this idea, I define the variable d_{ik} as the distance (in thousands of kilometers) between the cities where the main hubs of carriers i and $k \in C_j$ are located. The main hub of a carrier is defined as the city that, for that particular carrier, has the highest number of departing connections to other cities, as evidenced by the *Traffic by Flight Stage* database.[19] The measure of diversity within constellation C_j with respect to the availability of distinct cities/hubs at year t, labeled $DiversCity_t(C_j)$, is equal to $[\sum_i \sum_{k<i} d_{ik}]/[½m_t(C_j)(m_t(C_j) - 1)]$, where $m_t(C_j)$ is the number of members of constellation C_j at year t. This measure gives the average distance between the main hubs of all carrier-pairs within the constellation. If all carriers belong to different but closely situated countries, the value of $DiversCity_t(C_j)$ is likely to be small. Its value is largest when carriers belong to different and distant countries, i.e., when their headquarters are "scattered" around the globe.

Member-specific attributes

[18] This variable, as well as the other constellation-related variables discussed below, is measured twice, considering the composition of a carrier's constellation as defined both implicitly and explicitly.
[19] For a few carriers, the classification of certain cities as main hubs, as defined before, varies from period to period—possibly because those carriers operate through multiple international hubs. For such carriers, I consider the hub that most frequently presented the highest number of departing connections over all the years in the sample. However, this choice should not strongly affect the measure because multiple hubs are in the same country and hence their distance to other cities in different countries tends to be similar.

Relative seat capacity. A carrier's relative size within its constellation is measured by the variable $RelCapacity_{it}(C_j)$, which refers to the ratio of carrier i's available seat capacity (ASK) to the total capacity of its constellation, C_j, at year t.

Dominance of critical hubs. As previously discussed, foreign hubs are fundamental resources in global airline constellations, and they will be relatively more critical when they receive traffic from several other hubs. Consider, for instance, the hypothetical hub-and-spoke route network depicted in Figure 2. Hub H_2 is very important in this network because it receives traffic directly from three other hubs (H_1, $H_{3,}$ and H_4) and indirectly through their spokes. Intuitively, this is because hub H_2 is "in between" those other points and thus is expected to receive a large fraction of the overall flow of passengers coming from and going to other hubs and spokes. This suggests the use of the standardized *betweenness centrality* measure in network analysis (Freeman, 1979; Wasserman & Faust, 1994) to indicate the importance of each city in receiving traffic from the constellation's route network.[20] Cities with large betweenness centrality scores are likely to be central hubs in the international route network, whereas cities with low scores are likely to be either local hubs or spokes. In the network of Figure 2, H_2 indeed has the largest standardized score (70.91), followed by H_1 (61.82), and then H_3 and H_4 (34.55). The betweenness centrality of the other nodes (spokes) is zero. Based on this perspective, I use information from the *Traffic by Flight Stage* database to construct a matrix of global city-pairs for each year. Each entry is coded 1 if at least one member of a particular constellation C_j offers a flight from one city (row) to another city (column) at year t. Taking this matrix as an input, I use the software *UCINET 5.0* (Borgatti *et al.*, 1999) to compute the standardized betweenness centrality score of each city k, denoted $w_{kt}(C_j)$.

<Figure 2 around here>

[20] Suppose g_{uv} is the number of geodesics (shortest paths) linking two cites u and v, and $g_{uv}(k)$ the number of geodesics linking the two cities that contain city k. Then the betweenness centrality measure of city k is defined by $\sum_{v<u} g_{uv}(k)g_{uv}$ where $k \neq u, v$. The *standardized* measure corresponds to this value divided by the number of all possible city-pairs not including city k, i.e., $½(c-1)(c-2)$, where c is the total number of cities.

The next step is to measure how carriers dominate such critical hubs. Still using ICAO's *On-Flight Origin and Destination* statistics, I compute for each city-pair k the number of carrier-routes departing from that city offered by *all* carriers in the industry, whether they do or do not belong to the constellation, at year t.[21] I then define p_{ikt} as the proportion of all carrier-routes from city k serviced by carrier i at year t. This provides an indication of the extent to which a carrier dominates the traffic involving a particular city. The final measure, denoted as $DomHub_{it}(C_j)$, is equal to the sum $\sum_k w_{kt}(C_j)p_{ikt}$, where k indexes all cities belonging to the route network of the constellation. Intuitively, this measure indicates a carrier's dominance of the traffic (in terms of route counts) involving cities in the network of the constellation, weighted by the relative importance or criticality of those cities according to traffic aggregation.[22]

Bilateral ties to key constellation members. The variable $InsideTie_{it}(C_j)$ is the proportion of constellation C_j's passenger traffic (RPK) that comes from members to which carrier $i \in C_j$ is bilaterally tied at year t, i.e., it is the ratio of traffic coming from those members to the total traffic of the constellation excluding carrier i's traffic (i.e., variable $TotTraffic_t(C_j)$). This measures the extent to which the carrier is connected with key members of the constellation, i.e., members controlling large traffic flows.

Control variables

Carrier- specific attributes. As is usual in studies assessing determinants of firm performance, I employ some controls related to firm size. $Employees_{it}$, and $Routes_{it}$ measure respectively carrier i's number of employees (in thousands), and number of serviced international routes (in thousands, according to the *Traffic by Flight Stage* database) at year t.

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21 For instance, if a city is connected to only one other city in the route network, and the connection between them is serviced by two carriers, then the number of carrier-routes involving that city is 2.

22 Ideally, one should use information on the individual *traffic* of city-pair routes to compute this measure. However, the *Traffic by Flight Stage* database does not contain traffic information for all routes surveyed. Instead of disregarding routes for which data on traffic are missing, which would for some carriers discard information on their entire route networks, I opt instead to use a rough assessment of carriers' relative traffic based on route counts, as described above. Despite its limitations, the use of the *Traffic by Flight Stage* database is not without precedent in the airline industry literature (e.g. Clougherty, 2002; Park & Zhang, 2000).

Also, to control for possible differences in carriers' experience in the industry, I employ the variable Age_{it}, which indicates the time elapsed, at t, since the carrier's founding.

"Ego" network. Variables related to constellation membership are likely to be correlated with the structure of carriers' "ego" networks, defined as the set of firms to which they are *directly* tied in a bilateral way. Failure to control for this fact may generate a spurious correlation between constellation-related variables and operational performance: carriers may benefit from traffic emanating from their own network of direct ties rather than from membership in constellations. Thus, I include the variables $EgoTies_{it}$ and $EgoTraffic_{it}$, which measure respectively carrier i's total number of bilateral ties to other firms in the sample, and the sum of the individual traffic (billion RPKs) of those firms to which carrier i is bilaterally tied at year t.

Multi-market contact. Multi-market contact facilitates tacit collusion because a particular firm can retaliate against another firm's competitive hostility in a certain market through an escalation of competition in other shared markets (Bernheim & Whinston, 1990; Karnani & Wernerfelt, 1985). In the present study, controlling for multi-market contact is important because, as shown by Gimeno and Woo (1996), it may be correlated with resource similarity. Thus, failure to control for multi-market contact may bias the analysis of the impact of a constellation's resource profile on membership benefits.[23] Studies of multi-market contact in the airline industry have considered city-pair routes as the relevant markets or points of contact. Thus, using the *Traffic by Flight Stage* database, I first compute the variable r_{ikt} representing the number of international city-pair routes jointly serviced by two carriers i and k ($i \neq k$) at year t. For a certain carrier i belonging to a constellation C_j, and considering all other constellation members $k \in C_j$, I then compute the value $(\sum_k r_{ikt})/(m_t(C_j) - 1)$, where $m_t(C_j)$ is the number of members of constellation C_j at year t. The resulting measure, denoted $Contact_{it}(C_j)$, represents

[23] Namely, even if a firm controls non-critical resources within the group, it may not suffer intense competition from other members if they compete in several markets and, for this reason, tacitly collude. Although multimarket contact has been studied largely in the context of pricing decisions (e.g. Evans & Kessides, 1994; Gimeno & Woo, 1996), it may also influence the extent to which individual demand or capacity is affected by competitive rivalry (Gimeno, 1999), which in turn may affect the performance measure used in this study (load factor).

the average number of international route contacts between carrier i and other members of its constellation.

Country-specific controls. I employ a set of country-specific variables to control for time-varying effects related to carriers' domestic markets, which are likely to affect their performance: the country's per capita GDP ($GDPCap_{it}$, in thousands of US dollars), GDP percent growth ($GDPGrow_{it}$), and population (Pop_{it}, billion inhabitants). This information is obtained from the World Bank's *World Development Indicators* database.

Year-specific controls. Finally, I create a set of dummy variables representing each year in the observation window, denoted as $Year(t)$, in order to control for temporal effects such as variations in economic and regulatory conditions over time, as well as trends in the pattern of inter-firm alliances.

Table 2 lists all the variables described above. Since separate regressions are run for explicit and implicit constellations, summary statistics of those variables are presented separately for each case—respectively, Tables 3 and 4.

<Tables 2, 3 and 4 around here>

Method

To estimate equation (1), I use a linear specification for the function mapping constellation-specific ($\boldsymbol{x}(C_j)$) and member-specific ($z_i(C_j)$) attributes onto firm performance (y_{it}): $\pi(\boldsymbol{x}(C_j), z_i(C_j)) = \boldsymbol{x}_t(C_j)\boldsymbol{\beta} + z_{it}(C_j)\gamma$. I assume additionally that the carrier-specific term f_i takes the form $f_i = \boldsymbol{w}_{it}\boldsymbol{\delta} + \tau_t + e_{it}$, where $\boldsymbol{w}_{it}$ is a vector of firm-specific control variables, τ_t denotes year-specific effects, and e_{it} is an error term. Thus, (1) is rewritten as:

(3) $y_{it} = \boldsymbol{x}_t(C_j)\boldsymbol{\beta} + z_{it}(C_j)\gamma + \boldsymbol{w}_{it}\boldsymbol{\delta} + \tau_t + e_{it}$.

