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Alliances, Rivalry, and Firm Performance in Enterprise Systems Software Markets: A Social Network Approach

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Enterprise systems software (ESS) is a multibillion dollar industry that produces systems components to support a variety of business functions for a widerange of vertical industry segments. Even if it forms the core of an organization's information systems (IS) infrastructure, there is little prior IS research on the competitive dynamics in this industry. Whereas economic modeling has generally provided the methodological framework for studying standards-driven industries, our research employs social network methods to empirically examine ESS firm competition. Although component compatibility is critical to organizational end users, there is an absence of industry-wide ESS standards and compatibility is ensured through interfirm alliances. First, our research observes that this alliance network does not conform to the equilibrium structures predicted by economics of network evolution supporting the view that it is difficult to identify dominant standards and leaders in this industry. This state of flux combined with the multifirm multicomponent nature of the industry limits the direct applicability of extant analytical models. Instead, we propose that the relative structural position acquired by a firm in its alliance network is a reasonable proxy for its standards dominance and is an indicator of its performance. In lieu of structural measures developed mainly for interpersonal networks, we develop a measure of relative firm prominence specifically for the business software network where benefits of alliances may accrue through indirect connections even if attenuated. Panel data analyses of ESS firms that account for over 95% of the industry revenues, show that our measure provides a superior model fit to extant social network measures. Two interesting counterintuitive findings emerge from our research. First, unlike other software industries compatibility considerations can trump rivalry concerns. We employ quadratic assignment procedure to show that firms freely form alliances even with their rivals. Second, we find that smaller firms enjoy a greater value from acquiring a higher structural position as compared to larger firms.

Key words: technology standards; software industry; enterprise resource planning (ERP); software architecture; partnerships; social network theory; standards competition
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1. Introduction

Enterprise systems software (ESS) represents one of the largest software groups with sales exceeding 60 billion in 2003 and approximately 100 billion in 2006 (AMR Research—http://www.amrresearch.com). Firms such as SAP, Oracle, and JD Edwards have emerged as market leaders in this product space. The architecture of enterprise systems comprises of a database management system (DBMS) serving as the central repository of data, and a group of functional modules or ESS components that support business processes in areas such as production, payroll, supply chain, and human resources (Davenport 1998). Client organizations[1] purchase these components from one or more ESS firms (Markus 2000). Despite the components being acquired from a diverse set of vendors, a critical requirement from customers is that the

[1] Throughout this article, we use the terms "vendors" or "firms" to refer to producers of ESS components, and we use the term "client organizations" or "organizations" to refer to users of ESS components.

components work seamlessly with each other to be beneficial to the user organization. However, there are no dominant open (de jure) or proprietary (de facto) standards to facilitate interoperability between products of different ESS firms. Although standards for low level communication between information technology components exist, there are no uniform high-level compatibility rules to enable plug-n-play between products of different vendors (Yang and Papazoglou 2000). Therefore, component compatibility is established only through explicit alliances[2] such as those involving licensing of proprietary application programming interfaces (APIs), product development, and release agreements (David and Greenstein 1990). Although there have been a number of studies in information systems (IS) research that have examined the implementation or usage of these systems by organizations, there is little empirical research that has examined the competitive dynamics of software competition.

A variety of questions arise as firms develop their competitive strategies. Currently, there is little prior research that studies the formation of alliances in business software industries and the impact of such alliances on business performance. First, it is not clear if the alliance network is approaching equilibrium, which would be an indication that one (or a few) standards have achieved dominance. Second, although from a standards point of view it has been commonly asserted that firms should not engage in alliances with rivals (Axelrod et al. 1995), we suggest that ESS firms may not have that luxury due to the multicomponent nature of the industry where the likelihood of rivalry with any firm in this subsector is quite high either currently, or in the near future. Third, following the previous point, although alliances can bring performance benefits due to the resulting product-to-product compatibility, they are not only expensive to initiate and maintain, but also have the potential to lose customer base to the alliance partner if it already has a competing module or in the near future when the partner can likely launch one. Further performance benefits of their alliances may accrue to firms through both direct and indirect connections. Finally, an interesting question is if all firms stand to gain in the same manner from alliances, or if firms of a certain size are more uniquely positioned to better extract overall alliance benefits.

In several manufacturing sectors or other physical service industries alliances are generally considered to be "supply-side" motivated, i.e., a way to acquire resources (Das and Teng 2000, Eisenhardt and Schoonhoven 1996), e.g., in airlines, logistics, and automobile sectors. However, in most economics-based literature on software industries the central premise is that alliances are mostly "demand-side" motivated. That is, the primary (if not only) reason for a vendor to form alliances is to signal to the client organizations that its products are compatible with many other products and to actually maintain a high degree of compatibility. Indeed, we see that even platform leaders such as SAP, Oracle, and Microsoft, who have a great amount of required supply-side resources engage in alliances for the purposes of component interoperability with other vendors. It is however not clear if alliances are generally as beneficial such as in the airline sector where code-sharing alliances are formed to satisfy unserved sectors (Brueckner 2001, Morrish and Hamilton 2002), or in the semiconductor industry where costly technological knowhow is a reason for interfirm partnerships (Appleyard 1996, Hart and Estrin 1991).

Barring some recent exceptions (Chen and Forman 2006, West and Dedrick 2000), prior research in IS has largely ignored market level dynamics of systems vendors and focused more on corporate implementation of enterprise systems. Similarly, whereas the impact of maintaining compatible standards on firm performance has been studied by *analytical models* in economics (Economides 1989, Matutes and Regibeau 1988), the dyadic models considered in these fields are limited in their applicability to the ESS industry where there is a network of relationships. Thus, there is a paucity of empirical work in this area. We address these gaps in prior research by using social network analysis (Nohria and Eccles 1992) to better represent the competitive and alliance dynamics of ESS firms.

From a technology standpoint, a focal ESS firm's decision to form alliances with selective other firms is of strategic importance, as "…market selection

[2] Consistent with Gulati's (1998, p. 293) characterization, we are using a broad definition of alliances as "voluntary arrangements between firms involving exchange, sharing or codevelopment of products, technologies or services."

and incremental innovations induce each firm to converge towards the dominant standard and less adaptive firms are pushed out of the market," (Antonelli 1994, p. 204). In the ESS industry, alliances not only serve to accomplish technical compatibility, but they are also critical in enhancing the *compatibility perceptions* of the organizational end users. These perceptions are created and maintained by social interactions among alliance partners during joint conferences, trade shows, and training sessions that result in knowledge exchange among the partnering ESS firms, the implementation consultants, and other third parties. These perceptions are important in that client organizations require compatibility between components; by hosting such conferences ESS firms directly influence consultants (who are typical attendees of these conferences, and primary sales channel partners) and also client-organizations. Thus, vendor alliances help satisfy the demand-side need for compatibility. These perceptions can also be interpreted as a form of indirect network externality (Gupta et al. 1999) wherein the utility of product to a consumer increases with the number of other products the focal product is compatible with. In other words it provides the consumer with a greater number of product options.

Our thesis is that although firms incur costs of forming and maintaining an alliance with a direct partner, they gain access to social and technical resources through their ties with *both* directly and indirectly connected partners. Thus, central to our paper is the argument that because firms form alliances with multiple partners who form further partnerships, any performance benefits from standards-related network externalities should be studied in the context of the entire alliance network rather than by individually examining the multiple dyadic partnerships. Therefore, we adapt from prior literature a structural measure of firm prominence[3] that takes into account both, directly and indirectly connected partners while suitably attenuating the flow of network benefits to a focal from other firms as the network distance between them increases.

The data for our empirical analyses is drawn from multiple sources including a business software trade group's publications, Mergent Online company database, Security and Exchange Commission filings, Gale Group database, and OneSource Business Browser. The final list of firms, component markets, and alliances was then vetted by a manager and senior manager at Ernst & Young (now Cap Gemini Ernst & Young) for industry inputs. We employ two statistical methods. First, we employ the quadratic assignment procedure (QAP) commonly used in social network analysis. It is a resampling based method, for calculating the correct standard errors in network data. We use it to examine the relationship between rivalry and alliance formation. Second, we performed a panel data analysis to examine the relationship between network structural measures (both extant and our own derived) and firm performance.

The paper is organized as follows. In §2 we discuss the appropriateness of social network methods for this context and proceed with hypotheses development motivated by prior research. Section 3 describes the data and measures used in the study along with the results of the exploratory and confirmatory analyses. In §4 we present a discussion of our results along with their implications and avenues for further research.

2. Framework to Study Standards-Driven IT Industries

Literature on competition in standards-driven industry is somewhat limited in IS research; however, there is a significant amount of work done in this area in economics. For example, this research has studied the early VCR industry where VHS emerged as the winning standard (Grindley 1995), and the operating systems markets where multiple separate standards such as Unix, Windows, MacOS, etc. continue to coexist (Axelrod et al. 1995). The main emphasis of these models is on the accumulation of externality benefits, either by adopting a common standard or by constructing adapters to enable compatibility with competing products. Along these lines, Katz and Shapiro (1985) have argued that in a duopoly, firms with small user bases have strong incentives to make their products compatible with products of firms with larger user bases, and later work extends this finding to markets with multiple firms and components

[3] We use the terms "status" and "prominence" interchangeably to refer to a firm's structural position in this paper.

(Economides 1989). Generally, the analytical models conclude that it is beneficial for a firm to adopt the leading or dominant standard. However, there is little or no empirical support for most of these conclusions. Furthermore, prior works also acknowledge that when there are *no* explicit leading standards, the applicability of these models becomes somewhat limited (Economides 1989, p. 1184). Thus although analytical models have been the preferred mode of studying firms facing standards-related decisions, their appropriateness for empirically studying ESS firms is limited thus requiring the exploration of alternative methods.

