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Evolution of Supply Chain Collaboration: Implications for the Role of Knowledge

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John Wang
Montclair State University, USA

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Chapter 18

Evolution of Supply Chain Collaboration: Implications for the Role of Knowledge

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ABSTRACT

Increasingly, research across many disciplines has recognized the shortcomings of the traditional “integration prescription” for inter-organizational knowledge management. This research conducts several simulation experiments to study the effects of different rates of product change, different demand environments, and different economies of scale on the level of integration between firms at different levels in the supply chain. The underlying paradigm shifts from a static, steady state view to a dynamic, complex adaptive systems and knowledge-based view of supply chain networks. Several research propositions are presented that use the role of knowledge in the supply chain to provide predictive power for how supply chain collaborations or integration should evolve. Suggestions and implications are suggested for managerial and research purposes.

INTRODUCTION

Recent research indicates that the era of inter-organizational collaboration and knowledge-sharing has arrived under the guise of supply chain management. Investments in supply chain

management provide a competitive advantage to business. For example, AMR’s “Supply Chain Top 25” grew revenue an average of 29% over the prior year (Hofman and Aronow, 2012). Perhaps more telling for the scholar of knowledge-based organizations are the conclusions by the World

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Economic Forum (2012) that countries could grow their GDP six times more by using policies that address the management of supply chain processes instead of relying on tariffs. Supply chain processes tend to be knowledge-intensive and depend upon international collaboration, coordination with government entities such as customs, reliable physical infrastructure for transportation and communications, and standardizing inter-organizational procedures. In a very real sense, supply chain management really represents knowledge exchange management between firms, with most pundits espousing “integration” of knowledge and processes.

Integration of inter-organizational processes has long comprised the prescription for success in supply chain management and related literature (Frohlich & Westbrook, 2001; Gustin, Daugherty, & Stank, 1995; Stock, Greis, & Kasarda, 1999). Information sharing and various levels of coordination and collaboration have traditionally found strong empirical support (c.f., Daugherty, Ellinger, & Gustin, 1996; Lee, Padmanabhan, & Whang, 1997; Lummus & Vokurka, 1999; Narasimhan & Jayaram, 1998; Stank, Keller, & Closs, 2001; Tan, Kannan, & Handfield, 1998). Notwithstanding the oft-cited works that support the “integration prescription,” one systematic review of the literature revealed the link between integration and supply chain performance as shaky (Fabbe-Costes & Jahre, 2008). One simulation study found that information sharing may have no value at all or may even increase costs, depending on demand patterns (Jonsson and Mattsson, 2013). The mixed evidence suggests an incomplete theoretical understanding of integration and inter-firm collaboration.

One issue may be the implicit assumption that all collaboration is the same. Empirical studies that distinguish among the different manners of collaborating and the different outcomes to the various supply chain members remain relatively few, with Frohlich and Westbrook’s (2001) land-

mark article representing a sort of genesis of this body of literature. More recent work has found that supply chain strategies vary but seem to become more sophisticated the closer the firm is to the market (Bourlakis, et al., 2012), despite the additional economies of scale and other benefits that firms higher up the supply chain often have. This may reflect the presence of hypercompetitive environments characterized by the rapid rise and fall of firms (McNamara, Vaaler, & Devers, 2003; Wiggins & Ruefli, 2005); retail firms that are not responsive to customer needs do not last long. Hypercompetitive environments act to “dis-integration” supply chains as firms seek higher quality, lower cost or other product characteristics desired by the market.

Another important issue has been the realization that the traditional conceptualizations of supply chain management implicitly assume a “steady-state” condition. Increasingly turbulent economic and global systems mean that supply chains must be adaptable and resilient to manage their risks—yet methods for assessing and managing inter-organizational network change remains in a nascent status (Pettit, et al., 2013). Supply chain agility comprises a well-established conceptualization of responsive and adaptable inter-organizational networks of firms; however, supply chain agility primarily focuses on descriptive or normative theories rather than predictive capability (c.f., Gligor, et al., 2012).

In the past few years, supply chain literature has begun to treat supply chains as knowledge-based constellations of organizations. Researchers have increasingly focused on the question of when, how and why supply chain integration works (or doesn’t). Recent work has evaluated with whom companies integrate (Huo, 2012), the relationship of information flows to material flows (Prajogo and Olhager, 2012), short-term knowledge sharing vs. deeper knowledge generation (Jayaram and Pathak, 2013), product and process strategies as antecedents of supply chain integration strate-

gies (Droge, et al., 2012), and the technological platforms for sharing information and knowledge (Bendoly, et al., 2012). Implicit (and often explicit) to this work are supplier and customer relationship management, and the benefits of long-term vs. short-term relationships.