This equation is estimated in two ways, depending on the approach to defining the boundaries of C_j: in the first case, C_j corresponds to carrier i's constellation whose boundaries are defined implicitly (i.e., constellation- and member-specific variables refer to carrier i's implicit constellation, as defined by the cluster algorithm); in the second, it corresponds to carrier i's explicit constellation (if any).

However, estimating the model above entails two kinds of problems. First, not all firms in the sample belong to an explicit constellation. Since firms self-select whether they will join an explicit constellation or not, unobserved firm-specific factors (such as competencies to form and manage multilateral agreements) may cause systematic performance differences conditional on a firm having chosen a particular explicit constellation, and bias the estimates as a result. To test for the presence of selectivity bias, I employ the now-standard Heckman (1979) two-stage approach. In the first stage, considering all firms in the sample, I run a Probit model where the dependent variable ($Expl_{it}$) is binary and codes whether the firm belongs to any explicit constellation at t or not. As explanatory variables, I use all control variables described before (except for the multi-market contact control, which is not observed for non-members of explicit constellations) and a set of instrumental variables. The first instrument, $Expl_{it-1}$, is a dummy variable coded 1 if carrier i was a member of any explicit constellation in the previous year and 0 otherwise. Participation in explicit constellations is likely to involve sunk investments in contractual procedures, brand name, and information technology, which tend to increase the likelihood that firms will continue participating in such groups. The second instrument, $TiesExplicit_{it}$, measures the proportion of carrier i's bilateral ties at t that are to carriers belonging to any explicit constellation in that period. Members of an explicit group may attempt to lure new firms to which they have bilateral ties (Gomes-Casseres, 1996: 66). Taking the sub-sample of members of any explicit constellation in a given year, I next run an OLS regression of $LoadFactor_{it}$ on the inverse Mills ratio resulting from the Probit regression plus the set of controls (except for the multi-market contact variable, which is not included in the Probit equation).[24]

The second problem with the model specification (3) is that constellation-specific ($\boldsymbol{x}(C_j)$) and member-specific ($\boldsymbol{z}_i(C_j)$) attributes may be endogenous. That is, unobserved firm-specific

[24] Some firms are not included in the regressions for implicit groups in cases where the clustering algorithm fails to find a stable pattern of membership for those firms in a given year. Since this is a consequence of the clustering algorithm rather than an issue of self-selection, I do not employ the Heckman two-stage approach in regressions for implicit constellations.

attributes may be correlated with both performance and explanatory variables. For instance, some firms may have a superior ability not only to manage airline operations but also to select partners, which may in turn influence group attributes (e.g., total traffic). Ideally, if endogeneity is present, one should model (3) as a system of equations using instruments to identify the process generating all constellation- and member-specific attributes. However, I was unable to specify such a model due to the lack of sufficient instruments. A common way to control for the problem of endogeneity is to use a fixed-effects specification by removing within-carrier means, which satisfactorily removes fixed carrier-specific unobserved heterogeneity.[25] To assess whether the fixed-effects model is appropriate in my case, compared to a more straightforward random-effects specification, I perform Hausman tests by assessing whether lack of control for carrier-specific unobserved heterogeneity in the random-effects model significantly affects estimates. The test strongly favors the fixed-effects model in all of my regressions, thus suggesting that endogeneity bias is indeed a problem. Therefore, for robustness, I opt for employing fixed-effects estimates to test my hypotheses.[26]

RESULTS AND DISCUSSION

Composition of implicit and explicit constellations

Table 5 shows the evolution and the composition of explicit constellations. The period under analysis in this study has witnessed the progressive emergence of several constellations involving key international players, and the dissolution of other groups. In general, firms do not belong to more than one explicit constellation in a given year. There are some exceptions, but

[25] To be sure, there might be some source of *time-varying* unobserved heterogeneity that is not eliminated with fixed-effects. I believe, however, that any unobserved factor that may cause endogeneity bias—e.g., competencies to form and manage alliances—should be fairly fixed in the sample, especially because the observation window is not long.

[26] Finkel (1995) recommends the use of the lagged dependent variable in panel settings to control for adjustment processes. However, estimating a model like (3) with fixed-effects plus the lagged dependent variable may generate inconsistent estimates (e.g. Nickell, 1981). To correct for this problem, Gimeno (1999) adopts an instrumental variable approach by computing first differences of the lagged dependent variable and then using several lags as instruments. Since this would severely reduce the number of observations in my sample (given the short temporal window of my panel), I decided instead to not include the lagged dependent variable when running the fixed-effect model.

membership in more than one group appears to be an unstable pattern. For instance, Delta and Swissair formed the Atlantic Excellence group in 1997 while still members of the Global Excellence group with Singapore Airlines, but the latter soon departed and later joined the Star Alliance. Swissair, Austrian Airlines, and Sabena were also members of two groups in 1998 and 1999—Atlantic Excellence (with Delta) and Qualiflyer (with other European carriers). But the Atlantic Excellence group was soon dissolved: Delta exited in 1999 and created another group, SkyTeam, with another major international player, Air France, while Austrian Airlines later switched to the Star Alliance. In the rare instances in which a firm belongs to two constellations in a given year, I consider that the composition of its group is the union of the set of firms belonging to each constellation.

<Table 5 around here>

Table 6 presents the composition of implicit constellations, as determined by the tabu search clustering algorithm, and density tables for each year: diagonal entries represent the density of bilateral ties among firms within each group, whereas off-diagonal entries represent the density of bilateral ties among firms belonging to different groups.[27] In all cases, diagonal values are clearly higher than off-diagonal values, suggesting that the algorithm is capturing the operational definition of an implicit constellation as a cluster of firms that have more extensive ties to one another than to firms outside the group.[28] The boundaries of most implicit constellations changes markedly from period to period, in part because bilateral agreements are terminated and formed at a high rate in the industry (Baker, 2001). There also appears to be some correspondence between the composition of implicit groups and the evolving explicit groups, especially in the last years of the observation period, as depicted in Figure 3.[29] This

[27] The density of the group is simply the observed number of existing ties relative to the total possible number of ties between members. Formally, suppose that a constellation C_j with $m_t(C_j)$ members shows $b_t(C_j)$ pair-wise ties at year t. Then the measure of group density will be equal to $b_t(C_j)/[\frac{1}{2}m_t(C_j)(m_t(C_j)-1)]$ (Wasserman & Faust, 1994). Off-diagonal densities are computed similarly, except for the fact that pair-wise ties are now between firms belonging to different groups.
[28] As discussed above, implicit constellations do not need to be dense networks or "cliques." What really matters is the density of ties among group members *relative* to other firms in the industry.
[29] The graph was drawn using the software *KrackPlot 3.0* (Krackhardt, Blythe, & McGrath, 1994).

correspondence lends some support to the idea that some implicit groups may represent "expanded" versions of explicit constellations.[30]

<Table 6 around here>

<Figure 3 around here>

Constellation membership and performance

Table 7 shows the results of the regressions relating constellation membership to firm performance. I first present results where the boundaries of constellations are defined explicitly. Namely, I start by considering only the subset of firms that belong that an explicit constellation, and including in the regressions constellation-related variables based on the explicit group to which carriers belong. Next I consider all firms in the sample and consider the boundaries of their constellations as defined implicitly, that is, I include in the regressions constellation-related variables based on the composition of groups resulting from the cluster algorithm. Note that this sample includes two distinct subsets: members of explicit constellations and carriers that do not belong to any explicit constellation but are bilaterally tied to other firms (including members of explicit groups). Thus, as a *post-hoc* analysis, I split the sample and perform separate regressions for those distinct subsets. Please refer to Figure 3: Lufthansa (LFH) is a member of an explicit group (Star Alliance) and, according to the results of the cluster algorithm, belongs to an implicit group including British Midland (BMI), South African Airways (SAA), Malaysia Airlines (MA), etc. These other carriers, in turn, are members of the same implicit group but are not members of the Star Alliance or any other explicit constellation. This allows us to assess whether the impact of membership in implicit constellations varies depending on whether the carrier is already a member of an explicit group or not.

Constellation boundaries defined explicitly

[30] It is difficult to ascertain whether implicit groups influence the formation of explicit groups or vice-versa. Based on Tables 5 and 6, it seems that some key members of some clusters (such as American Airlines/British Airways/Qantas and KLM/Northwest) later formalized their agreements. In other cases, the formation of implicit groups appears to be simultaneous to or resulting from the emergence of explicit groups, as in the case of the Star Alliance. A more detailed analysis of the determinants of constellation formation, however, is beyond the scope of this paper.

Models (1) and (2) in Table 7 refer to the sub-sample of firms belonging to explicit constellations; all models are significant ($p < .01$). Model (1) tests for the presence of selectivity bias involving the sub-sample of explicit constellations using the two-stage Heckman model, where the first stage (a) estimates, via Probit, a firm's decision to join an explicit constellation, and the second (b) applies the OLS performance regression. For the first stage, all instruments are significant: being part of an explicit constellation at $t-1$ ($Expl_{it\text{-}1}$) and holding a large proportion of bilateral ties to members of existing explicit constellations ($TiesExplicit_{it}$) increases the likelihood of being part of an explicit constellation at *t*. However, when included in the OLS regression, the resulting inverse Mills ratio ($InvMills_{it}$) is insignificant, thus suggesting that selectivity bias is not a matter of concern here.