The relationship between standards and alliances was first suggested by Saloner (1990) who observed that implicit and explicit alliances can facilitate the development of common standards ensuring product compatibility. Whereas this study still argued at the firm-dyad level, another study on software standards (Axelrod et al. 1995) examines standard coalitions and competition between them. This work also acknowledges that using economic models such as conventional game-theoretic analysis to empirically study complex alliance compositions is "especially difficult because payoffs for each firm depend upon the choices made by all other firms" (p. 1497); although an important assertion in this study is that firms will avoid rivals in forming coalitions. In the ESS industry although there are no distinct coalitions,[4] firms indeed form alliances with multiple partners leading to a network of alliances. Thus although there is a need to abstract and capture a firm's competitive positioning within the network, lack of distinct coalitions does not allow us study group competition, rather there is still a need to characterize an individual ESS firm's relative power vis-à-vis other ESS firms.

Just as one approach to analyzing firm behavior in markets is through economic paradigms, theories from social sciences such as economic sociology (Walker et al. 1997), and actor network theory (Monteiro 2000) are also increasingly employed to represent complex social, economic, and technological perspectives (Chellappa and Saraf 2000, Fomin and Keil 2000). ESS firms achieve compatibility by forming alliances and because they form multiple alliance partnerships we employ a social network approach to study both the strategic behavior regarding alliance formation as well as the resulting impact on firm performance. Thus, a richer and more suitable approach to study the ESS industry is through the use of methods developed in social network analysis.

2.1. Using Social Network Theory to Study the ESS Industry

Social network theory has typically been used to study a set of individuals with links between them representing specific social ties, including interaction ties (Contractor et al. 1996), friendship ties (Zeggelink et al. 1996), and marital ties (Padgett and Ansell 1993). Research in organizational behavior, human communication, and computer-mediated communication has also adapted this approach to study networks of members within an organization (Barley 1990). Most of this early work in social networks focused on within-firm issues where the actors typically represent employees and the relationship linkages were enclosed within the boundaries of the particular organization. During the last decade, the social network metaphor proposed earlier by Tichy et al. (1979) has been considerably extended to analyze market level behavior where linkages in the network represent various types of relationships between firms (Ahuja 2000). For example, such networks have been used to study pricing strategies of investment banks (Podolny 1993), power relations between corporations and investment banks (Baker 1992), and niche overlap in a patent citations in the semiconductor industry (Podolny et al. 1996). More recently, IS research has also begun to employ social network theory, e.g., to study virtual groups (Ahuja and Carley 1999) and electronic networks of practice (Wasko and Faraj 2005), albeit at the individual level.

Whereas one goal is to realistically represent the alliance structure in the ESS industry, our objective is also to empirically consider the net value to an ESS firm from such alliances and its overall effect on the focal firm's performance. Social network research provides a number of structural measures, particularly measures of status (Burt 2000), that serve as a useful

[4] A preliminary clique analysis of the alliance network through UCINET confirms this. For example, in a two-path length analysis, three firms (SAP, Microsoft and Oracle), are members of a majority of cliques, i.e., these three firms are never more than two path lengths away in a majority of the cliques. There is great commonality amongst the cliques.

starting point to capture the relative net value from alliances. The ESS alliance network has firms as its nodes and linkages representing the alliances between them. The main theses of our research is that firms augment their status by virtue of their alliances; and if this status or (relative) firm prominence can be appropriately computed based on the mechanics in the ESS industry, it will serve as a performance indicator.

The theoretical basis for linking a network measure and firm performance stems from other models of networked firms (Podolny 1993), wherein the prominence of an actor or node is determined by linkages with other firms. There are two competing views of networks, the pipes and prisms views (Podolny 2001). Although the former is a more common view of networks in early research, the latter is finding increasing acceptance in recent sociological research on markets, "In this second view, a tie between two market actors is not only to be understood as a pipe conveying resources between those two actors; in addition, the presence (or absence) of a tie between two market actors is an informational cue on which others rely to make inferences about the underlying quality of one or both of the market actors" (Podolny 2001, p. 34). In a study of investment banks, Podolny (1993) shows that syndicate relations between these banks may not only lead to resource transfers but that the relationships may provide some basis of status ordering to other market actors such as corporate issuers and investors. He goes on to suggest that others may rely on these informational cues from a focal actor's pattern of relations to make inferences on the quality of the focal actor. We draw upon this prism interpretation for characterizing alliance networks in the ESS industry.

In the ESS alliance networks as well, along the lines of other industries, there is a potential for access to knowledge, technological capabilities, newer markets, production know-how, research and development (R&D) joint ventures, etc. (Liebeskind et al. 1996, Walker et al. 1997). However, our research suggests that the significance of alliances lies in signaling standards dominance where consumers can make inferences about the overall component compatibility of the focal actor. Podolny (2001) suggests that in such prism views of networks status indicators such as centrality measures enumerate the significance of a network rather than structural holes (Burt 1992). Furthermore, for reasons discussed later in this section, we do not adopt an extant measure as is but develop a specific prominence measure that accurately captures the significance of linkages for our particular context, the ESS industry. However, we shall first examine alliance formation itself so as to understand the selectiveness (or lack thereof) of alliance-partner choices.

2.2. Strategic Issues During Alliance Formation

Whereas the impact of alliances on partnering firms has been often examined, recent literature notes that prior research has often ignored the important question of how alliance partners are selected (Chung et al. 2000). Any complexity in alliance partner selection is only exacerbated in the ESS industry; multicomponent firms are more likely to be rivals and although alliances are costly to initiate, absence of uniform standards means that alliances are the key way a firm can make its components compatible. It has been asserted that in the software industry rivalry is avoided when standards coalitions are set up (Axelrod et al. 1995). Indeed literature on alliance success suggests that failure can occur from rivalry as it can act as a destabilizing characteristic within an alliance (Park and Ungson 2001). One underlying logic is a game theoretic explanation wherein it has been suggested that a prisoner's dilemma problem (where in firms have an incentive to deviate from institutional rules) might emerge in alliances between rivals (Parkhe 1993). Thus the collective benefit of an alliance might be foregone for individual performance gains leading to the failure of an alliance with rivals.

The most important argument against forming alliances with rivals comes from the resource-based view of the firm. Alliance with a rival was seen as a way to internalize partner skills (Hamel 1991), and in fact such alliances are reported to have been the cause of erosion of U.S. firm's resource bases and competitive advantages to Japanese alliance partners (Mankin and Reich 1986). In another theoretical work (Khanna et al. 1998) it has been suggested that the impact of rivalry on rival partners needs to be accommodated particularly when considering learning alliances. This is consistent with the results of a study on a multi-industry sample of alliances, which found a reduction in knowledge transfer in alliances between rivals (Mowery et al. 1996). Thus some extant alliance research might make a strong case that rational firms will avoid alliances with rivals.

Although it is true that ESS firms might also prefer not to provide any advantages to their rivals, in the absence of an explicit alliance and industry-wide open standards, an ESS firm's potential customer base would be reduced to only those customers that have already implemented components from the focal firm. For example, for PeopleSoft's human resources module to be appealing to customers who do *not* have PeopleSoft components for financials, accounting and other business components, an alliance between PeopleSoft and these companies becomes essential. Informal interviews with ESS vendors also highlighted the predicament of choosing a competitor as an alliance partner but they uniformly expressed the view that this did not necessarily deter their alliances with them. This implies that i2 Technologies may have an incentive to form an alliance with PeopleSoft even if they have many software components in common. Because ESS firms operate in the same strategic segments, they are likely to have high similarity in terms of their knowledge bases (Cohen and Levinthal 1990). Therefore, alliances enable transfer of highly specific knowledge related to product interface designs, customers, and more generally about their technological trajectories. In the absence of alliances such exchanges are not possible and rivalry considerations might put up a weak opposition to alliance benefits in this industry.

Literature in technology innovation and dominant design also provides some insights into alliances in high-technology industries. This work provides an understanding of the process through which a certain technology might become dominant (Henderson and Clark 1990, Suarez and Utterback 1995), and suggests that firms invest their resources so as to align with dominant technological designs, and competencies are acquired through exchange of knowledge bases and by aligning information processing structures. Alliances allow vendors to extend their influence throughout the industry and from a technology viewpoint it provides a bigger "*functionality footprint*" implying that the focal firm's technical architecture is likely to become embedded in the directly as well as indirectly connected partner's products. Thus in this industry it could be argued that a combination of user-driven compatibility needs and the possibility of propagating one's own technical architecture overwhelms any rivalry considerations in alliance formation. Generally, literature on alliances suggests avoidance of rivals, however under special circumstances such as in the absence of a dominant firm and a single obvious technology, the creation of implicit and explicit alliances among rivals or potential rivals is a distinct possibility (Saloner 1990). Indeed Chan-Olmsted and Jamison (2001) argue that in many technological realms where competition in one area spills over to another, cooperation with rivals may be a necessity.

Rivalry manifests itself in two market dimensions: first, the commonality in the software component markets; and second, the commonality in the different vertical industry segments for which these components are offered. Thus we examine the rivalry along both these dimensions in studying the choice of alliance partners.

Hypothesis 1. *Extent of rivalry is unlikely to impact the choice of an alliance partner for an ESS firm.*

Alliances in this industry are driven by the demand-side need for compatibility amongst software components, in the absence of explicit common standards. The question therefore is if a firm should simply form alliances with as many firms as possible to signal compatibility with all products in the market? Or is there a manner in which overall benefits accrue thus helping firm performance? To answer these questions we first examine the alliances linkages and benefits flow in the ESS industry.