Interestingly, little research has attempted to map supply chains, and then relate supply chain macro-level characteristics to knowledge needs. Methodological challenges mean that most past work has been static in nature or relied on assumptions that environmental conditions remain constant. Few studies have assessed longitudinal evolution of supply chains despite the important potential public policy and strategic contributions of such research. In a sense this work represents an extension of the intra-firm organizational influence on knowledge management proposed by Nickerson and Zenger (2004).

This research assesses the patterns of collaboration and firm mortality in supply chains by use of simulation. The pace of technological advance, sensitivity to economies of scale, and various market scenarios provide the environmental control variables; evolutionary outcomes and degree of interfirm collaboration comprise the observations at each level of a four-tier supply chain. The resulting patterns of supply chain evolution provide the basis for developing implications for different degrees of inter-firm knowledge management.

LITERATURE REVIEW

Studying and modeling supply chain evolution from a knowledge-exchange perspective requires a multi-disciplinary approach. Classical supply chain governance theory, adaptation, and evolution literatures provide the conceptual model for the subsequent simulation of inter-organizational evolution. Particular emphasis is paid to the integration between firms using a newly developed measure called the collaboration index.

Supply Chain Theory

Ronald Coase's 1937 work on transaction costs offers the theoretical roots of supply chain management, prompting one scholar to describe the reduction of transaction costs as "the heart of the interest in supply chain management (Hobbs, 1996, p.26)." Williamson, the researcher most associated with transaction costs, stated, "...whereas TCE examines individual transactions, SCM introduced a broader systems perspective in which related transactions are grouped and managed as chains (Williamson, 2008, p. 5)." Transaction cost economics (TCE), sometimes referred to as transaction cost analysis (TCA), offers perhaps the most extensive empirical support of any of the extant exchange governance theories, with between 250 and 500 citations appearing annually in scholarly works since the early 1990s (David and Han, 2004).

Many scholars trace the origins of supply chain management to Forrester's 1958 *Harvard Business Review* article where he stated (p. 37): "Management is on the verge of a major breakthrough in understanding how industrial company success depends on the interaction between the flows of information, materials, money, manpower, and capital equipment." Williamson's conceptualization of TCE emphasizes the adaptability of the interactions between firms as "the central problem of economic organization" (1991, p. p. 278)—and it is this adaptive response to environmental pressures that motivates this study of supply chain evolution. Williamson (1975, 1986) founded his theoretical framework on two primary assumptions of human behavior (bounded rationality and opportunism) and two dimensions of transactions (frequency and asset specificity).

Bounded Rationality and Opportunism

Bounded rationality and opportunism are the two primary dimensions of uncertainty. Uncertainty

embodies any unanticipated change to the circumstances surrounding an exchange (Rindfleisch & Heide, 1997). Bounded rationality describes the behavioral uncertainty resulting from the cognitive limits of managers who try to anticipate every contingency in a market exchange (Leiblein, 2003). Opportunism refers to the behavioral uncertainty resulting from self-interest seeking behavior. According to TCA, high environmental uncertainty increases transaction costs of due to the need to adapt contractual agreements to compensate for unanticipated variations in volumes, technology/product design, sources of supply, doubtful customer loyalties, and other unforeseen circumstances.

The dimensions of uncertainty are manifestations of information asymmetries, unaligned goals, or lack of commitment. Industry standardization may reduce the risks from lack of commitment; the low cost of tracking electronic trails in technology intensive environments diminish the occurrence of information asymmetries (Garicano and Kaplan, 2001). Networks and other hybrid forms of governance are characterized by standards or norms and a high degree of shared information. This leads to reduced uncertainty without incurring the costs associated with vertical integration while avoiding most opportunity costs in turbulent environments that require switching partners.