<Table 7 around here>

Model (2) shows fixed-effects estimates for the sub-sample of firms belonging to explicit groups, adding all constellation-related variables. The model provides support for Hypothesis 1: the aggregate traffic of the explicit constellation ($TotTraffic_t(C_j)$) significantly explains differences in load factors ($p < .01$).[31] Namely, load factors increase by around 1.1 percentage point if the traffic coming from other constellation members increases by 100 billion RPKs. Although the variable measuring hub diversity ($DiversHub_t(C_j)$) is significant ($p < .01$), its sign opposes what was predicted by Hypothesis 2: diversity appears to *reduce*, rather than increase, performance. A 1,000 km increase in the average distance between members' main hubs decreases load factors by 0.57 percentage points. There are at least two possible explanations for this result. First, it may be consistent with theoretical arguments that diversity makes it more difficult for firms to integrate their resources and cooperate. Proximity and similarity of resource endowments facilitate inter-firm monitoring, sharing of experiences, and the pursuit of common goals (e.g. Caves & Porter, 1977; Gnyawali & Madhavan, 2001; Kraatz, 1998). For instance, having firms from distant locations in the group may increase the firms' difficulty in

[31] Tests for hypothesized effects are one-tailed.

understanding country-specific conditions and monitoring one another. Second, $TotTraffic_t(C_j)$ may be picking up part of the effect of increased hub diversity. Thus, even though hub diversity has a direct negative effect on performance, it may have an indirect positive effect by increasing the aggregate traffic of the constellation along with the possibility of exploiting complementarities. Some support for this conjecture is found by noting in Table 3 that $DiversHub_t(C_j)$ and $TotTraffic_t(C_j)$ have a significant and positive correlation, around 0.66 ($p < .01$).

As for the member-specific attributes considered in the analysis, $RelCapacity_{it}(C_j)$ is significant ($p < .05$), thus supporting Hypothesis 3. If a carrier's share of the total seat capacity of its constellation increases by 10 percentage points, its load factor should increase around 1.3 percentage point. $DomHub_t(C_j)$, however, shows no significant effect on carriers' load factors. This result rejects Hypothesis 4: control of critical hubs appears to have no role in explaining differences in operational performance for carriers involved in different constellations. $InsideTie_{it}(C_j)$, in turn, is insignificant, thus rejecting Hypothesis 5 in the context of explicit groups: holding bilateral ties to key firms in its explicit constellation has no consistent effect on a member's operational performance. The relative size of a carrier appears to have a larger role in explaining differential performance within explicit constellations than its connectivity (via bilateral ties) to other members.

Constellation boundaries defined implicitly

Models (3) to (5) in Table 7 show regressions results for implicit constellations (i.e., where the composition of groups is obtained from the cluster algorithm). All models are significant ($p < .01$). Model (4), including all firms in the sample, show that the aggregate traffic of the implicit constellation ($TotTraffic_t(C_j)$) does not significantly affect operational performance. Hub diversity ($DiversHub_t(C_j)$), in turn, is significantly positive, but only marginally so ($p < .10$). Thus, there is no robust support for Hypotheses 1 and 2 in the context of implicit constellations. The member-specific attributes $RelCapacity_{it}(C_j)$ and $DomHub_t(C_j)$ are also insignificant at conventional levels, thus failing to support Hypotheses 3 and 4 when constellation membership is defined implicitly. However, the member-specific attribute $InsideTie_{it}(C_j)$ shows a significant coefficient ($p < .05$): a 10 percentage point increase in the proportion of the implicit constellation's traffic coming from members to which a certain firm holds bilateral ties increases that firm's load factor by around 0.15 percentage points ($p < .05$). This result lends support for Hypothesis 5 in the context of implicit constellations: the extent of carriers' bilateral connectedness to members holding large traffic flows explains inter-firm performance differences within the same group.

A caveat associated with this result is that, since the boundaries of implicit groups are invariably assessed with error, the effect of constellation-related variables should be attenuated relative to explicit groups. However, $InsideTie_{it}(C_j)$ shows an opposite pattern: it is significant in the context of implicit groups and insignificant in the regression for explicit constellations, despite the fact that error in the measurement of that variable should be larger in the first case. This finding can be explained in two ways. First, the absence of general agreements in implicit constellations implies that a firm must establish direct ties to other members to increase its access to their resources and markets. In explicit airline constellations, as agreements become more comprehensive and general, the extent of passenger traffic that carriers can capture from other members through bilateral deals should not differ much across firms. Furthermore, explicit airline constellations have generally established decision-making committees and boards involving executives from member carriers (Baker, 2001). The absence of such joint decision-making groups in implicit constellations makes bilateral ties much more instrumental in delivering direct access to other members to influence collective strategies through voice. A second explanation is that carriers in explicit constellations may be less heterogeneous in terms of their bilateral connectedness to other members. This can be observed in Table 5: the network of bilateral ties within explicit constellations is generally dense, or at least denser than most implicit groups (Table 6). Thus, the data may simply lack sufficient heterogeneity to infer whether bilateral ties within explicit groups matter or not.

To further examine this issue, models (4) and (5) perform a *post-hoc* analysis by considering how the effect of bilateral ties changes across two-subsets of firms: carriers that are non-members of explicit groups but are bilaterally connected to other firms, and carriers that are members of explicit constellations.[32] $InsideTie_{it}(C_j)$ is only significant in model (4). This finding confirms that bilateral connections in the context of implicit groups have a larger impact on operational performance for firms that are not members of any explicit group. Apparently, when a carrier belongs to an explicit group, most of its internalized traffic comes from partners from its own explicit group. Non-members of explicit airline groups, in contrast, will have to establish bilateral connections to carriers handling large traffic flow (including, in some cases, members of explicit groups) in order to increase their operational performance.[33] This result potentially explains why most explicit constellations have a subset of firms that are not part of the group, but are bilaterally linked with some key carriers of the constellation (Figure 3).

Note, in addition, that both the effect of a firm's total number of direct bilateral ties ($EgoTies_{it}$) and the size of the traffic handled by its direct partners ($EgoTraffic_{it}$), which are used as control variables, are insignificant across all models. This result casts doubt on the role of ego networks in explaining inter-firm performance differences in the present context: patterns of constellation membership appear to be more important than the overall structure of direct ties managed by firms. Possibly, bilateral associations *in general* do not guarantee that firms will be able to internalize externalities (passenger traffic) from their partners. Thus, if a carrier *A* agrees to develop a codesharing agreement with another carrier *B,* but carrier *A* spends more time and effort in exploiting complementary routes with other carriers to which *A* also holds bilateral agreements, then carrier *B* may not benefit from the association. Presumably, membership in the

[32] The number of observations in regression (5) is slightly smaller than in regression (2) because in a few cases the cluster algorithm could not find a consistent pattern of grouping for some members of explicit constellations (see footnote 14).

[33] As a final examination of the data (not reported here), I jointly included in the regression variables related to implicit and explicit constellations, to see whether implicit groups have any additional effect on operational performance of carriers beyond the effect of explicit constellation membership. Obviously, this is only possible for the subset of carriers that belong to an explicit group. All variables related to implicit constellations are found to be insignificant, thus confirming that bilateral connectedness to key carriers has a larger role in explaining performance differences for non-members of explicit groups

same implicit constellation makes the flow of passenger traffic more confined to a particular set of firms—i.e., firms with more ties to one another than to other firms in the industry. Thus, holding bilateral ties to partners from the same implicit constellation may grant more benefits than holding ties to firms in general.[34]

CONCLUDING REMARKS

Contributions

This study moves beyond research focusing on ego networks or the web of alliances surrounding particular firms and shows that there is value in examining the impact of membership in competing constellations. Although past research has studied constellations, the performance implications of membership in those competing groups remain an under-explored topic. Using the airline industry as an empirical context, I analyze two patterns of multiple-firm partnering that have emerged in that industry: explicit (formal, multilateral agreements) and implicit constellations (informal clusters of firms that have more bilateral ties to one another than to firms outside the group). The major argument is that membership in constellations can allow carriers to capture externalities from other firms in the form of direct or indirect traffic flow, which should increase their operational performance (load factors). I find that membership in explicit airline constellations does enhance operational performance, and that the effect is larger in the case of constellations with large aggregate traffic and for carriers contributing to a large portion of the group's capacity. In implicit constellations, in contrast, membership benefits seem to be more related to the extent to which the carrier is bilaterally connected to key members, after controlling for the effect of a carrier's own ego network.

[34] I also evaluate ego networks trying to adjust for the "strength" of bilateral associations, since the effect of implicit constellation membership may simply follow from the fact that constellation members might represent the most important partners in a carriers' ego network. I thank an anonymous referee for suggesting this adjustment. One of the adjustments I perform is to add weights to certain types of ties based on the existence of some ownership relation: if the tie involves an equity stake, then it receives weight 2; otherwise, it receives weight 1. I also added weights based on the number of activities involved in the alliance, such as codesharing, marketing, etc. (Gimeno, 2003). Even with these adjustments, the ego-related variables remain insignificant.

Thus, the way the boundaries of constellations are defined is critical to the analysis of membership benefits. This point is particularly important because the literature on competing constellations has focused on distinct approaches to demarcate the boundaries of multiple-firm alliances. While some scholars have focused on alliance networks defined as webs of bilateral ties (e.g. Burgers *et al.*, 1993; Nohria & Garcia-Pont, 1991; Vanhaverbeke & Noorderhaven, 2001; Walker, 1988), which I refer to as implicit constellations, other scholars have paid more attention to multilateral alliances involving overarching agreements applicable to multiple firms (e.g. Das & Teng, 2002; Doz & Hamel, 1998; Hwang & Burgers, 1997), which I refer to as explicit constellations. The present study suggests that it is worth analyzing patterns of membership in different ways, because they are likely to have distinct implications for firm performance.

Results from this study also have important managerial implications. Faced with competing constellations, managers would like to know the performance implications of partnering with a given group of firms. In other words, managers should decide not only whether they should join a constellation, but also which constellation to join. Data from the global airline industry show that this decision does matter, at least with respect to operational performance. Thus, when considering alternative explicit constellations, airline managers should pay extra attention to the size of the constellation's aggregate traffic. Also, carriers contributing with a large portion of the explicit constellation's seat capacity should expect to reap larger benefits. In contrast, when designing of their web of bilateral ties, airline managers should consider that more alliances *in general* might not imply more traffic. Although alliances are widespread in the global airline industry, there is evidence that carriers have formed implicit groups whereby firms have more ties to one another than to actors outside their group. The data show that carriers benefit more from ties to key firms inside those groups than to firms in general. Since implicit airline groups appear to be, in several cases, expanded versions of explicit constellations, it follows that a carrier connected to key members of an explicit group may be able to capture passenger traffic even if it does not belong to that group.