2.3. Alliances and Firm Performance

Alliances in the ESS industry are explicitly initiated for the purpose of managing technological compatibility. These result in both *technical* compatibility and perceptions of compatibility to client organizations. We call the latter *social* compatibility. Technical compatibility results when the partners align their product interface designs at the data, application, and business process levels (Yang and Papazoglou 2000). Economic models of standards competition primarily describe technical compatibility as providing access to user bases of partners (Katz and Shapiro 1985, Matutes and Regibeau 1988). Performance benefits from technical compatibility have been documented in both economics and IS literature (Brynjolfsson and Kemerer 1996, Kaufman et al. 2000). *Social compatibility* between two vendors represents the presence of human skills, in terms of expertise of third-party integration vendors, consultants, and implementers trained in integrating components from the two vendors. Thus higher social compatibility between two vendors signals a lower cost of integration of their components to the marketplace. Alliance partners also engage in joint presales efforts, technical conferences, and trade shows where third party integrators and consultants get to learn about custom integration through middleware technologies (McKeen and Smith 2002). Thus social compatibility resulting from alliances serves to also increase the market's *perception of compatibility* between alliance partners. IS literature also espouses the notion of soft IT skills or human IT skills (Bharadwaj 2000), which underlie IT-based competitive advantage of firms (Boynton 1994). Our concept of social compatibility builds on this dimension wherein through alliances firms can enjoy alliance partners' soft-skill resources. Interestingly, because literature in economics only considers an adoption of standards rather than formation of alliances, the increased perception of compatibility to the market is generally ignored. Indeed the nontechnical advantages of alliances such as access to soft-skill resources have to be separately modeled, often through adapters (Matutes and Regibeau 1988).

Our theses is that if a vendor has a greater user base, better technology, or a higher reputation, its alliance partner is likely to benefit from its linkage with the focal firm due to both higher technical and social compatibility. Prior social network literature also clearly distinguishes between resources themselves and the ability to obtain them by virtue of memberships in different social structures (Portes 1998). Thus actors can attain a certain "status" or "power" or "prominence" by virtue of their alliance choices that determines their structural position in the alliance network. We use the definition of status (or prominence) as in Knoke and Burt (1983): "An actor is prominent if the ties of the actor make the actor particularly visible to the other actors in the network" (p. 172). In the ESS industry, prominence captures the relative power of the product standards of the focal firm. Prominent firms are more selective in their partnerships as they are keen on avoiding any dilution of their reputation and are often stricter in enforcing quality standards (Stuart et al. 1999). To form an alliance with a partner of higher prominence, the focal firm may have to invest in upgrading its own technology, and develop additional capabilities that are complementary and useful to partnering firms, e.g., hiring a high profile CIO, engaging in high-profile advertising or developing relationships with specific consultants and implementers. To exploit and sustain the opportunities afforded by relationships with partner firms, organizations also have to invest in continuous learning mechanisms (Metcalfe and Miles 1994). These costs are in addition to the direct costs of licensing fees and the cost of incorporating the partnering firms' technologies. Typically, dominant firms continually adapt newer technologies and they expect their smaller alliance partners to rapidly follow the technological trajectories set by them. At times it may also require partner firms to invest in jointly sponsoring user conventions, trade shows, etc. Thus, these costs not only include the cost of making product interfaces compatible (maintaining technical compatibility) but also include the cost of maintaining the market's perceptions of compatibility with alliance partners (social compatibility).

Client organizations not only implement components from ESS firms that have partnerships, but they also purchase and implement components from unrelated firms. This is particularly true of client organizations that are multinational and where decision making is often decentralized. This implies that if a third ESS firm is compatible with a direct partner of a focal firm, then the third firm's components are likely to be more compatible with the focal firm as compared to the components of a completely unconnected firm. Thus product bundling across different component makers can provide further market access to even indirect affiliates. The prism view of networks (Podolny 2001, p. 35) suggests that the pattern of exchange relationships in which a firm engages "is not only relevant because of the resources that flow between firms but also because of how the pattern of those resource flows affect the perceptions of third parties." Such perceptions are related to "altercentric uncertainty," one where client organizations may be uncertain of firms' product compatibility. As long as there is some form of uncertainty in this dimension, status becomes relevant in a market.

There are two fundamental aspects of status or prominence acquisition; status in these markets is a signal of quality (or compatibility and technological dominance) and therefore firms will be exclusive in their choice of partners. Second, there is also a consensus among network scholars that prominence should be measured by looking not only at the direct or adjacent links but also indirect paths involving intermediaries (Marsden and Friedkin 1993). At the same time it has also been suggested that indirect ties are often mediated by the intermediate relationships (Holm et al. 1999, p. 475). Thus, although firms may not incur the actual cost of an indirect connection, benefits (both real and perceptual) may be available through these indirect linkages because of the partners they have chosen. We summarize these characteristics of ESS alliances vis-à-vis the development of a prominence metric in the appendix.

In other words, by virtue of its direct and indirect linkages, an ESS firm can be understood to have access to an aggregate network resource that we call the sociotechnical capital of the firm. Unlike in economic models, this is simply not a sum of user bases; this term is derived from an umbrella concept called "social capital" that is understood to be the sum of resources accruing to an individual or group by virtue of their location in the network of their more or less durable social relations (Adler and Kwon 2000). This resource is not a substitute for intrinsic capability and exogenous to the network; rather it is a complement to these exogenous abilities of the firm (Portes 1998). Note that a difference in the ESS context is that such resources are not merely supply-side resources, rather the primary network resources are acquired through the compatibility gains from the client organizations and the resulting benefits to the ESS firms. There are many measures that operationalize the net relative status or prominence acquired by an actor by virtue of access to social capital (Burt 2000). The simplest way to capture prominence in an alliance network is to directly use the number of alliances formed *by* and *with* the focal firm, called out-degrees and in-degrees, respectively (Freeman 1978). However, because these simplistic measures do not capture the influence of indirect ties, Freeman's (1978) closeness and betweeness measures have been used (Ibarra and Andrews 1993) to measure the structural position of an actor. These still face limitations in that they do not weigh influences from other actors by their structural position. Therefore, in order to accommodate the unique characteristics of ESS alliance networks, where we can consider direct benefits and costs as well as *attenuated* indirect benefits, we adapted our own structural measure of centrality using Braun (1997) and Bonacich (1987). The derivation of our prominence measure is described in the appendix and specific differences between Bonacich's (1987), and ours is discussed in the online appendix.[5]

Prior research that employs social network methods suggests prominence in alliances results in better performance in many different industries. As discussed earlier, these are generally from supply-side firm transfers, e.g., preferential treatment from suppliers and higher returns from quality (Benjamin and Podolny 1999), better access to specialized knowledge, R&D resources, etc. (Podolny et al. 1996). We suggest that an ESS firm with a high status in the network of alliances is most attractive to client organizations and hence is likely to perform better than a lower status counterpart. Hence we propose the following hypothesis.

Hypothesis 2. *The performance of an ESS firm is related to its prominence within its network of directly and indirectly connected partners.*

Firm size is an indicator of a firm's internal resources, and it is generally supposed that small firms will be less able to appropriate benefits of alliances than their larger counterparts. An obvious risk is the encroachment of a smaller firm's market by a larger firm. A more long-term risk is when a larger firm, once it has acquired know-how of the smaller firm, begins to charge a premium for licensing and other relationships over time (Henderson and Clark 1990). More recently, a study by Lavie (2007, p. 1189) argues that even in software "alliances with well-endowed partners may in fact undermine the market performance of firms." The reasoning behind this argument is that although alliances between large and small firms can create overall value to the alliance, value appropriation becomes the forte of the larger firm due to bargaining power. So evidently it is critical to distinguish between the network resources from

[5] Additional information is contained in an online appendix to this paper that is available on the *Information Systems Research* website (http://isr.pubs.informs.org/ecompanion.html).

alliances and the relative power of partners in that portfolio (Bae and Gargiulo 2004). Others (Hagedoorn and Schakenraad 1994, p. 300) have also suggested that large firms are in a better position to extract value from alliances where, "although firms of all sizes will occasionally be engaged in a process of restructuring, in particular large firms are more suited to channel their restructuring activities through joint ventures and other forms of interfirm cooperation."

On the other hand, resource dependence theory (Pfeffer and Salancik 1978) suggests that it is the large firms that are more dependent on alliances than small firms when it comes to technological alliances. It has been argued that "Larger firms usually seek out smaller, innovative firms for their technological know-how. Therefore, the relative bargaining power of the small partner in a strategic alliance, and especially in a technological alliance, will be significantly higher than that of the large partner," (Das et al. 1998, p. 31). In fact from a management of alliances perspective, literature suggests that small firms can not only respond to market opportunities more quickly than larger firms, they are also more effective than their larger counterpart in managing alliances. Hoang and Rothaermel (2005) suggest that although small firms generally have one top-level manager to take responsibility for all of their alliances, the organizational complexity of large companies makes it difficult for them to collectively share know-how acquired from alliances or to capitalize on the market access provided by their partners. Although this work studies the pharmaceutical industry, the authors note that the findings are particularly applicable to other alliance-heavy technology industries such as the ESS industry. The organizational complexity of large firms is an obstacle to exploiting scope advantages, whereas for small firms alliances help them to offset their scale and scope disadvantages (Sarkar et al. 2001).