In terms of predictive outcomes, TCA claims that firms employ vertical integration as a means of easing the burden of performance evaluation. This follows from TCA's assertion that evaluation problems give rise to measurement costs. However, Ouchi (1979) provides an alternate view that measurement costs are incurred in order to distribute rewards across parties in an equitable fashion. If equitable distribution does not occur, an individual firm may eventually reduce its individual efforts, incurring opportunity costs resulting from the productivity losses. Ouchi's insight harkens to the classical team production problem (Alchian & Demsetz, 1972) wherein labor that requires cooperative production. In this

perspective, vertical integration will occur when equitable distribution becomes difficult—such as when margins are low for a highly commoditized item (resulting in larger players using bargaining power to increase their profits at the expense of suppliers or customer) or when the contribution of individual players becomes expensive or difficult to measure relative to the value of productivity (again leading to paying below market value). In either case, performance will eventually suffer as either the firm acquiring the difficult-to-measure inputs or the buyer/coordinator of the inputs will reduce their level of effort to match their reward. Additionally, uncertainty may also lead to more market-based exchanges due to the increased flexibility in partner-selection (Rindfleisch & Heide, 1997).

Empirical evidence demonstrates mixed results regarding TCA's predictions of the effects of uncertainty, probably largely due to the difficulty of measuring the construct (David & Han, 2004; Rindfleisch & Heide, 1997). Because uncertainty is a multidimensional construct, it is best studied via longitudinal or dynamic methods such as the current study that take into account factors such as environmental dynamism, environmental heterogeneity, and innovation. Any insights gathered with regard to uncertainty would be an important contribution.

TCA's Exchange Factors

Two kinds of exchange factors appear in the model, derived from TCA's exchange factors that predict the optimal interfirm governance form. Exchange factors include 1) frequency and 2) asset specificity.

Frequency

Generally speaking, as two firms conduct more exchanges with each other, they find more efficient ways of conducting the exchanges, driving down the transaction costs on a per unit basis.

Frequency of transactions has different effects on the governance form depending on asset specificity and behavioral uncertainty. The costs of monitoring behavior in close partnerships mean that as long as there is no behavioral uncertainty, open market transactions are very efficient. When the costs of motivating partners to align their interests outweigh the costs of more integrated forms of governance, then firms move away from open market transactions. This insight suggests a U-shaped relationship between economies of scale and frequency of transactions—relatively few players at the early and late stages of an industry's life cycle mean fewer options for switching and more “lock in” leading to more frequent transactions between the remaining firms. During the highly competitive rapid growth phase, the appearance of many firms provides many opportunities to switch to a better partner, and less incentive to stick with the same partner, thus lowering frequency. Additionally, a rapid rate of technological advance forces firms to keep up with successful innovators or perish.

Asset Specificity

Asset specificity provides a means for limiting the effects of bounded rationality and technological uncertainty. By investing in resources customized for the specific conditions of exchange between two firms, more information becomes available for managerial decision making. Increased information reduces the coordination costs between firms, as described under previously under bounded rationality (Garicano and Kaplan, 2001). In addition to reducing coordination costs between firms, asset specificity becomes desirable as a means of “locking in” sources of supply or buyers in the presence of environmental turbulence for two reasons. Firstly, successful innovation flourishes under conditions of frequent interaction and interdependence between firms (Varadarajan & Cunningham, 1995); market transactions do not allow for interfirm learning and exchange of ideas, but asset specificity ensures closer or even

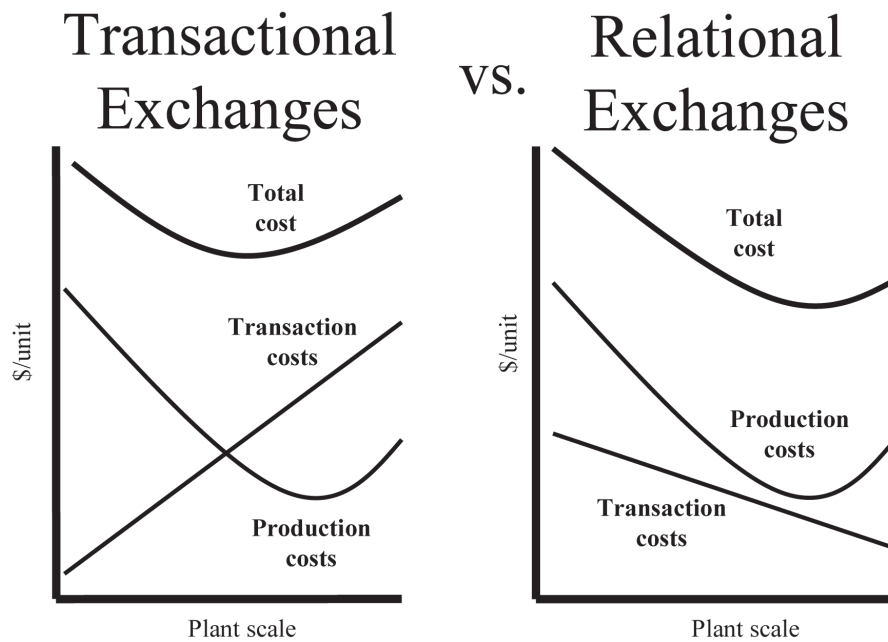
exclusive relationships. Secondly, greater leaps in innovation increase the costs of failure while also increasing the incentives for achieving success (Chesbrough & Teece, 1996); increasing asset specificity reduces the risk to each firm while increasing the chances of successful innovation.