Limitations and possible extensions

This study has important limitations. Its results are confined to a single industry and thus may not be generalizable to other contexts. Many variables under analysis here are industry-specific, although they relate to general theoretical concepts. The implicit and explicit patterns of multiple-firm partnering in the airline industry are idiosyncratic, although some analogies can be made. Consider, for instance, the computer and microprocessor industry. Firms have not only established clusters of bilateral alliances (involving, for instance, technology licensing and marketing), which can be interpreted as implicit constellations, but also formal consortiums for R&D and production (Axelrod et al., 1995; Hwang & Burgers, 1997; Vanhaverbeke & Noorderhaven, 2001), which correspond to explicit constellations. Similarly to the present study, one could analyze those informal and formal interfirm associations and try to examine their impact on firm performance. Other industries that apparently have experienced the emergence of multiple-partner alliances include, for instance, telecommunications (Joshi, Kashlak, & Sherman, 1998), financial services (Domowitz, 1995), and automobiles (Burgers *et al.*, 1993; Garcia-Point & Nohria, 2002; Nohria & Garcia-Pont, 1991).

A related criticism is that, because international traffic in the airline industry is heavily regulated, the only real way for global airlines to benefit from foreign resources is to form alliances. In other industry contexts, firms may expand their networks and develop their own resources *internally*, i.e., by increasing the size and scope of their operations. I believe, however, that the theoretical framework and the results presented here have applicability in other contexts for several reasons. Even in situations where firms are free to acquire foreign resources, the internalization of large networks within a single firm is often either unfeasible or excessively costly (Richardson, 1972). Some resources, such as knowledge of local markets or competencies in specific technical fields, are difficult to replicate, because they often result from specific learning processes and demand complex, interdependent skills (Dierickx & Cool, 1989; Reed & DeFillippi, 1990). The acquisition of existing firms holding such resources is likely to reduce incentives for innovation, as those firms will not be subject to market-based selection pressures

(Kogut, 2000). For this reason, Nohria and Garcia-Pont (1991) claim that constellations are crucial in *global* contexts precisely because firms cannot hope to fully control and have access to local resources. Furthermore, even in cases where regulation does not prevent the acquisition of foreign resources, firms may be hesitant about such acquisitions if they perceive a risk that such investments will be expropriated by discretionary local governments (Henisz, 2000). Thus, there are circumstances in which the internal expansion of networks is difficult, and thus membership in constellations becomes an important organizational decision. However, an assessment of the benefits of constellation membership in other industries, particularly in contexts where firms have more freedom to choose alternative organizational modes, is certainly warranted.

Another limitation of this study is that the demarcation of the boundaries of implicit constellations is inherently difficult and error-prone, which may cause problems in comparing explicit and implicit groups. Of course, this problem is present in any study assessing the boundaries of organizational forms that are not readily observable (Hannan & Freeman, 1989). Thus, the empirical results involving implicit constellations must be taken with caution. Although the tabu search optimization algorithm employed here is an improvement over typical methods such as hierarchical clustering, there is a clear need to define a general criterion for choosing an optimal number of partitions based on the network of bilateral ties.

This study also uses an operational performance measure (load factor), which ignores sources of costs other than capacity and hence may overestimate the benefits of constellation membership. Specifically, I cannot tell whether the positive externalities attained from constellation membership outweigh the costs to form and manage those groups. This is particularly critical in the case of explicit constellations, since firms may incur substantial expenses to negotiate agreements, establish committees to oversee the affairs of the group, create common communication interfaces, and so forth. Studies that attempt to assess sources of costs associated with constellation membership are needed.

Finally, I cannot ascertain the particular mechanisms that are driving the results presented here, even when results are consistent with the theoretical predictions. For instance, what are the precise factors that influence the emergence of general agreements and allow firms to internalize traffic in explicit constellations? What is the role of decision-making committees in explicit constellations and how are they managed? What is the nature of negotiation and influence tactics within constellations, for instance when firms decide to redesign their route networks? How do firms create and benefit from bilateral associations in implicit groups? A more micro-analytic examination of those processes can contribute greatly to our understanding of how constellations are organized and managed.

References

Axelrod R, Mitchell W, Thomas RE, Bennett DS, Bruderer E. 1995. Coalition formation in standard-setting alliances. *Management Science* **41**(9): 1493-1508

Baker C. 2001. The global groupings, *Airline Business*, Vol. 17: 40-45

Bamberger GE, Carlton DW, Neumann LR. 2001. An empirical investigation of the competitive effects of domestic airline alliances, *National Bureau of Economic Research Working Paper*: Cambridge

Barley SR, Freeman J, Hybels R. 1992. Strategic alliances in commercial biotechnology. In N Nohria, RG Eccles (Eds.), *Networks and organizations: structure, form, and action*. Harvard Business School Press: Boston

Barney JB, Hoskisson RE. 1990. Strategic groups: untested assertions and research proposals. *Manageral and Decision Economics* **11**: 187-198

Behn BK, Riley Jr. RA. 1999. Using nonfinancial information to predict financial performance: the case of the U.S. airline industry. *Journal of Accounting, Auditing & Finance* **14**(1): 29-56

Bernheim BD, Whinston MD. 1990. Multimarket contact and collusive behavior. *RAND Journal of Economics* **21**: 1-26

Borgatti SP, Everett M, Freeman LC. 1999. *UCINET 5.0*. Analytic Technologies: Natick

Brandenburger A, Nalebuff BJ. 1996. *Co-opetition*. Currency Doubleday: New York

Brueckner JK, Spiller PT. 1994. Economies of traffic density in the deregulated airline industry. *Journal of Law & Economics* **37**: 379-415

Brueckner JK, Whalen WT. 2000. The price effects of international airline alliances. *Journal of Law & Economics* **43**: 503-544

Burgers WP, Hill CWL, Kim WC. 1993. A theory of global strategic alliances: the case of the global auto industry. *Strategic Management Journal* **14**: 419-432

Caves DW, Christensen LR, Tretheway MW. 1984. Economies of density versus economies of scale: why trunk and local service airline costs differ. *RAND Journal of Economics* **15**: 471-489

Caves RE, Porter ME. 1977. From entry barriers to mobility barriers: conjectural decisions and contrived deterrence to new competition. *The Quarterly Journal of Economics* **91**: 241-261

Chen M-J. 1996. Competitor analysis and interfirm rivalry: toward a theoretical integration. *Academy of Management Review* **21**(1): 100-134

Chen Z, Ross TW. 2000. Strategic alliances, shared facilities, and entry deterrence. *RAND Journal of Economics* **31**(2): 326-344

Clougherty JA. 2002. US domestic airline mergers: the neglected international determinants. *International Journal of Industrial Organization* **20**: 557-576

Das TK, Teng B-S. 2002. Alliance constellations: a social exchange perspective. *Academy of Management Review* **27**(3): 445-456

Dierickx I, Cool K. 1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science* **35**(12): 1504-1513

Doganis R. 2001. *The airline industry in the 21st century*. Routledge: London

Domowitz I. 1995. Electronic derivatives exchanges: implicit mergers, network externalities, and standardization. *The Quarterly Review of Economics and Finance*(35): 163-175

Doz YL, Hamel G. 1998. *Alliance advantage: the art of creating value through partnering*. Harvard Business School Press: Boston

Dyer JH, Nobeoka K. 2000. Creating and managing a high-performance knowledge-sharing network: the Toyota case. *Strategic Management Journal* **21**: 345-367

Dyer JH, Singh H. 1998. The relational view: cooperative strategy and sources of interorganizational competitive advantage. *Academy of Management Review* **23**: 660-679

Economides N. 1996. The economics of networks. *International Journal of Industrial Organization* **14**: 673-699

Economides N, Flyer F. 1997. Compatibility and market structure for network goods, *Working paper, Stern School of Business*: New York

Economides N, Salop SC. 1992. Competition and integration among complements, and network market structure. *The Journal of Industrial Economics* **40**(1): 105-123

Encaoua D, Moreaux M, Perrot A. 1996. Compatibility and competition in airlines: demand side network effects. *International Journal of Industrial Organization* **14**(701-726)

Evans WN, Kessides IN. 1994. Living by the "golden rule": multimarket contact in the U.S. airline industry. *Quarterly Journal of Economics* **109**(2): 341-366

Farrell J, Saloner G. 1985. Standardization, compatibility, and innovation. *RAND Journal of Economics* **16**(1): 70-83

Finkel SE. 1995. *Causal analysis with panel data*. SAGE Publications: Thousand Oaks

Freeman LC. 1979. Centrality in social networks: conceptual clarification. *Social Networks* **1**: 215-239

Garcia-Point C, Nohria N. 2002. Local versus global mimetism: the dynamics of alliance formation in the automobile industry. *Strategic Management Journal* **23**: 307-321

Gimeno J. 1999. Reciprocal threats in multimarket rivalry: staking out 'spheres of influence' in the U.S. airline industry. *Strategic Management Journal* **20**: 101-128

Gimeno J. 2003. The competitive evolution of alliance networks, *Working paper, INSEAD.*

Gimeno J, Woo CY. 1996. Hypercompetition in a multimarket environment: the role of strategic similarity and multimarket contact in competitive de-escalation. *Organization Science* **7**(3): 322-341

Glover F. 1989. Tabu search - part I. *ORSA Journal on Computing* **1**(3): 190-206

Gnyawali DR, Madhavan R. 2001. Cooperative networks and competitive dynamics: a structural embeddedness perspective. *Academy of Management Review* **26**(3): 431-445

Gomes-Casseres B. 1994. Group versus group: how alliance networks compete. *Harvard Business Review* **July-August**: 62-74

Gomes-Casseres B. 1996. *The alliance revolution: the new shape of business rivalry*. Harvard University Press: Cambridge

Grandori A, Soda G. 1995. Inter-firm networks: antecedents, mechanisms and forms. *Organization Studies* **16**(2): 183-214

Gulati R. 1998. Alliances and networks. *Strategic Management Journal* **19**: 293-317

Gulati R. 1999. Network location and learning: the influence of network resources and firm capabilities on alliance formation. *Strategic Management Journal* **20**: 397-420