Thus extant research clearly differs on whether large or small firms are better suited to extract value from alliances, and who benefits most from alliances. In Hypothesis 2, we had suggested that all firms benefit from forming alliances and increasing their prominence. However we argue that smaller ESS firms stand to gain more from their alliances than their larger counterparts if they strategically raise their prominence by increasing the number of partnerships they form or by ensuring that these are with higher status firms. Note that our main thesis is ESS firms gain from internalizing the perceived and true compatibility on the client side. Because an important way in which a smaller firm acquires prominence is through alliances with other prominent firms, it has a relatively higher opportunity to appeal to a larger base (by virtue of its partnership with other firms) than a larger firm has (because the smaller firm begins with a smaller intrinsic base). This argument finds some support from a study of networks involving status transfer where young and small firms are known to benefit more from large alliance partners than do old and large organizations (Stuart 2000). Therefore we have the following hypothesis.

HYPOTHESIS 3. *The impact of network prominence on firm performance is greater for smaller firms.*

3. Methods and Models

In this section, we shall first describe the unique data set used in this study along with the construction of measures. But before we empirically analyze this data to test our propositions, we first provide a visual description of the network data so as to underscore the alliance dynamics at work in this industry.

3.1. Data

We collected data from two independent sources; our first source is an unbiased (not related to any ESS firm or user organization) industry group (Reed Elsevier Inc.) that employed a consulting organization to collect revenue and other information for nearly a complete set of ESS firms to be included in its publication (MSI index and newsletter). Because most of the firms in the ESS industry are privately held firms, the only way to acquire revenue, component markets competed in, and other information is to directly solicit this information from the firms. To this end, the consulting organization sends out a survey every other year to collect this information and nearly all ESS firms (big and small) participate in this survey. Although the term "survey" is used, it is actually a reporting of factual numbers from the top 100 firms in this field, i.e., the survey does not include subjective or perceptual questions. The list of firms, to whom the survey is sent to, is compiled by a group of consultants who are highly experienced professionals in the industry. Over the three time periods considered in our research, the actual sample consisted of only 97, 98, and 95 firms (even if it is a Top 100 list) because there was incomplete data from a few firms.

Although this data source provides much of the revenue and product portfolio information of ESS firms, additional elements such as firm size and alliances had to be acquired from other independent sources. These include Mergent Online company database, Security and Exchange Commission filings, Gale Group database, and OneSource Business Browser; we compared the information from the primary data source with publicly available ones and found no discrepancy.

Data on alliances was gathered through a formalized process. First, we collect the list of partners from a focal firm's business website (on an ongoing basis and updated for each time period). Second, for public firms we had a research assistant compare this list with formalized agreements announcements (available on public databases such Lexis-Nexis and Mergent). Partnership data on websites of most ESS vendors is reported under the label of "Partners" or "Complementary Software Providers" and most partnerships were accompanied by a release that could be verified through Lexis-Nexis. Each firm in the list was contacted over telephone by a revolving group of research assistants over the data collection period. Once this list was drawn, it was compared with a manager and senior manager at Ernst & Young (now CGEY) who have extensive knowledge on the partnerships between ESS firms because they implement most of these modules. Implementation consultants have a list of firms that have entered into formalized agreements as it is critical to component compatibility and application programming interface (API) information. For some private firms, follow-up phone calls were necessary to confirm that online information was up to date. We were able to verify this information with CGEY for the first two time periods, for the third period we had to rely largely on our research assistants' expertise as our contacts had left the firm. To the best of our knowledge this is a comprehensive list, as there are no secondary data sources that maintain this information.

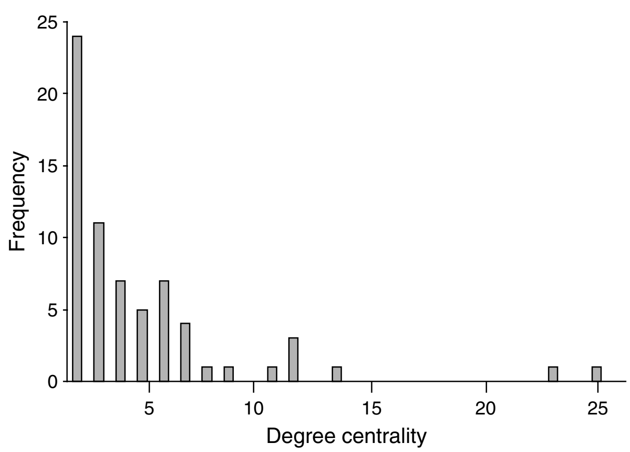
Alliances are time-bound agreements (usually related to software versions), and firms update this information. In our context, an alliance refers to any formalized interorganizational arrangement that includes basic technology licensing agreements to joint research and development. This abstraction is also consistent with Gulati's (1998), who defines strategic alliances as "voluntary arrangements between firms involving exchange, sharing or co-development of products, technologies or services" (p. 293). As per our coding scheme, whenever an ESS firm had an alliance with another firm in the list of vendors we assigned that as a "one" in our alliance matrix. Note that whereas a few firms categorize the type of alliance partnerships, most do not; and even those that do categorize are not consistent with each other in the definition of their categories. However, when a partnership is initiated by a focal firm it is not always necessary that the partner firm also announces this partnership even though products from both firms are compatible. For example at times Firm A initiates a partnership with Firm B and then Firm A announces that it is Firm B compatible. Firm B on the other hand may make no announcement at all. However, irrespective of who initiates and declares the partnership products of both firms are now considered compatible in the marketplace. Implementation consultants co-pitch these products once such announcements have been made. We also code these differences as partnerships initiated *by* and *with* the focal ESS firm.

Firms compete in a number of different software component markets, e.g., enterprise resource planning; customer relationship management; advanced planning and scheduling; supply chain planning; transportation; and logistics, business intelligence modules. In addition these firms also customize their generic products for specific vertical industry segments, e.g., aerospace and defense, automotive, consumer packaged goods, electronics and computer industry, food and beverages, pharmaceuticals, service parts, etc. The information about the specific components was acquired from a combination of the above-mentioned sources. Note that these categorizations are part of the MSI Index. Overall, we have data for three time cross sections between 1999 and 2003 for an initial panel of 69 ESS firms with a total of 182 usable observations.

3.2. Descriptive and Visual Analyses of Network Data

Just as summary statistics provide a description of data for typical empirical studies, descriptive network statistics and network visualization tools provide preliminary insights into network data. One network measure that provides some insights into the network structure is the degree centrality (Freeman 1979) measure. For example, Figure 1 provides the distribution of degree centrality for one sample time cross-section in our analysis. In the visual representation of this data (Figure 2), each ESS firm would be node or actor. We can see that whereas some nodes appear to be highly central, the distribution of degree is skewed. We can draw two qualitative inferences from this visualization. The first pertains to whether the network is random or if it is a manifestation of an underlying phenomenon, possibly one we are theorizing. For this we examine the density of alliance linkages in the network for the year under consideration. The theoretical limit of alliance network density is (i.e., number of possible links) $n!/((n-2)!2!) = 2{,}080$ (Wasserman and Faust 1994). Against this, in our network there are a total of 196 links that suggests a network density of approximately 9.4% (196/2,080). Prior literature on technology alliances (Hagedoorn and Duysters 1999) refers to networks with 40% density as being highly dense, and hence by comparison our network with less than 10% density is a lightly dense network. The graph implies that firms have not formed alliances with every other firm suggesting that the ESS firms have selectively invested in alliances—an indication of underlying rational decision making.

Figure 1 Firm Degree Distribution (1999)



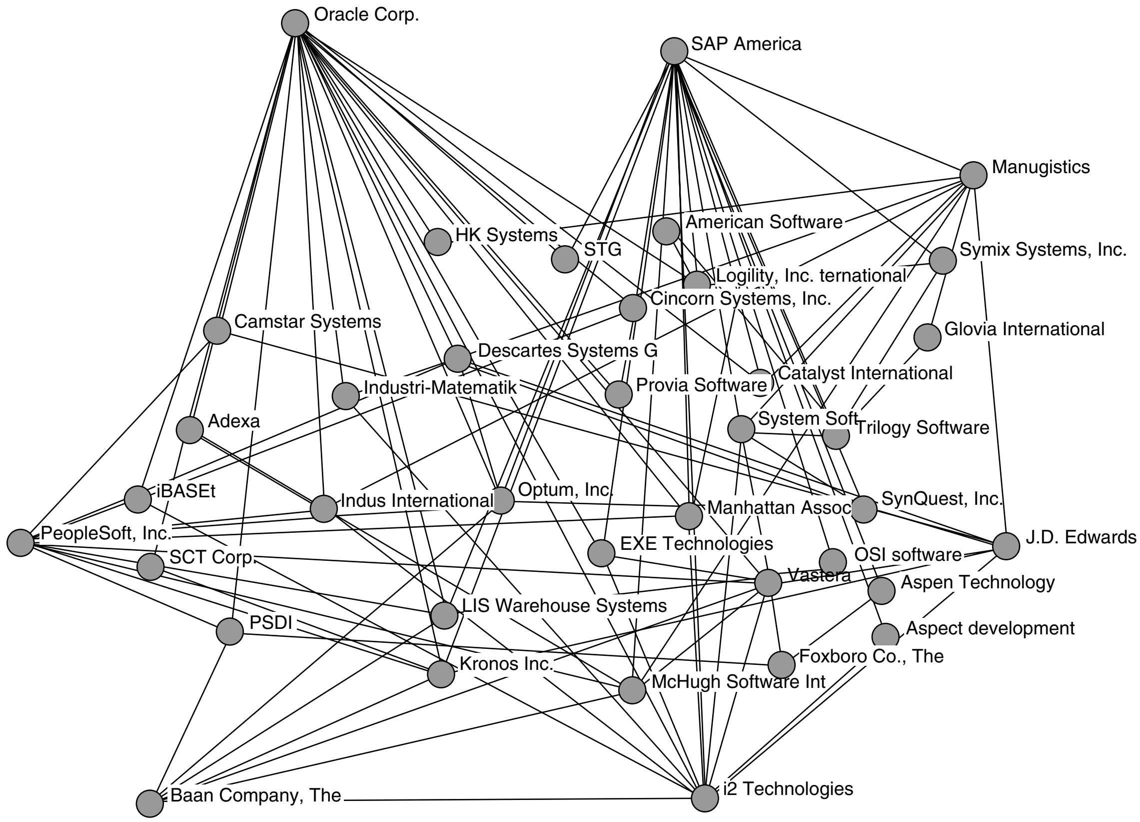
A second observation from the alliance data is that some firms (e.g., SAP, i2, Manugistics, Baan & PeopleSoft with more than 10 links each) with high degree centrality are also linked to each other. In this regard, a recent analytical work on network formation provides a useful lens to interpret this feature. Work by Bala and Goyal (2000) suggests that when linkages between profit-maximizing firms (actors) are a result of rational decisions of the actors, then certain distinct network structures will emerge in equilibrium. They observe (see Figure 3), "in the case of two-way flow of benefits, networks with a single star and linked stars are strict Nash." (p. 1186). More specifically, their findings are that if all actors are rational then eventually the networks will be empty or if connected, they will converge to a limit network with a star or a linked-star configuration.