Shortcomings of TCA

As Williamson (2008) himself pointed out, TCE limits itself to individual transactions, rather than grouping transactions and considering them as part of a system. TCE represents essentially a contractual approach to explaining inter-firm transactions, which leads to several theoretical shortcomings (for a more detailed expose, see Deitrich, 2012). Overlooked in most current TCA scholarship is the importance of production factors. Coase's (1937) original vision involved balancing the marginal contribution of owning production versus managing via exchanges on the open market. The balancing act occurs in “an outside network of relative prices and costs” (Coase, 1937: p. 389). It is a relatively recent development that firms now have the tools to actively manage this balancing act across multiple firms. The active collaboration across multiple firms in order to lower transaction costs or take advantage of lower external production costs is the essence of supply chain management.

The means of managing collaboration across multiple firms may vary from purely open market, one-time exchanges to exclusive, long-lasting relationships. These two classifications form the anchors for what has been described as a conceptually useful continuum of interfirm exchange governance from purely “transactional” to purely “relational” exchanges (Heide, 1994). In essence, transactional and relational exchanges offer different strategies for cost tradeoffs between transaction and production costs (see Figure 1). Transactional exchanges make the explicit assumption that as a firm's capacity grows it must deal with more

Figure 1. Conceptualization of total cost curves for transactional and relational exchanges



open market transactions, and transaction costs will eventually increase per unit as the result of having more trading partners whose needs must be tracked, and more information to be gathered and compared before making purchasing decisions, and generally increased costs of greater managerial scope. Relational exchanges limit interactions to one or very few trading partners, thus lowering transaction costs on a per unit basis as the result of greater efficiencies—analogueous to economies of scale or learning curve effect, but applied to interfirm collaboration. At some point, production will reach diseconomies of scale, raising unit production costs and ultimately raising total costs.

Despite a strong empirical record, TCA theory does suffer some drawbacks (Joshi and Campbell, 2003). It lacks explanatory power for how firms organize themselves in a network then adapt their exchange behavior based upon changes to the production and demand environments. TCA has also been criticized for focusing on exogenous market factors and failing to explain firm-level decisions (Hunt and Morgan, 1995). As a theory

of interfirm collaboration TCA suffers from being firm-centered (or at best dyadic) and static in nature (Rindfleisch and Heide, 1997)—a far cry from the supply chain reality of networks with highly dynamic firm interactions. Recent theoretical work into complex adaptive systems offers a new paradigm for studying systems characterized by adaptive agents who repeatedly interact and adapt to their environment (Surana, et al., 2005).

Adaptation in Supply Chains

Recently several new theoretical perspectives of supply chain management have been proposed that incorporate the complex adaptive systems (CAS) perspective (c.f., Mena, et al., 2013; Pilbeam, et al., 2012; Schoenherr, et al., 2011). CAS theory offers a way of studying supply chain networks of firms that adapt their behavior based upon experience and the outcomes of interactions (Choi, et al., 2001; Surana, et al., 2005; Vargo and Lusch, 2004). Complex adaptive systems developed from

complexity science and arose out of the study of open systems. In the organizational context, a system consists of interconnected components that interact; such systems are “open” because they exchange resources with the environment. When the members of a system have many interactions that result in a whole that is interdependent with the environment, they comprise a complex system (Anderson, 1999). The idea of complex systems underlies Forrester’s (1958, 1961) dynamic models now commonly used as the bases for studying the beer game or the bullwhip effect in supply chain analysis (Lee, Padmanabhan, & Whang, 1997a; Lee, et al., 1997b).