Gulati R, Nohria N, Zaheer A. 2000. Strategic networks. *Strategic Management Journal* **21**: 203-215

Hanlon P. 1999. *Global airlines: competition in a transnational industry* (Second ed.). Butterworth Heinemann: Oxford

Hannan MT, Freeman J. 1989. *Organizational ecology*. Harvard University Press: Cambridge

Harrigan KR. 1988. Joint ventures and competitive strategy. *Strategic Management Journal* **9**: 141-158
Heckman JJ. 1979. Sample selection bias as a specification error. *Econometrica* **47**(1): 153-161
Henisz WJ. 2000. The institutional environment for multinational investment. *Journal of Law Economics and Organization* **16**: 334-364
Hirschman AO. 1970. *Exit, voice, and loyalty*. Harvard University Press: Cambridge
Holloway S. 1998. *Changing planes: a strategic management perspective on an industry in transition*. Ashgate: Aldershot
Hwang P, Burgers WP. 1997. The many faces of multi-firm alliances: lessons for managers. *California Management Review* **39**(3): 101-117
Joshi MP, Kashlak RJ, Sherman HD. 1998. How alliances are reshaping telecommunications. *Long Range Planning* **31**(4): 542-548
Karnani A, Wernerfelt B. 1985. Multiple point competition. *Strategic Management Journal* **6**: 87-96
Katz ML, Shapiro C. 1985. Network externalities, competition, and innovation. *The American Economic Review* **75**: 424-440
Katz ML, Shapiro C. 1994. Systems competition and network effects. *Journal of Economic Perspectives* **8**(2): 93-115
Klemperer P. 1987. Markets with consumer switching costs. *The Quarterly Journal of Economics* **102**: 375-394
Kogut B. 2000. The network as knowledge: generative rules and the emergence of structure. *Strategic Management Journal* **21**: 405-425
Kraatz MS. 1998. Learning by association? Interorganizational networks and adaptation to environmental change. *Academy of Management Journal* **41**(6): 621-643
Krackhardt D, Blythe J, McGrath C. 1994. KrackPlot 3.0: An improved network drawing program. *Connections* **17**(2): 53-55
Lawless MW, Anderson PC. 1996. Generational technological change: effects of innovation and local rivalry on performance. *Academy of Management Journal* **39**(5): 1185-1217
Lazzarini SG, Chaddad FR, Cook ML. 2001. Integrating supply chain and network analyses: the study of netchains. *Journal on Chain and Network Science* **1**(1): 7-22
Lorenzoni G, Ornati OA. 1988. Constellations of firms and new ventures. *Journal of Business Venturing* **3**: 41-57
McEvily B, Zaheer A. 1999. Bridging ties: a source of firm heterogeneity in competitive capabilities. *Strategic Management Journal* **20**: 1133-1156
Money RB. 1998. International multilateral negotiations and social networks. *Journal of International Business Studies* **29**(4): 695-710
Morrison SA, Winston C. 1995. *The evolution of the airline industry*. The Brookings Institution: Washington D.C.
Nickell S. 1981. Biases in dynamic models with fixed effects. *Econometrica* **49**(6): 1417-1426
Nohria N, Garcia-Pont C. 1991. Global strategic alliances and industry structure. *Strategic Management Journal* **12**: 105-124
Odell M, Spiegel P. 2002. BA refuses to pay price for approval, *Financial Times*:
Osborne MJ, Rubinstein A. 1994. *A course in game theory*. The MIT Press: Cambridge
Oum TH, Yu C. 1998. *Winning airlines: productivity and cost competitiveness of the world's major airlines*. Kluwer Academic Publishers: Boston

Park J-H, Zhang A. 2000. An empirical analysis of global airline alliances: cases in North Atlantic markets. *Review of Industrial Organization* **16**: 367-383

Park NK, Martin X. 2001. When do resources enhance firm value? Testing alliance and resource effects on firm value, *Working paper, Stern School of Business*:

Pfeffer J, Salancik GR. 1978. *The external control of organizations*. Harper & Row: New York

Powell WW, Koput KW, Smith-Doerr L. 1996. Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology. *Administrative Science Quarterly* **41**: 116-145

Pustay MW. 1992. Toward a global airline industry: prospects and impediments. *Logistics and Transportation Review* **28**(1): 103-128

Ray G, Barney JB, Muhanna WA. 2004. Capabilities, business processes, and competitive advantage: choosing the dependent variable in empirical tests of the resource-based view. *Strategic Management Journal* **25**: 23-37

Reed R, DeFillippi RJ. 1990. Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review* **15**(1): 88-102

Richardson GB. 1972. The organization of industry. *The Economic Journal* **82**(327): 883-896

Rowley T, Behrens D, Krackhardt D. 2000. Redundant governance structures: an analysis of structural and relational embeddedness in the steel and semiconductor industries. *Strategic Management Journal* **21**: 369-386

Schefczyk M. 1993. Operational performance of airlines: an extension of traditional measurement paradigms. *Strategic Management Journal* **14**: 301-317

Taneja NK. 1988. *The international airline industry: trends, issues, and challenges*. Lexington Books: Lexington

Teece DJ. 1992. Competition, cooperation, and innovation: organizational arrangements for regimes of rapid technological progress. *Journal of Economic Behavior and Organization* **18**: 1-25

ter Kuile A. 1997. Hub fever, *Airline Business*: 66-71

Tirole J. 1988. *The theory of industrial organization*. MIT Press: Cambridge

Uzzi B. 1996. The sources and consequences of embeddedness for the economic performance of organizations: the network effect. *American Sociological Review* **61**: 674-698

Vanhaverbeke W, Noorderhaven NG. 2001. Competition between alliance blocks: the case of the RISC microprocessor technology. *Organization Studies* **22**(1): 1-30

Walker G. 1988. Network analysis for cooperative interfirm relationships. In FJ Contractor, P Lorange (Eds.), *Cooperative strategies in international business: joint ventures and technology partnerships between firms*: 227-240. Lexington Books: Lexington

Wasserman S, Faust K. 1994. *Social network analysis*. Cambridge University Press: Cambridge

Whitaker R. 1996. Emerging mega-alliances, *Airline Business*, Vol. 12: 31

Williamson OE. 1985. *The economic institutions of capitalism*. The Free Press: New York

Youssef W, Hansen M. 1994. Consequences of strategic alliances between international airlines: the case of Swissair and SAS. *Transportation Research-A* **28A**(5): 415-431