Extending this observation to the ESS industry, and comparing Figures 2 and 3, we can see that the ESS industry has many peripheral nodes connecting to each other even if there are a few likely candidates for central nodes. This suggests that perhaps this industry is in a continuous state of flux or at some intermediate stage (Bala and Goyal 2000). A similar observation can be made for subsequent years as well. An important guidance provided by this observation is that the equilibrium findings of analytical economic models require further empirical examination. Note that, for illustrative purposes, in this section we used all firms available during year 1999, even if they dropped out of the sample during later years. The network data for later years also has the same characteristics.

3.3. Measures

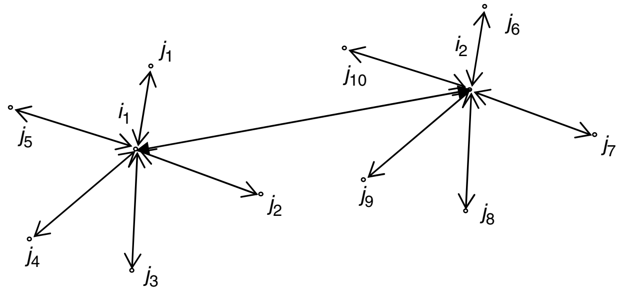
ESS firms report total and software revenues separately, where the former also includes consulting revenues for some firms, whereas the latter is exclusively from sales or licensing of their software. For our context software revenues (LSREV) is the appropriate dependent variable to indicate firm performance. Along the lines of extant studies (Jayachandran et al. 1999), we use natural log transformation for the dependent variable due to high variances in this firm performance metric. Furthermore, to avoid any causal

Figure 2 **Alliance Network of a *Sample* of ESS Firms (Year 1999)**



ambiguity, the control and independent variables are measured in year t, and the dependent variable is measured in year $t+1$ (Li and Greenwood 2004). Consistent with literature, we use number of employees (EMP given in thousands) to represent firm size. We only had access to total number of employees in a firm. This did not pose a problem because only a few firms had additional consulting business that was separate from the main ESS function. Furthermore, because we log the revenue and reduce the order of magnitude of the employees, using total instead of software revenue did not change the dependent variable significantly. Also note that any merger or acquisition activity has to be controlled for and we use a binary variable (MAQ) for this purpose; this also implied that some firms were not present in all time periods. In addition, information on some firms was not available for all time cross sections and therefore we have an unbalanced panel from an econometric point of view.

Figure 3 **Example of a Linked Star Network with Two Sponsors (i_1 and i_2)**



Empirical network studies have employed a variety of measures for prominence depending on their theoretical context and use various labels to refer to these, e.g., degree centrality (Freeman 1979), prominence, status or prestige (Knoke and Kuklinski 1982), brokerage (Burt 1992) and power, or Bonacich centrality

(Bonacich 1987).[6] For example, some of the empirical studies that operationalize these measures are: in-degree centrality (Mossholder et al. 2005, Stuart 1998), out-degree centrality (Sasovova 2006), status (Podolny et al. 1996) and brokerage (Burt 2000).

For reasons described earlier, extant measures of prominence are limited in their theoretical applicability to the ESS industry (see the online appendix). For example, the closeness-based and betweenness-based measures capture the network-wide influence on a focal actor, but the moderating effect of intermediating actors' prominence on the focal actor is not captured (Ibarra and Andrews 1993). Bonacich's (1987) measure overcomes both limitations, i.e., it considers not only adjacent actors but also indirectly connected ones. However, Bonacich does not provide a rational argument for the nature and the extent of mediation of the influence of indirectly connected actors (refer to Braun 1997) for a detailed comment). Braun (1997) develops a rational choice model of status that is similar in spirit to other analytical models of network formation (Bala and Goyal 2000), wherein a clear economic rationale is provided for firms' decision to invest in interfirm relationships. Furthermore, Braun also provides a way to compute an empirically tractable measure that can be used in empirical studies of networks. Our research extends this model by Braun to specifically capture distinct characteristics of ESS firms and alliances.

In-degree and out-degree centrality is a count of number of alliances formed *with* and *by* a firm, respectively, whereas degree centrality is simply the total number of linkages. Bonacich's (1987) centrality is given by

$$c_i(\alpha, \beta) = \sum_{j=1}^{n} R_{ij}(\alpha + \beta c_j). \tag{1}$$

In this measure (BON), R_{ij} is the matrix of relationships, whereas the parameter β indicates the degree and direction (positive or negative) of one actor's score on the score of other actors, and parameter α is used to normalize the measure such that $\sum_i c_i(\alpha, \beta)^2$ equals the number of actors in the network.

[6] These groups of measures are often referred to as *prominence* measures. See a detailed review on p. 172 in Wasserman and Faust (1994).

For our own measure (STC), where the industry network is considered to be representative of collective rational decisions of all firms, we can write the focal firm i's prominence (S_i) in its network of alliances (see the appendix) as:

$$s_i = \frac{\sum_{p=0}^{n-1} \sum_k z_{ik}^p}{1+n} + \frac{\sum_{p=0}^{n-1} \sum_k z_{ik}^p \sum_j r_{kj} s_j}{1+n}, \tag{2}$$

where r_{ij} as a fraction of firm j's dependence on all other firms directly connected to it and z_{ij} is the power matrix representation of adjacency matrices R.

3.4. Models

To test the propositions put forth in the earlier section, we conduct a panel data analyses that has the ability to control for omitted variables that differ between firms but are constant over time (and vice versa). Formally, we test the following model:

$$\begin{aligned}\text{LSREV}_{i,\,t+1} = {} & \beta_0 + \beta_1 \text{MAQ}_{i,\,t} + \beta_2 \text{EMP}_{i,\,t} + \beta_3 \text{STC}_{i,\,t} \\ & + \beta_4(\text{EMP}_{i,\,t} \times \text{STC}_{i,\,t}) + v_i + \varepsilon_{i,\,t}.\end{aligned} \tag{3}$$

Because one of our goals is to compare our measure with extant ones, in addition to Equation (3), we also test three other models where we replace our derived firm prominence metric STC, with IDEG (number of alliances formed *with* the focal firm), ODEG (number of alliances formed *by* the focal firm), TDEG (Degree Centrality) and BON (Bonacich's measure). This gives us the following three models.

$$\begin{aligned}\text{LSREV}_{i,\,t+1} = {} & \beta_0 + \beta_1 \text{MAQ}_{i,\,t} + \beta_2 \text{EMP}_{i,\,t} + \beta_3 \text{IDEG}_{i,\,t} \\ & + \beta_4(\text{EMP}_{i,\,t} \times \text{IDEG}_{i,\,t}) + \beta_5 \text{ODEG}_{i,\,t} \\ & + \beta_6(\text{EMP}_{i,\,t} \times \text{ODEG}_{i,\,t}) + v_i + \varepsilon_{i,\,t}\end{aligned} \tag{4}$$

$$\begin{aligned}\text{LSREV}_{i,\,t+1} = {} & \beta_0 + \beta_1 \text{MAQ}_{i,\,t} + \beta_2 \text{EMP}_{i,\,t} + \beta_3 \text{TDEG}_{i,\,t} \\ & + \beta_4(\text{EMP}_{i,\,t} \times \text{TDEG}_{i,\,t}) + v_i + \varepsilon_{i,\,t}\end{aligned} \tag{5}$$

$$\begin{aligned}\text{LSREV}_{i,\,t+1} = {} & \beta_0 + \beta_1 \text{MAQ}_{i,\,t} + \beta_2 \text{EMP}_{i,\,t} + \beta_3 \text{BON}_{i,\,t} \\ & + \beta_4(\text{EMP}_{i,\,t} \times \text{BON}_{i,\,t}) + v_i + \varepsilon_{i,\,t}\end{aligned} \tag{6}$$

In addition to control and independent variables, v_i is the firm-specific residual and $\varepsilon_{i,\,t}$ is the standard residual with mean zero and uncorrelated with the other terms in the model. Note that a balanced or unbalanced panel can be analyzed either as a fixed-effects model or as a random-effects (a mixed) model.

The difference in the two analyses essentially relates to the assumptions made on the firm-specific residual. Although the *fixed-effects model*s make a strong assumption that $\sigma_v = 0$ (firms are unchanged over time), we can instead think of each firm as having its own systematic baseline where each intercept is the result of a random deviation from some mean intercept. In the *random-effects model*, the intercept is a draw from some distribution for each firm and instead of trying to estimate n (number of firms) parameters as in the fixed effects case, we only need to estimate parameters describing the distribution and hence a σ_v is reported. More importantly the results from the random-effects model can be generalized to a time period outside the sample period.

3.5. Regression Results

We used the alliance matrices of the ESS firms in order to compute the centrality measures. For STC, the matrix was symmetrized and transformed to a normalized column matrix. For example, for all 23 partners who maintained alliances with a top focal firm, the strength of relationship of each alliance partner with the focal firm was normalized to 1/23 in the matrix. The matrix resulting from such normalization was asymmetric because each firm had varying number alliance linkages. The strength of each individual relationship is therefore reduced thus capturing the nonexclusivity in the relationship.

Such careful considerations are not present in the extant structural measures because they were not specifically created for such firm relationships. Table 1 presents the descriptive statistics of the variables considered in our models. The high correlations among the network measures imply that these measures are attempting to capture the same information. And indeed this is not a problem in our models because the impact of the network measures are tested through separate regressions as our intention is to compare and contrast the appropriateness of our measure. Also, there are no collinearity issues with the independent variables considered for each model (VIF less than 3.12).

Our analyses also accounts for endogeneity problems that are common in OLS estimations where they may be a correlation of the error term with one or more of the regressors, and thus rendering the ordinary least squares (OLS) estimates inconsistent. A strictly exogenous regressor would demonstrate zero correlation with the error term and normally the Hausman specification test (m-statistic) confirms this. Given the correct specification, the panel data analyses automatically control for the correlation between explanatory variables and the time-invariant, individual-specific error component in the disturbance (the remaining component is assumed to be purely random). The Hausman test as used in panel data analyses is essentially a test for the correct specification, that is, the correct way to deal with the error term, and our analysis ($p = 0.32$) clearly shows that we cannot reject the null hypothesis of the test that the effects are indeed random.

Table 2 presents the estimates and standard errors for the four models considered. First, all four models tell us that controlling for firm size is critical as expected, and that merger and acquisition (MAQ) activity is not a significant predictor of performance in this model. The results also lend support to Hypotheses 2 and 3 (Hypothesis 1 is tested in §3.4 below) using any of the structural measures. This implies that structural position in an alliance network is clearly important. However, note that in Model 1 (given by Equation (4)), we see that only in-degrees is significant, thus although it might appear that alliance

Table 1 Descriptive Statistics

Variables		Mean	Std. dev.	1	2	3	4	5	6	7
Software revenue (natural log)	LSREV	4.05	1.36	1.000						
Firm size (no. of employees in 1,000s)	EMP	2.62	7.26	0.569	1.000					
Firm prominence	STC	0.12	0.17	0.603	0.689	1.000				
Degree centrality	TDEG	3.79	5.51	0.564	0.711	0.965	1.000			
In-degrees	IDEG	2.33	3.98	0.457	0.580	0.826	0.874	1.000		
Out-degrees	ODEG	2.32	3.95	0.513	0.564	0.834	0.817	0.483	1.000	
Bonacich centrality	BON	6.99	8.92	0.549	0.672	0.970	0.986	0.857	0.831	1.000

Table 2 Random Effects Model of Firm Performance

Independent variables	Model 1	Model 2	Model 3	Model 4
Intercept	4.023*** (0.114)	4.044*** (0.114)	4.020*** (0.115)	**4.024***** (**0.113**)
Firm size EMP	0.096*** (0.019)	0.101*** (0.019)	0.103*** (0.021)	**0.096***** (**0.020**)
Firm merged or acquired MAQ	0.147 (0.146)	0.170 (0.145)	0.171 (0.146)	**0.175** (**0.146**)
In-degrees IDEG	0.075** (0.036)			
Out-degrees ODEG	0.035 (0.035)			
Degree centrality TDEG		0.086*** (0.023)		
IDEG × EMP	−0.002** (0.001)			
ODEG × EMP	−0.000 (0.001)			
TDEG × EMP		−0.002** (0.001)		
Bonacich centrality BON			0.039*** (0.013)	
BON × EMP			−0.001* (0.000)	
ESS firm prominence STC				**2.630***** (**0.700**)
STC × EMP				**−0.059**** (**0.036**)
σ_υ	0.686***	0.680***	0.684***	**0.632*****
σ_ε	0.465***	0.475***	0.490***	**0.496*****
BIC	545.7	538.2	541.9	**537.8**
No. of observations	182	182	182	**182**

Note. Standard errors are in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

formed *by* a firm is not important, Model 2 (given by Equation (5)) sheds further light. Model 2, which uses total degrees, essentially counts two firms to have an alliance irrespective of the fact whether one or both firms have declared the alliance. The BIC of this model tells us that Model 2 is a much better fit than Model 1 suggesting that alliances are important performance indicators irrespective of who initiates them. We use the Schwarz' Bayesian information criterion (BIC) to compare the models where, given any two estimated models, the model with the lower value of BIC is the one to be preferred. The BIC is a decreasing function of residual sum of squares, the goodness of fit, and an increasing function of the number of free parameters to be estimated. The BIC penalizes free parameters more strongly than does the Akaike information criterion (AIC) and is generally considered to be a better metric than AIC or −2 log-likelihood measures.

In both BON and STC, two firms are considered to have an alliance independent of whether one of both parties have announced because it is clear that alliances formed by a firm are important as well. Thus from a significance point of view although all measures of structural position, namely, degree centrality, Bonacich centrality and our own measure of status are all predictors of firm performance; comparing BIC we can clearly see our extended measure provides the best model fit. This suggests that not only are alliances important but also suitably attenuating impacts of indirect partners is a better abstraction of compatibility benefits from alliances in this industry. Furthermore, although the main effects are positive, the interaction of all alliance measures with firm size is negative, indicating that the impact of alliances on firm performance decreases as firm size increases. This implies that as long as the alliance measure is significant, smaller firms always benefit more through alliances than larger firms. Table 2 also reports the variance of firm-specific residuals and uncorrelated error term with zero mean; both these estimates are highly significant suggesting that the firm-specific effect on firm performance can be drawn from a distribution whose variance is 0.632 (from Model 4).

3.6. Results of QAP (Quadratic Assignment Procedure) Analysis

To test Hypothesis 2, we used the quadratic assignment procedure (QAP), developed by Hubert (1987) and used in prior organizational research (Krackhardt and Kilduff 1986). Note that this hypothesis suggests that extent of rivalry does not deter alliance formation, and because we cannot directly test the *nonexistence* of a relationship, one appropriate approach would be to test the *existence* of a relationship between nonrivalry, i.e., commonality in software component offerings and the probability of alliance formation.

QAP is a nonparametric data analytic method that can be used to examine the degree of similarity between structures. QAP correlation essentially tells us if two $N \times N$ matrices representing connections are similar to each other beyond a level that one could be expected through chance arrangement. In a QAP regression, the dependent variable matrix is regressed on one or more independent matrices, and the significance of R-square and regression coefficients provides the model fit. QAP has several advantages over traditional linear model hypothesis in that it takes advantage of the dyadic information represented in each matrix. Besides, it also does not make any parametric assumptions about the data and is generally used for nonindependent relationships (Krackhardt and Kilduff 1986). The biggest advantage of QAP is that it is immune to the highly complex autocorrelation structure of network data that cannot be analyzed using standard regression approaches such as logit or probit models[7] (Krackhardt 1987, 1988). The algorithm proceeds by first performing a standard multiple regression analysis across the corresponding cells of the dependent and independent matrices. Then the rows and columns of the independent matrix are randomly permuted and the standard multiple regression analysis is performed again to get the R-square and the coefficient values. The significance is determined by repeating the regression hundreds of times and comparing the coefficients of randomly generated matrices with those from the actual matrix regression (Krackhardt and Porter 1986). QAP was used by Stohl (1993) to compare a semantic network of managers' interpretation of the word "participation" and other matrices of similarity. Barley (1990) used QAP to determine whether the observed social network in a radiology department departed significantly from an institutional ideal network.

For our analyses, QAP regression was performed using the symmetrized alliance matrix as the dependent matrix. Three additional types of matrices were created that were used as dependent matrices. First, an $N \times N$ adjacency matrix (SFTOVLP) that has the dyadic software component overlap in its cells was computed; one matrix for each of the three years. That is, the cell entries represent the number of software components two firms offer in common. Second, the $N \times N$ market overlap matrix (MKTOVLP) was also computed whose cells represent the number of vertical industry segments two firms compete in. Third, we also created a matrix (SFTOVLP $\times$ MKTOVLP)[8] as an interaction effect. Three market overlap matrices were created, one for each year. Diagonals of these matrices represent the number of software components offered by a firm and the number of vertical industry segments it competes in, respectively. Diagonals were ignored during the QAP regression. We ran the QAP regressions for alliances formed each year and as discussed earlier, the number of ESS vendor firms varies due to various mergers and acquisitions in this market. For Year 1, we have 76 firms, for Year 2, our data has 81 firms and in the third time period we have a total of 70 firms.

Multiple regression quadratic assignment procedure as implemented in UCINET 6 (Borgatti et al. 2002) was used to test Hypothesis 1. We used the semi-partialling MR-QAP test that is robust against multicollinearity (Dekker et al. 2003), and the results are reported in Table 3. Because the number of companies differs across years, the total number of observations (given by $n(n-1)$) for the first year is $76 \times 75 = 5{,}700$, and 6,480 and 4,830, respectively, for the second and third time periods. For our data analysis, we ran over ten thousand iterations in UCINET to determine the significance levels of the coefficient estimates of the SFTOVLP, MKTOVLP, and the interaction matrices and their R-squares. Significance of the coefficients is computed nonparametrically as the number of permutations UCINET performed on the randomly generated matrices that had the coefficients smaller than the estimates from the regression involving the actual sample matrices. Thus, for example, in Year 1, the significance of the coefficient (column 4) of SOFTOVLP (0.026) indicates that 2.6% of the regressions using the randomly generated matrices yielded coefficients of SOFTOVLP that were larger than 0.0927 (column 3). A similar computation is done to find the significance of the R-squares. All regressions are significant (p-values 0.004, 0.055, 0.059) considering the threshold p-value at 0.1. However, the coefficients for Year two and three are not significant at p-value of 0.1.