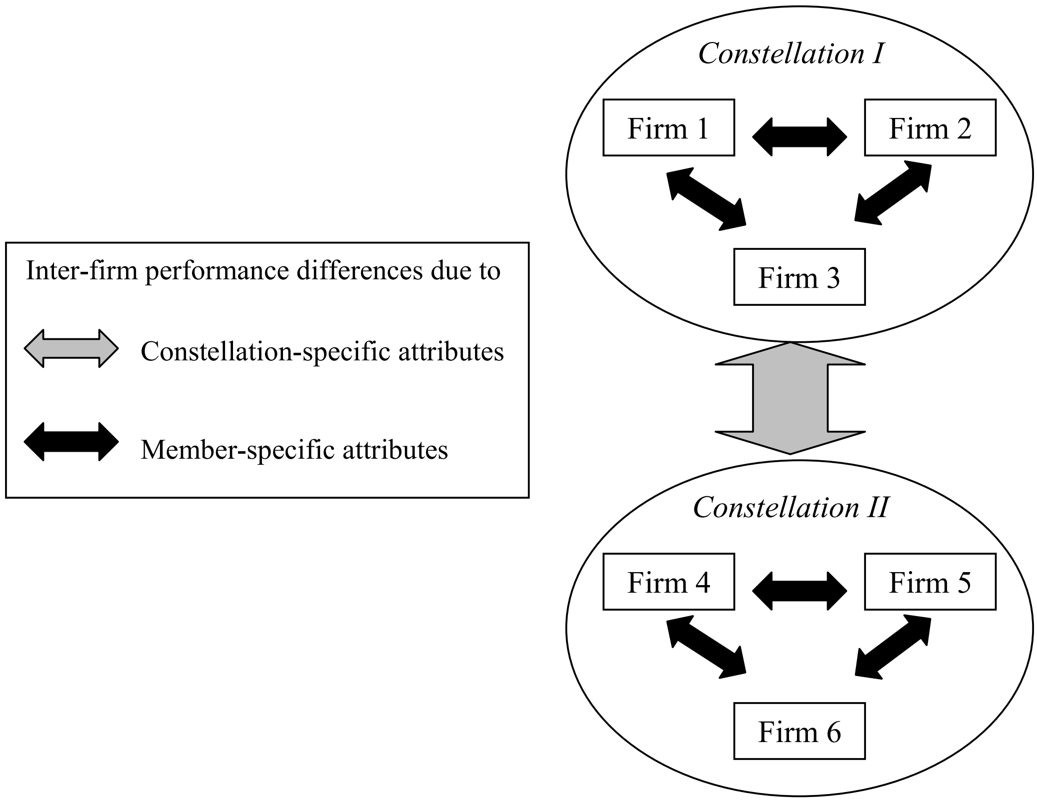

Figure 1. Differential performance stemming from constellation membership

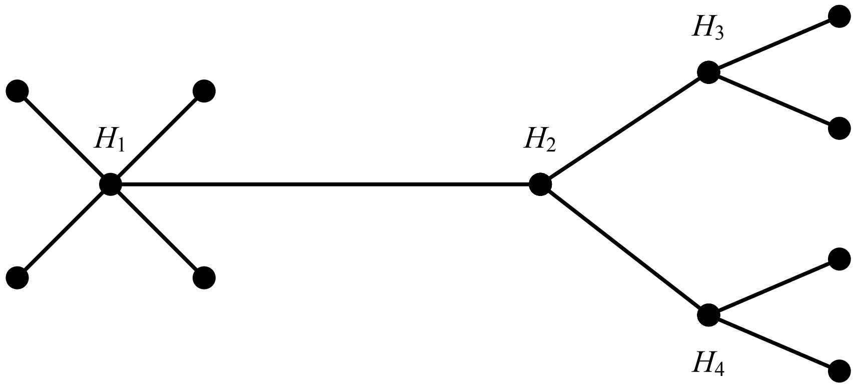

Figure 2. A hypothetical route network

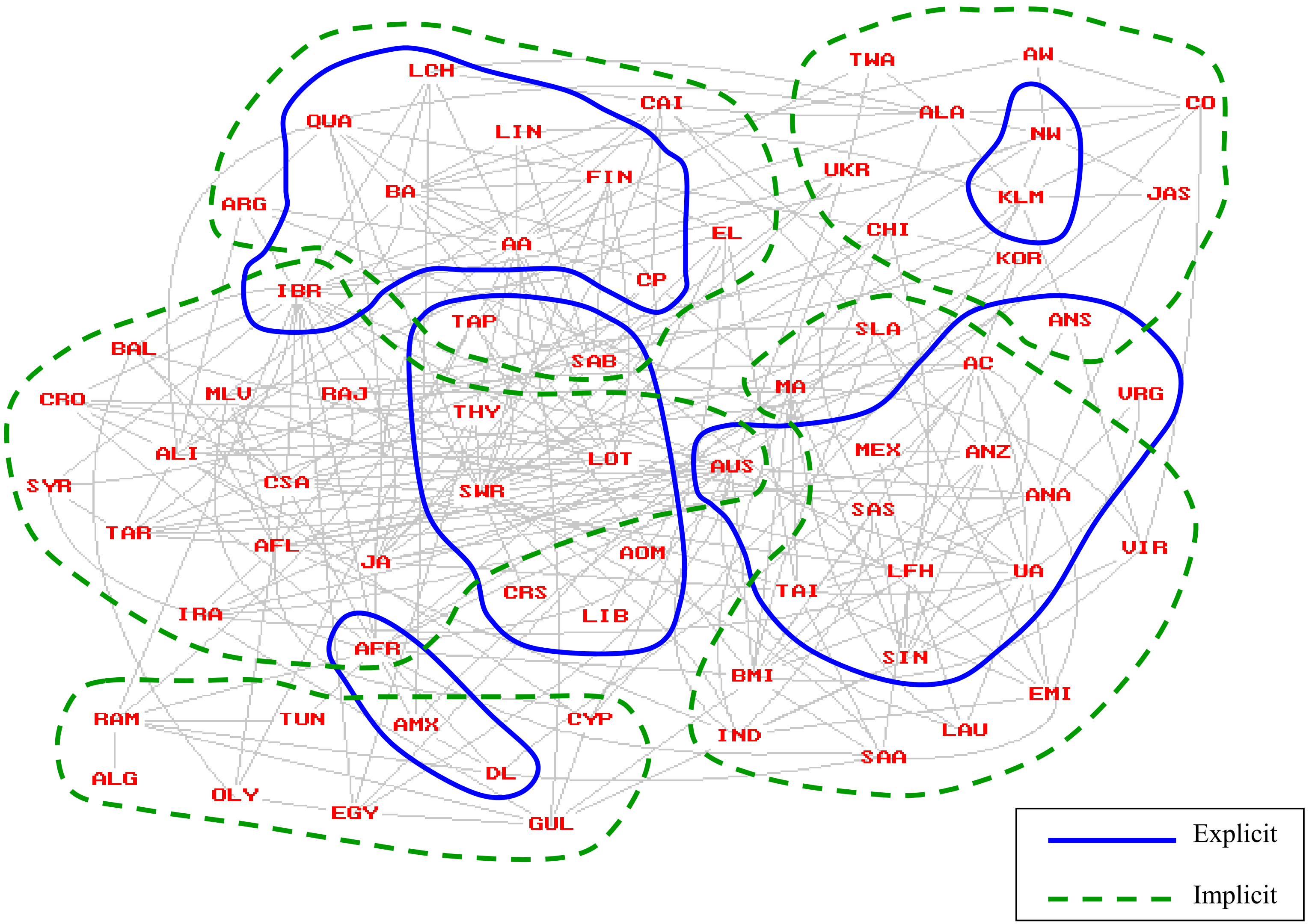

Figure 3. Implicit and explicit airline constellations in early 2000
Note: Abbreviations of carrier names as indicated in Table 1; gray lines represent bilateral ties.

Table 1. Airline carriers included in the sample

Carrier name (abbreviation)	Traffic*	Country	Carrier name (abbreviation)	Traffic*	Country
Aer Lingus (LIN)	8.889	Ireland	Japan Air System (JAS)	15.472	Japan
Aeroflot (AFL)	16.557	Russia	Japan Airlines (JA)	88.999	Japan
Aerolineas Argentinas (ARG)	11.111	Argentina	KLM Royal Dutch Airl. (KLM)	60.331	Netherlands
Aeromexico (AMX)	14.390	Mexico	Korean Air (KOR)	40.467	South Korea
Air Algerie (ALG)	3.051	Algeria	LanChile (LCH)	9.931	Chile
Air Canada (AC)	44.806	Canada	Lauda Air (LAU)	4.562	Austria
Air China (CHI)	18.116	China	Lloyd Aero Boliviano (LAB)	1.701	Bolivia
Air France (AFR)	91.801	France	LOT Polish Airlines (LOT)	4.757	Poland
Air-India (IND)	12.006	India	Lufthansa (LFH)	94.170	Germany
Air Liberte (LIB)	4.707	France	Malaysia Airlines (MA)	37.947	Malaysia
Air New Zealand (ANZ)	22.232	New Zealand	Malev Hungarian Airlines (MAL)	3.168	Hungary
Alaska Airlines (ALA)	19.273	United States	Mexicana de Aviacion (MEX)	13.498	Mexico
Alitalia (ALI)	40.618	Italy	Northwest Airlines (NW)	127.324	United States
All Nippon Airways (ANA)	58.042	Japan	Olympic Airways (OLY)	8.860	Greece
America West Airlines (AW)	30.742	United States	Qantas Airways (QUA)	63.495	Australia
American Airlines (AA)	187.542	United States	Royal Air Maroc (RAM)	7.185	Morocco
Ansett Australia (ANS)	17.110	Australia	Royal Jordanian Airlines (RAJ)	4.207	Jordan
AOM French Airlines (AOM)	9.248	France	Sabena (SAB)	19.379	Belgium
Austrian Airlines (AUS)	8.799	Austria	Scandinavian Airlines (SAS)	22.647	Sweden
Balkan Bulgarian (BAL)	0.808	Bulgaria	Saudi Arabian Airlines (SAU)	20.229	Saudi Arabia
British Airways (BA)	118.890	United Kingdom	Singapore Airlines (SIN)	70.795	Singapore
British Midland (BMI)	3.837	United Kingdom	South African Airways (SAA)	19.321	South Africa
Canadian Airlines Intern. (CAI)	23.395	Canada	Sri Lankan Airlines (SLA)	6.860	Sri Lanka
Cathay Pacific (CP)	47.097	Hong Kong	Swissair (SWR)	34.246	Switzerland
Continental Airlines (CO)	96.949	United States	Syrian Arab Airlines (SYR)	1.422	Syria
Croatia Airlines (CRO)	0.644	Croatia	TAP Air Portugal (TAP)	10.385	Portugal
Crossair (CRS)	2.073	Switzerland	TAROM (TAR)	2.075	Romania
CSA Czech Airlines (CSA)	3.294	Czech Republic	Thai Airways International (TAI)	42.236	Thailand
Cyprus Airways (CYP)	2.785	Cyprus	Trans World Airlines (TWA)	43.798	United States
Delta Air Lines (DL)	173.411	United States	Tunisair (TUN)	2.694	Tunisia
Egyptair (EGY)	9.086	Egypt	Turkish Airlines THY (THY)	16.492	Turkey
El Al (EL)	14.125	Israel	Ukraine Intern. Airlines (UKR)	0.401	Ukraine
Emirates (EMI)	19.413	Un. Arab Emirates	United Airlines (UA)	204.187	United States
Finnair (FIN)	7.460	Finland	US Airways (USAir) (USA)	75.380	United States
GB Airways (GB)	1.971	United Kingdom	Varig (VRG)	26.286	Brazil
Gulf Air (GUL)	12.739	Bahrain	VASP Brazilian Airlines (VSP)	4.918	Brazil
Iberia Airlines (IBR)	40.015	Spain	Virgin Atlantic Airways (VIR)	29.471	United Kingdom
Iran Air (IRA)	6.229	Iran			

* Passenger traffic in 2000, in billions of RPK (revenue passenger kilometers), from IATA's *World Air Transport Statistics*.

Table 2. Description of variables

Measure	Description
<u>*Performance*</u>	
LoadFactor$_{it}$	Load factor: the ratio of carrier *i*'s total traffic (RPK) to its overall traffic capacity (ASK) at year *t* (%).
<u>*Constellation-specific attributes*</u>	
TotTraffic$_t(C_j)$	Total passenger traffic (sum of members' RPKs in billions) of constellation C_j at *t*, excluding carrier *i*'s individual traffic.
DiversHub$_t(C_j)$	The average distance (in thousands of km) between the major hubs of all carrier-pairs within constellation C_j at *t*.
<u>*Member-specific attributes*</u>	
RelCapacity$_{it}(C_j)$	The ratio of carrier *i*'s passenger capacity (ASK) to the total capacity of its constellation C_j at *t*.
DomHub$_{it}(C_j)$	Roughly speaking, carrier *i*'s dominance of the traffic involving cities in the route network of constellation C_j weighted by the relative importance of those cities/hubs in aggregating traffic.
InsideTie$_{it}(C_j)$	Total passenger traffic (RPK) coming from members of constellation C_j to which carrier $i \in C_j$ has bilateral ties at *t*, divided by the total traffic of constellation C_j (i.e., *TotTraffic*$_t(C_j)$).
<u>*Control variables*</u>	
Employees$_{it}$	Carrier *i*'s number of employees at *t* (in thousands).
Routes$_{it}$	Carrier *i*'s number of serviced international routes at *t* (in thousands).
Age$_{it}$	Time elapsed, at *t*, since carrier *i*'s founding (years).
EgoTies$_{it}$	Number of direct bilateral ties of carrier *i* at *t*.
EgoTraffic$_{it}$	Aggregate traffic (in billions of RPKs) of carriers to which carrier *i* has direct bilateral ties at *t*.
Contact$_{it}(C_j)$	Average number of international route contacts between carrier *i* and other members of its constellation C_j at *t*.
GDPCap$_{it}$,	GDP per capita of carrier *i*'s country at *t* (in thousands of US dollars).
GDPGrow$_{it}$	GDP growth (%) of carrier *i*'s country at *t*.
Pop$_{it}$	Population (in billions of inhabitants) of carrier *i*'s country at *t*.
Year(*t*)	Set of dummy variables coded 1 if the observation is from year *t* and 0 otherwise.

Note: ASK = available seat kilometers; RPK = revenue passenger kilometers.

Table 3. Summary statistics: explicit groups (N = 86)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.$LoadFactor_{it}$	1																				
2.$TotTraffic_{t}$	.14	1																			
3.$DiversHub_{t}$	.27	.66	1																		
4.$RelCapacity_{it}$	.30	-.46	.09	1																	
5.$DomHub_{it}$	.11	-.29	.03	.38	1																
6.$InsideTie_{it}$	.36	-.16	.22	.41	.41	1															
7.$Employees_{it}$	.29	-.11	.33	.80	.30	.35	1														
8.$Routes_{it}$	.11	-.02	.21	.35	.71	.28	.53	1													
9.Age_{it}	.15	.10	.22	.36	.43	.28	.41	.46	1												
10.$EgoTies_{it}$	.19	.05	.06	.15	.36	.42	.27	.41	.33	1											
11.$EgoTraffic_{it}$	.29	.48	.42	-.12	.13	.43	.07	.19	.24	.68	1										
12.$Contact_{t}$	.14	-.18	.15	.45	.59	.25	.52	.70	.28	.24	.07	1									
13.$GDPCap_{it}$,	-.02	-.24	.04	.38	.47	.34	.36	.32	.00	.31	.01	.35	1								
14.$GDPGrow_{it}$	.32	.13	.21	.10	-.14	.16	.05	-.16	-.01	-.05	.20	-.13	.12	1							
15.Pop_{it}	.18	-.22	.16	.83	.12	.23	.85	.29	.31	.03	-.17	.30	.21	.02	1						
16.*Year95*	-.09	-.15	.22	.15	.16	.20	.04	.04	-.04	-.01	-.06	.06	.18	.03	.03	1					
17.*Year96*	-.01	-.14	.22	.15	.15	.20	.02	.03	-.03	.05	.01	.00	.16	.02	.04	-.04	1				
18.*Year97*	-.05	-.09	.00	.04	.06	.18	.05	.15	-.02	.05	-.02	.32	.06	-.06	.00	-.07	-.07	1			
19.*Year98*	-.08	-.17	-.31	-.06	-.07	.00	-.06	-.05	-.12	-.07	-.21	-.07	-.03	-.26	-.01	-.09	-.09	-.17	1		
20.*Year99*	-.06	-.03	.06	.02	.01	-.25	.04	.04	.03	-.05	-.05	.10	-.01	-.16	.02	-.11	-.11	-.22	-.28	1	
21.*Year00*	.19	.33	.02	-.11	-.11	-.04	-.05	-.12	.11	.05	.24	-.26	-.14	.37	-.04	-.15	-.15	-.28	-.35	-.47	1
Mean	70	273	7.0	.18	9.3	.73	26	.28	57	9.2	353	11	23	3.5	.07	.03	.03	.12	.17	.27	.37
Std. Dev.	5.4	171	3.7	.20	7.8	.26	26	.20	20	5.5	171	8.4	10	2.8	.10	.18	.18	.32	.38	.45	.49

Table 4. Summary statistics: implicit groups ($N = 401$)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1.$LoadFactor_{it}$	1																				
2.$TotTraffic_{t}$	.14	1																			
3.$DiversHub_{t}$	.26	.64	1																		
4.$RelCapacity_{it}$	.35	-.26	.01	1																	
5.$DomHub_{it}$	.24	-.21	-.04	.56	1																
6.$InsideTie_{it}$	.20	.18	.11	.19	.11	1															
7.$Employees_{it}$	.35	.02	.19	.84	.54	.24	1														
8.$Routes_{it}$	.27	-.04	-.03	.52	.81	.16	.65	1													
9.Age_{it}	.13	-.01	-.05	.31	.45	.16	.37	.46	1												
10.$EgoTies_{it}$	.22	.16	-.10	.22	.28	.48	.32	.47	.31	1											
11.$EgoTraffic_{it}$	.28	.46	.26	.06	.05	.72	.17	.15	.17	.71	1										
12.$Contact_{t}$	.27	.12	.16	.40	.54	.15	.59	.79	.30	.40	.19	1									
13.$GDPCap_{it}$,	.44	.27	.28	.45	.20	.32	.45	.26	.11	.28	.37	.28	1								
14.$GDPGrow_{it}$	.22	.01	.07	.00	-.06	.00	.03	-.09	.00	-.08	.00	-.08	-.02	1							
15.Pop_{it}	.00	.08	.05	.19	-.03	.01	.26	.01	-.08	.00	.00	.02	.02	.19	1						
16.*Year95*	-.08	-.11	-.04	.00	.01	-.12	.00	.02	-.01	-.12	-.17	.14	-.01	-.01	.01	1					
17.*Year96*	-.04	-.02	.06	-.01	-.07	-.08	-.02	-.01	-.03	-.10	-.11	-.03	.01	.06	.00	-.21	1				
18.*Year97*	.03	-.06	.01	.00	.01	-.05	-.01	.03	-.01	-.06	-.07	.09	.00	-.01	-.04	-.20	-.21	1			
19.*Year98*	-.03	-.01	.00	.00	.01	-.03	.00	-.01	-.01	.03	-.01	-.03	-.02	-.15	.00	-.20	-.21	-.20	1		
20.*Year99*	.00	.09	-.04	.01	.04	.09	.02	.00	.02	.10	.12	-.06	.01	-.05	.02	-.20	-.20	-.20	-.20	1	
21.*Year00*	.11	.14	.01	.01	.00	.19	.02	-.03	.03	.15	.25	-.11	.02	.17	.01	-.20	-.20	-.20	-.20	-.19	1
Mean	67	389	6.4	.07	4.6	.37	17	.21	51	7.0	258	4.8	15	3.4	.10	.17	.17	.17	.17	.16	.16
Std. Dev.	6.3	178	2.4	.09	4.8	.24	19	.17	20	4.4	171	3.9	12	3.1	.19	.37	.38	.37	.38	.37	.37

Table 5. Description of explicit constellations

Year	Name	Date founded	Total traffic[a]	Diversity of hubs[b]	Density[c]	Members[d]
1995	Global Excellence	1990	205.09	11.29	1.00	DL, SIN, SWR.
1996	Global Excellence	1990	226.14	11.29	1.00	DL, SIN, SWR.
1997	Atlantic Excellence	Feb 1997	203.08	4.11	1.00	AUS, DL, SAB, SWR.
	Global Excellence[e]	1990	240.68	11.29	1.00	DL, SIN, SWR.
	Star Alliance	May 1997	354.58	7.28	0.60	AC, LFH, SAS, TAI, UA.[f]
1998	Atlantic Excellence	Feb 1997	216.82	4.11	1.00	AUS, DL, SAB, SWR.
	Qualiflyer	May 1998	87.75	1.20	0.46	AOM, AUS, CRS, LAU, SAB, SWR, TAP, THY.
	Star Alliance	May 1997	394.47	8.40	0.53	AC, LFH, SAS, TAI, UA, VRG.
1999	Atlantic Excellence[g]	Feb 1997	225.87	2.85	0.67	AUS, DL, SAB, SWR.
	Oneworld	Sep 1998	422.32	10.65	0.50	AA, BA, CAI, CP, QUA.[h]
	Qualiflyer	May 1998	91.28	1.28	0.48	AOM, AUS, CRS, SAB, SWR, TAP, THY.[i]
	Star Alliance	May 1997	445.49	10.59	0.50	AC, ANZ, ANS, LFH, SAS, TAI, UA, VRG.
	"Wings"[j]	1999	177.52	6.68	1.00	KLM, NW.
2000	Oneworld	Sep 1998	483.32	9.48	0.61	LIN, AA, BA, CP, FIN, IBR, LCH, QUA.
	Qualiflyer	May 1998	101.29	1.25	0.39	LIB, AOM, CRS, LOT, SAB, SWR, TAP, THY.[k]
	SkyTeam	Sep 1999	279.60	6.13	1.00	AMX, AFR, DL.[l]
	Star Alliance	May 1997	624.81	10.00	0.42	AC, ANZ, ANA, ANS, AUS, LFH, MEX, SAS, SIN, TAI, UA, VRG.[m]
	"Wings"	1999	187.66	6.68	1.00	KLM, NW.

Notes:
[a] See description of variable $TotTraffic_t(.)$, Table 2.
[b] See description of variable $DiversHub_t(.)$, Table 2.
[c] The observed number of existing bilateral ties relative to the total possible number of ties between members of each explicit constellation.
[d] Abbreviations of names as listed in Table 1.
[e] Dissolved in November 1997.
[f] Varig joined the group in October 1997.
[g] Dissolved in November 1999.
[h] Finnair and Iberia joined the group in September 1999.
[i] Air Europe is also a member, but was not included in the analysis due to missing data. However, estimates indicate that it contributes to only about 6.2% of the constellation's total traffic.
[j] "Wings" is an unofficial name of the group. The alliance between KLM and Northwest exists since 1989, but I consider that the group was only officially institutionalized with the announcement that Continental and Alitalia would join the group in early 1999, which was later called off.
[k] Air Littoral, Portugalia and Volare are also members, but were not included in the analysis due to missing data. However, estimates indicate that they, together, contribute to only about 2.4% of the constellation's total traffic.
[l] Korean Airlines joined the group in July 2000.
[m] British Midland (bmi) joined the group in July 2000.
Sources: IATA's *World Air Transport Statistics*; *Airline Business*, several issues; analyses by the author.