Our results show support for Hypothesis 1. Because we are testing for the converse of the proposed

[7] Even after penalizing the standard errors for clustered observations belonging to the same actor (as done in logit models), the more complex interdependencies because of the network ties cannot be filtered out (Krackhardt 1987, 1988).

[8] For example, if a firm offered a software component X and also competed in a vertical industry segment Y, then it was coded as participating in the market segment XY.

Table 3 Quadratic Assignment Procedure Results (Dependent Variable: Alliance Matrix)

Independent variable matrices		Nonstandardized coefficient	Standardized coefficient	Significance	Proportion as large	Proportion as small
Year 1						
Intercept		0.012660	0			
SFTOVLP		0.013526	0.092799	0.026*	0.026	0.974
MKTOVLP		0.004423	0.060382	0.085*	0.085	0.915
SFTOVLP X MKTOVLP		−0.00076	−0.03397	0.226	0.774	0.226
R-square	0.009					
Adjusted *R*-square	0.009					
Probability	0.004*					
n	5,700					
Year 2						
Intercept		0.020346	0			
SFTOVLP		−0.00096	−0.00834	0.462	−0.00096	−0.00834
MKTOVLP		0.004243	0.066658	0.109	0.004243	0.066658
SFTOVLP X MKTOVLP		0.000271	0.017498	0.383	0.000271	0.017498
R-square	0.006					
Adjusted *R*-square	0.005					
Probability	0.055*					
n	6,480					
Year 3						
Intercept		0.016129	0			
SFTOVLP		0.00757	0.076123	0.106	0.106	0.895
MKTOVLP		0.002179	0.035939	0.249	0.249	0.752
SFTOVLP X MKTOVLP		−0.00031	−0.02132	0.316	0.684	0.316
R-square	0.005					
Adjusted *R*-square	0.005					
Probability	0.059					
n	4,830					

*$p < 0.1$.

hypothesis, if our results show that there exists at least a weak *or* no relationship then our hypothesis is validated, i.e., the coefficients have to be positive if significant or not significant at all. We can see from Table 3 that for the first time period both SFTOVLP and MKTOVLP are positive and significant whereas the interaction variable is not. This implies that greater the commonality in component markets, i.e., greater the component rivalry between two firms, then *higher* is the likelihood of alliance formation between them. Similarly, greater the commonality in vertical industry segments served, *higher* is the likelihood of alliance formation between them. The interaction variable is testing for the following proposition: given a degree of commonality in software component markets, does increase in commonality in vertical industry segments affect the probability of alliance with a firm? The insignificant coefficient for this variable across all time periods tells us that this is not a possibility. Thus the analysis clearly demonstrates that because two firms are great rivals, it does not necessarily imply that the firms will not form a partnership; in fact the results for the first time period hint toward the converse. These findings take significance in the context of the software industry where others have assumed that firms will avoid rivals (Axelrod et al. 1995).

Our alliance matrix is relatively sparse (less than 10% of total possible linkages), and as discussed earlier a combination of sparseness of alliances and a skewed distribution of degree centrality clearly show that alliances are conscious decisions and not some random occurrence in this industry. Hence it is also not unusual that our model *R*-squares is low as other studies have also shown that QAP analysis using sparse matrices will yield low *R*-squares, e.g., in modeling rare events logistic regressions (King and Zeng 2001).

4. Discussion and Conclusions

We have argued here that user requirements govern important aspects of competition in the business software industry. Therefore it is perhaps as critical for IS researchers to study the firm and industry-level aspects of enterprise systems software as it is to examine their intra-organizational adoption and usage. Currently, little is known about the competition between vendors who supply these enterprise systems components. Research in economics provides some insights on competition in industries driven and defined by standards and compatibility; however, these are generally highly stylized analytical models involving duopolies and usually two components (Economides 1989, Matutes and Regibeau 1988). Furthermore, there has been a distinct paucity of empirical research in this field, which is perhaps reflective of the difficulty in acquiring firm-level information in such industries. This paper aims at addressing this gap by employing social network methods as an alternative framework to study this industry.

Competition in enterprise systems software (ESS) is defined by lack of common standards where the ESS firms produce multiple components and client organizations often build a system through components from multiple firms. So, even if ESS firms are capable of producing components for multiple functional areas and even if they would prefer that organizational end users purchased all components from them, these firms form alliances to maintain technical compatibility as well as to signal compatibility to client organizations. Thus alliances are mainly motivated by demand-side need for compatibility rather than typical reasons of resource sharing, specialization, etc. (as commonly seen in extant research on alliances in strategy). Although not a direct network effect, the demand-side hint at the existence of indirect network externality benefits. This is consistent with phenomenon observed in interdependent hardware and software markets where firms often "have an incentive to free-ride on each others' demand creation efforts" (Gupta et al. 1999, p. 396).

First, we see that the current configuration of alliance networks is not in equilibrium, suggesting that equilibrium findings of analytical models cannot be directly applied. This implies that there are no dominant standards that characterize the settings in stylized analytical models of firm competition. Second, we examine the formation of linkages themselves and show that compatibility considerations can trump rivalry concerns, i.e., firms form alliances even with rivals—at the very least rivalry does not prevent alliance considerations. Third, we propose an approach to measure the standards dominance of an ESS firm given there is no de jure or de factor (monopolistic or oligopolistic) standard in the market. Because extant structural measures were primarily conceived for interpersonal networks and do not accurately capture the net value from forming linkages, we derive our own measure (based on an extant measure) by including attenuated benefits from indirectly connected firms. We then show this prominence measure indeed is a performance indicator even after controlling for size of the firm. We also compare our measure against extant structural measures. Finally we show that small firms stand to gain more by forming partnerships with prominent firms and thus acquiring a higher prominence than larger firms do.

4.1. Conclusions

An important contribution of our work to IS research is that it develops a cogent link between corporate IT standards (a well-developed concept in IS research) and ESS firm competition. Corporate IT standards underscore the need for common standards within an organization. This requirement often contradicts the behavior of functional groups that prefer to buy system components that are the best-of-breed. ESS firms have to internalize these client-side requirements in their competitive strategies. One option is to make themselves attractive by forming alliances and thus appearing to be compatible with a wide range of firms. Our research suggests that firms can achieve this through a careful selection of alliance partners—not based on rivalry considerations but rather based on their prominence within the network of alliances. Recent research in economics is now developing stylized models of platform competition where firms learn to internalize network effects on the client side (Rochet and Tirole 2006). There is also some evidence of such demand-side forces directing firm relationships in marketing (Stewart 1996), e.g., co-branding initiatives. In co-branding two firms form an alliance not because of resource considerations, but rather to jointly promote a product containing components from both firms, e.g., Intel-inside and AT&T and iPhone campaigns. Firms engage in these initiatives because consumers value "compatibility" between two brands they prefer. Our research would suggest that if the market is not in equilibrium and there are no firms owning a dominant standard, the relative dominance can be determined through their prominence in a co-branding network. Our research would also recommend nonexclusive relationships across multiple partners, and that it is key for small firms to engage in these relationships.

Although we do see the social network approach increasingly adopted in IS research, it has largely focused on studying individual level interactions rather than firm relationships, e.g., teams within hospitals (Kane and Alavi 2008). When studying firm-level relationships, our research also suggests that any network analysis should be preceded by descriptive visual analysis so as to compare with equilibrium structures. If firms engage in strategic partnerships as a result of their cost-benefit analyses, the visual analyses provide insights about how far away the industry is from the emergence of monopolistic or oligopolistic markets. This observation might be helpful for future work on entry and exit into an industry sector. Furthermore, we also recommend that a rational choice model such as Braun's (1997) can be extended easily to accommodate unique elements of a particular sector, just as we were able to do for the ESS industry.

4.2. Limitations and Future Research

Our study has the general limitations of any empirical study, namely the availability of data. As the data for alliances and revenue had to be collected from independent sources, we are limited to a three time-period sample of ESS firms. Furthermore, data on the number of site licenses, individual component revenues and other fine-grained measures are unavailable due to the fact that a sizable number of ESS firms are privately held and public information on them is not forthcoming. Although this does not detract from our analysis, such fine-grained measures can also lend greater insights into product-line decisions of ESS vendors. In this study we only consider the ESS firms in the actor network; implementers, consultants, and middle-ware vendors are not included. Given their significant impact on alliances in the ESS industry it might be interesting to incorporate their role in any future studies by using a multimode network approach that allows for inclusion of heterogonous actors. Similarly we have not explicitly parameterized the number of markets in which firms compete versus cooperate; this may be needed for an empirical extension to this study.

Note that alliances serve as a proxy for both social and technical resources. In this empirical study, we are unable to segregate the types of resources such as knowledge spillover effects, reputation effects, and access to larger user bases from product compatibility. It should be noted however that network analysis using such multidimensional ties becomes increasingly complex and therefore most studies on interfirm networks consider an alliance to be representative of more than one type of resource flow. Typically a qualitative approach through interviews of managers and clients of ESS firms is useful for isolating the nature of distinct types of resource transfers. Perhaps, future empirical studies can employ the survey method to empirically distinguish between different dimensions of compatibility and their differential implications to ESS vendors and IT buyers alike. Similarly, there are no explicit measures of tie strength although alliances range from licensing to co-development. However, there are no industry-wide norms that we can use to explicate these differences.