Table 6. Description of implicit constellations

Year/	Code	Total traffic[a]	Diversity of hubs[b]	Members[c]	Density table[d] 1	2	3	4	5
1995	1	413.71	4.84	LIN, AMX, ALA, AW, BA, CO, GB, KLM, MEX, NW, USA.	*.22*				
	2	431.46	3.95	AFL, AC, CHI, AFR, ANA, AUS, BAL, CSA, DL, FIN, IBR, LOT, LFH, MLV, SAB, SWR, TAR, THY.	.04	*.36*			
	3	317.06	8.79	ARG, IND, ANS, BMI, EMI, MA, RAJ, SLA, TAP, TWA, UA, VIR.	.00	.06	*.24*		
	4	129.38	3.37	ALG, ALI, CYP, EGY, GUL, IRA, KOR, OLY, RAM, SAU, SYR, TUN.	.03	.06	.04	*.23*	
	5	510.21	10.50	ANZ, AA, CAI, CP, JAS, JA, LAB, QUA, SAS, SIN, SAA, TAI, VRG, VSP.	.04	.06	.04	.02	*.23*
1996	1	456.39	8.33	LIN, LIB, ANZ, AW, BA, CAI, GB, LCH, NW, QUA, SAS, USA, VRG.	*.22*				
	2	119.66	4.73	AFL, AMX, ALG, AFR, BAL, CRO, EGY, MEX, RAM, TUN, THY.	.00	*.24*			
	3	480.78	8.96	ARG, AA, ANS, BMI, CP, JAS, JA, MA, RAJ, SIN, SAA, SLA, TAP, TAI, VIR.	.05	.01	*.25*		
	4	522.58	4.98	AC, CHI, ALI, ANA, AUS, CO, CSA, DL, FIN, IBR, KOR, LAU, LOT, LFH, MLV, SAB, SWR, TAR.	.05	.06	.08	*.35*	
	5	357.94	6.64	IND, CYP, EMI, GUL, IRA, KLM, LAB, OLY, SAU, SYR, TWA, UA, VSP.	.03	.03	.04	.04	*.22*
1997	1	529.65	7.05	LIN, CHI, ALA, AW, DL, EL, FIN, KLM, KOR, NW, SAB, SIN, TAP.	*.26*				
	2	281.95	3.20	AFL, AMX, AFR, ALI, AUS, BAL, CO, CRO, CSA, IBR, LOT, MLV, SWR, TAR, THY, UKR.	.08	*.39*			
	3	531.64	8.83	ARG, AC, IND, ANZ, ANS, BMI, CP, EMI, LAU, LFH, MA, SAS, SAA, SLA, TAI, UA, VIR.	.04	.05	*.29*		
	4	80.37	4.86	ALG, CYP, EGY, GUL, IRA, LAB, OLY, RAM, SAU, SYR, TUN, VSP.	.01	.06	.03	*.20*	
	5	543.78	9.08	LIB, ANA, AA, BA, CAI, GB, JAS, JA, MEX, QUA, VRG.	.04	.04	.07	.01	*.25*
1998	1	112.22	3.94	LIN, AOM, CRO, EGY, LAU, MA, OLY, RAJ, SAB, SLA, TAP, THY.	*.20*				
	2	453.14	4.63	AFL, AMX, CHI, AFR, IND, ALI, AUS, BAL, CSA, DL, FIN, IBR, KOR, LOT, MLV, SWR, TAR, UKR.	.10	*.39*			
	3	603.75	9.16	ARG, AW, AA, BA, CAI, CO, JAS, JA, LCH, LAB, QUA, VSP.	.01	.07	*.26*		
	4	273.25	5.39	ALG, ALA, CYP, GUL, IRA, KLM, NW, RAM, SAU, SYR, TWA, TUN.	.03	.06	.03	*.23*	
	5	576.00	9.29	AC, ANZ, ANA, ANS, BMI, EMI, LFH, MEX, SAS, SIN, SAA, TAI, UA, VIR.	.06	.06	.05	.02	*.38*
1999	1	88.46	2.20	LIN, ALG, AOM, CYP, EL, FIN, OLY, RAM, SAB, TAP, TUN.	*.24*				
	2	432.07	4.98	AFL, AMX, CHI, AFR, IND, AUS, BAL, CSA, DL, IBR, KOR, LOT, MLV, SWR, TAR, UKR.	.09	*.41*			
	3	639.17	9.57	AC, ANZ, ANA, ANS, BMI, EMI, LFH, MEX, SAS, SIN, SAA, TAI, UA, VRG, VIR.	.01	.05	*.42*		
	4	840.43	8.16	ALA, ALI, AW, AA, BA, CAI, CO, JAS, JA, KLM, LCH, NW, QUA.	.05	.10	.05	*.38*	
	5	126.57	4.91	CRO, EGY, GUL, IRA, MA, RAJ, SLA, SYR, TWA, THY.	.03	.11	.07	.04	*.31*
2000	1	521.70	8.68	LIN, ARG, AA, BA, CAI, CP, EL, FIN, LCH, QUA, SAB, TAP.	*.41*				
	2	364.13	2.54	AFL, AFR, ALI, AUS, BAL, CRO, CSA, IBR, IRA, JA, LOT, MLV, RAJ, SWR, SYR, TAR, THY.	.13	*.43*			
	3	234.20	5.41	AMX, ALG, CYP, DL, EGY, GUL, OLY, RAM, TUN.	.05	.09	*.22*		
	4	706.03	8.36	AC, IND, ANZ, ANA, BMI, EMI, LAU, LFH, MA, MEX, SAS, SIN, SAA, SLA, TAI, UA, VIR.	.03	.09	.03	*.38*	
	5	469.98	7.92	CHI, ALA, AW, ANS, CO, JAS, KLM, KOR, NW, TWA, UKR.	.07	.06	.01	.05	*.29*

Notes:
[a] See description of variable *TotTraffic*$_t$(.), Table 2.
[b] See description of variable *DiversHub*$_t$(.), Table 2.
c Abbreviations of names as listed in Table 1. Composition of groups as revealed by clustering algorithm based on the matrix of bilateral ties among firms.
d Diagonal entries indicate density of constellation, which is simply the observed number of existing bilateral ties relative to the total possible number of ties between members. Off-diagonal entries indicate density of ties between constellation members and members of other groups.
Sources: IATA's *World Air Transport Statistics*; *Airline Business*, several issues; analyses by the author.

Table 7. Constellation membership and performance: regression results

	Constellation boundaries defined explicitly			Constellation boundaries defined implicitly		
	Heckman two-stage			All firms	Non-members of explicit constellations	Members of explicit constellations
	(1a) Probit Prob($Expl_{it}$ = 1)	(1b) OLS $LoadFactor_{it}$	(2) $LoadFactor_{it}$	(3) $LoadFactor_{it}$	(4) $LoadFactor_{it}$	(5) $LoadFactor_{it}$
<u>*Constellation-specific*</u>						
$TotTraffic_t(C_j)$			0.011**	0.000	0.000	-0.002
			(0.004)	(0.002)	(0.002)	(0.003)
$DiversHub_t(C_j)$			-0.568**	0.161†	0.119	0.210
			(0.193)	(0.100)	(0.120)	(0.190)
<u>*Member-specific*</u>						
$RelCapacity_{it}(C_j)$			12.891*	4.168	3.765	-5.650
			(7.477)	(4.523)	(6.002)	(6.432)
$DomHub_{it}(C_j)$			-0.068	-0.015	-0.039	-0.015
			(0.078)	(0.076)	(0.106)	(0.098)
$InsideTie_{it}(C_j)$			0.076	1.512*	1.948*	-1.847
			(1.358)	(0.888)	(1.060)	(1.555)
<u>*Controls*</u>						
$Employees_{it}$	0.034**	0.094†	-0.391**	0.017	-0.049	-0.260
	(0.011)	(0.052)	(0.144)	(0.066)	(0.091)	(0.162)
$Routes_{it}$	-0.382	0.165	13.310†	-1.949	-0.212	8.837
	(0.933)	(3.798)	(7.546)	(4.349)	(5.519)	(6.801)
Age_{it}	0.011	-0.013	-0.252	0.279*	0.097	0.824†
	(0.007)	(0.033)	(0.482)	(0.111)	(0.131)	(0.448)
$EgoTies_{it}$	0.062	0.046	-0.045	0.012	-0.083	0.031
	(0.039)	(0.163)	(0.166)	(0.104)	(0.149)	(0.152)
$EgoTraffic_{it}$	0.000	0.004	0.002	0.002	0.004	0.001
	(0.001)	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)
$Contact_t(C_j)$			-0.091	-0.056	0.006	-0.192
			(0.054)	(0.074)	(0.092)	(0.125)
$GDPCap_{it}$,	0.024*	-0.099	-0.290	-0.164*	-0.023	-0.349
	(0.011)	(0.067)	(0.235)	(0.082)	(0.103)	(0.250)
$GDPGrow_{it}$	0.044	0.609**	0.327**	0.238**	0.195**	0.284**
	(0.038)	(0.220)	(0.083)	(0.047)	(0.053)	(0.093)
Pop_{it}	-5.220*	-7.513	601.634**	84.928**	91.675**	399.523
	(2.043)	(12.406)	(208.982)	(26.272)	(27.055)	(239.001)
$Expl_{it-1}$	2.471**					
	(0.329)					
$TiesExplicit_{it}$	2.545**					
	(0.553)					
$InvMills_{it}$		-0.142				
		(1.092)				
N	513	91	86	401	323	78
χ^2	290.9**					
F		2.13**	9.29**	6.38**	3.31**	7.59**

** $p < .01$ * $p < .05$ † $p < .10$ (one-tailed tests for hypothesized effects). The table shows parameter estimates and standard errors in parenthesis (fixed-effects estimates, except for the Heckman two-stage model). All models include year-specific dummy variables (not reported here).