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Appendix. Deriving the Prominence Measure for the ESS Industry

Consider a network of n ESS firms and a set of linkages among these representing alliances. We assume that each firm has made a rational decision at a particular point in time in terms of the choice of its alliances. Furthermore, it has also invested in its relationships such that its net benefits (less costs incurred in maintaining these) are maximized, that is, every vendor seeks to maximize access to resources in excess of costs. Thus, the profit maximization function of each firm is $\max_j[b_i - c_i]$, where c_i, and b_i are the costs and benefits of a focal firm i across all directly and indirectly connected firms j. As discussed in the body of the paper, the distinct characteristics of ESS alliances can be summarized into the following three assumptions.

1. The greater are the exogenous (nonnetwork based) resources of the alliance partners, the greater will be the social and technical resources accessible to the focal ESS firms.

2. The higher the relative prominence of the focal ESS firm, the higher is the cost incurred by alliance partners to maintain a relationship with the focal firm.

3. An ESS firm can access resources from indirectly connected firms at no direct cost to itself. This indirect access is mediated by the intermediate firms.

Let us call the exogenous resource base of a firm as $e_j(e_j > 0, \forall j)$ and normalized for the whole network $(\sum_{j=1}^{n} e_j = 1)$. In the absence of alliances with other firms a firm's access to resources is $b_j = f(e_j)$. Furthermore, let r_{ij} represent a focal firm i's strength of relationship with adjacent firms j, and let $r_{jk}, \forall i \leftrightarrow k = 2$ represent the strength of relationship between firms one and two path lengths away. All relationships in our model are normalized and we represent r_{ij} as a fraction of firm j's dependence on all other firms directly connected to it. Therefore we can construct an adjacency matrix R as a $n \times n$ column stochastic matrix with elements r_{ij}, such that for each j, $\sum_i r_{i,j} = 1$. Then combining Assumptions 1 and 3, we can write a firm's aggregate access to resources through its network as

$$\begin{aligned} b_i &= \sum_j r_{ij} e_j + \sum_j \sum_k r_{ij} r_{jk} e_k \\ &\quad + \sum_j \sum_k \sum_l r_{ij} r_{jk} r_{kl} e_l + \cdots \quad \forall i \neq j, k, l \\ &\qquad i \leftrightarrow j = 1,\ i \leftrightarrow k = 2,\ i \leftrightarrow l = 3, \ldots. \end{aligned} \tag{7}$$

Now consider an array of power matrices where $z_{ij}^0 = 1_{i=j}(=0)_{i \neq j}$, $z_{ij}^1 = r_{ij}$, $z_{ik}^2 = \sum_j r_{ij} r_{jk}, \ldots, z_{in}^n$. In matrix notation z_{ik}^2 can be represented as $z^2 = R \cdot R$, and $z^p = R^p$, where p is the path length between two firms. Therefore Equation (7) can be rewritten in matrix notation and normalized as

$$\begin{aligned} b_i &= \frac{\sum_j r_{ij} e_j + \sum_j z_{ij}^2 e_j + \sum_j z_{ij}^3 e_j + \cdots + \sum_j z_{ij}^P e_j}{n(P+1)} \\ \Rightarrow \quad b_i &= \frac{\sum_p^{p=1} \sum_k z_{ik}^p e_k}{n(P+1)} \end{aligned} \tag{8}$$

or further reduced to (where P is the maximum path length of the geodesic between any two ESS firms in the network)

$$b = \frac{\sum_{p=1}^{P} (Z^p . e)}{n(P+1)}. \tag{9}$$

The interpretation of the matrix element Z in $b = \sum_{p=1}^{n} (Z^p . e)$ is similar to Braun's (1997, p. 133) abstraction. Braun's notion of a power matrix is the degree to which the system-wide investment into an actor l depends on actor i's relationships with its network members. In other words, Z reflects the "actor dependency" structure. Therefore in our context, the matrix element $\sum z_{il}$ expresses a focal firm i's fraction of control over the investments received by firm l. In a completely connected network (everyone is connected with everyone else) of n actors, between any two actors, there are: one path of length 1, $(n-2)$ paths of length 2, $(n-2)(n-3)$ paths of length 3 and so on. In our abstraction each path represents access to resources. Hence if the network were completely connected there are $1 + (n-2) + (n-3)(n-2) + (n-4)(n-3)(n-2) + \cdots$ ways in which resources can flow from one ESS firm to another. Note that therefore access to resources diminishes as the path length increases. For computation of our metric, we take the maximum number of indirect paths as the maximum of the *geodesics* between all pairs of actors in the network, where a *geodesic* is the shortest path between the actors (Wasserman and Faust 1994), given by P. In our computation, a firm's aggregate access to resources is normalized as $b = (\sum_{p=1}^{n} (Z^p . e)) / (n(P+1))$. For the focal firm i, let c_i be the aggregate cost incurred in forming alliances and be the relative prominence of its alliance partners; formally we can state Assumption 2 as $c_i \propto \sum s_j$, $\forall i \leftrightarrow j = 1$, that is

$$c_i = \sum_j r_{ij} s_j, \quad \forall i \neq j,\ i \leftrightarrow j = 1. \tag{10}$$

Therefore we can now write the profit maximization problem of a firm as

$$\max \left[\frac{\sum_{p=1}^{P} (Z^p . e)}{n(P+1)} - \sum_j r_{ij} s_j \right]. \tag{11}$$

We assume that all firms are rational and will allocate their investments r_{ij} so as to maximize their profits, so we consider the first order condition of Equation (11) by differentiating with respect to r_{ij}, and rearranging the terms we have

$$\begin{aligned} s_j &= \frac{\sum_{p=0}^{P-1} \sum_k z_{jk}^p e_k}{n(P+1)} \quad \text{which in matrix notation is} \\ S &= \frac{\sum_{p=0}^{P-1} (Z^p . e)}{n(P+1)}, \end{aligned} \tag{12}$$

where S is the column vector of statuses of the firms.

We need the prominence measure purely as a function of its network linkages and prominence of the directly and indirectly connected partner firms. So, we endogenize benefit as a function of the innate capability of a firm, similar to Braun (1997) we assume a linear form of $b_a = (1+n)e_a - 1$, and substituting for cost, we have for any k, $e_k = (1+c_k)/(1+n) = (1/(1+n) + 1/(1+n)) \cdot \sum_j r_{kj} s_j$. Multiplying both sides by $(\sum_{p=0}^{p-1} \sum_k z_{ik}^p) / (n(P+1))$, we have from Equation (12)

$$S_i = \frac{\sum_{p=0}^{p-1} \sum_k z_{ik}^p + \sum_{p=0}^{p-1} \sum_k z_{ik}^p \sum_j r_{kj} s_j}{n(n+1)(P+1)}, \tag{13}$$

$$\begin{aligned} \text{Or} \quad S &= \frac{(\sum_{p=0}^{P-1} Z^p).J}{n(n+1)(P+1)} \\ &\quad + \frac{(\sum_{p=1}^{P} Z^p).S}{(n+1)} \quad \text{(in matrix notation)}. \end{aligned} \tag{14}$$

We can further reduce these terms for empirical assessment. Rearranging Equation (14), we have $S = (I - X)^{-1} YJ$, where $Y = (\sum_{p=0}^{P-1} Z^p)/(n(n+1)(p+1))$, $X = (\sum_{p=1}^{P} Z^p)/(n+1)$. The power series of S is as follows

$$S = \frac{1}{n(n+1)(P+1)} \left(I - \frac{\sum_{p=0}^{P} Z^p}{1+n} \right)^{-1} \left(\sum_{p=1}^{P-1} Z^p \right) J$$

$$\Rightarrow \quad \frac{1}{n(n+1)(P+1)} \sum_{l=0}^{l=\infty} \left(\frac{\sum_{p=1}^{P} Z^p}{1+n} \right) \left(\sum_{p=0}^{P-1} Z^p \right) J. \qquad (15)$$

The above power series is valid because $\|(\sum_{p=1}^{P} Z^p)/(n+1)\| < 1$. From Kincaid and Cheney (1996), we can confirm the existence of the inverse if the norm $\|(\sum_{p=0}^{P} Z^p)/(n+1)\| \leq 1 \Rightarrow \|\sum_{p=1}^{P} Z^p\| \leq (n+1)$, where $\sum_{p=0}^{P} Z^p$ is also a stochastic matrix with column sums equal to n. Let $(1/n)\sum_{p=0}^{P} Z^p = G$, then the inverse is always said to exist if and only if $\|G\| \leq (n+1)/n$. Matrix G, being a column stochastic, its norm is $\|G\| = \max_{1\leq j\leq n} \sum_{i=1}^{n} \mid a_{ij} \mid \Rightarrow 1$. Because $(n+1) > n$ in our case, the existence of the inverse is confirmed. For further empirical measurements e and c can be reduced to

$$c = Rs = R \frac{1}{n(n+1)(P+1)} \sum_{l=0}^{l=\infty} \left(\frac{\sum_{p=1}^{P} Z^p}{1+n} \right)^l \left(\sum_{p=0}^{P} Z^P \right) J$$

$$= \frac{1}{n(n+1)(P+1)} \sum_{l=0}^{l=\infty} \left(\frac{\sum_{p=1}^{P} Z^p}{1+n} \right)^l \left(\sum_{p=1}^{P} Z^p \right) J.$$

This can be further reduced to

$$e = \left(\sum_{p=0}^{P-1} (Z^p) \right)^{-1} S \;\Rightarrow\; e = \frac{1}{n(n+1)(P+1)} \sum_{l=0}^{l=\infty} \left(\frac{\sum_{p=1}^{P} Z^p}{1+n} \right)^l J.$$

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