Complex adaptive systems build on the idea that “adaptation builds complexity” (John H. Holland, 1995). In a CAS, members of a system are called entities (Surana, Kumara, Greaves, & Raghavan, 2005). Each entity communicates with other entities and the environment, accumulating experience (learning), continuously interacting, and changing its behavior, and its own structure as well as the system’s structure. The CAS perspective has been applied successfully for many years to the study of socio-economical processes, to include economics (J. H. Holland & Miller, 1991; Limburg, O’Neill, Costanza, & Farber, 2002; Markose, 2005), organizational learning (Chiva-Gomez, 2003; McElroy, 2000; Morel & Ramanujam, 1999), psychology (Dooley, 1997; Goldstone & Sakamoto, 2003), linguistics (Kirby, 2000), anthropology (Abel, 1998), military strategy (Ilachinski, 2000), innovation (Eisenhardt & Tabrizi, 1995), and strategy (Bettis & Prahalad, 1995).

There are six characteristics that make the CAS paradigm particularly appropriate for the study of supply chains: 1) interactions, 2) interdependencies, 3) high non-linearity, 4) self-organization, 5) evolution, and 6) dynamism. Interestingly, CAS possess the most salient qualities that both Coase (1937) and Williamson (1991) ascribed to market exchanges: movement from one equilibrium point to another, continuously dynamic,

firm dependence on an outside network of other firms and prices, and made up of autonomous but not entirely independent actors. As such, the CAS paradigm offers a strong foundation for the study of supply chains as both markets and systems.

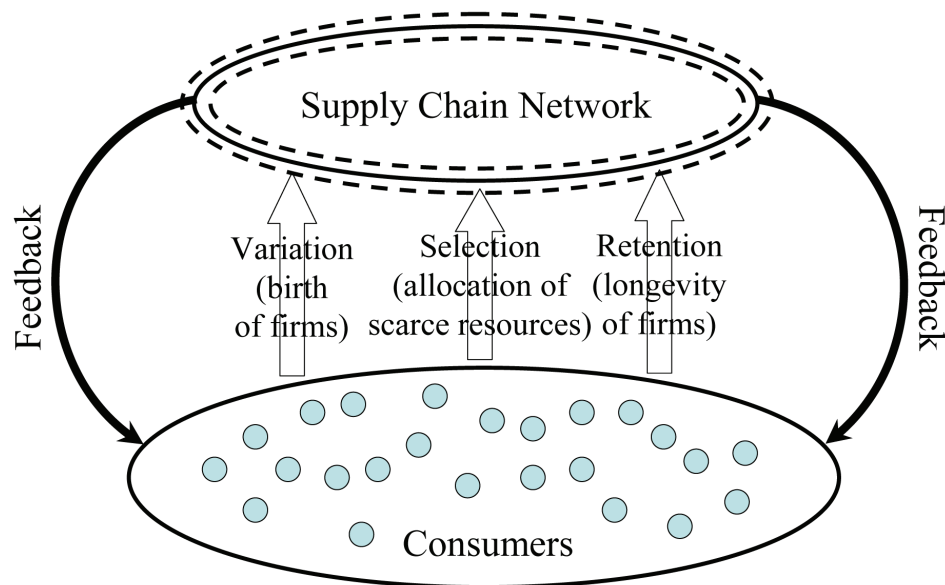
Complex adaptive systems theory describes increasingly complex networks as more expensive and fragile to maintain, but their diversity of structures provides greater robustness to environmental fluctuations. While the increased diversity and complexity of structures increase resilience in the face of random attacks or environmental shifts, they also increase vulnerability to targeted attacks or in the event that certain key system nodes succumb to environmental shifts (c.f., Holme, Kim, Yoon, & Han, 2002). This happens as the result of the high number of interactions that occur with certain key members of the system.

Supply Chain Evolution

“Evolution” as a word has become commonplace in contemporary society, so a precise definition is required for supply chain networks. Van de Ven and Poole (1995) provided perhaps the most cited definition in organizational studies for evolution: “cumulative changes in structural forms of populations of organizational entities across communities” (p. 517-518). They further elaborate that, “evolution explains change as a recurrent, cumulative, and probabilistic progression of variation, selection, and retention of organizational entities” (Van De Ven & Poole, 1995, p. p. 518).

This definition suggests three primary processes shape evolution: variation, selection, and retention. *Variation* creates novel forms of organizations. *Selection* results from the allocation or appropriation of scarce resources amongst competitors. *Retention* describes how certain organizational forms perpetuate. Figure 2 summarizes the conceptual relationships of evolutionary forces when a supply chain network is modeled as a CAS.

Figure 2. Modeling framework



Selection

From the perspective of supply chain evolution as interpreted via the TCA lens, the allocation or appropriation of scarce resources occurs via the choice of both the right trading partners and the right mode of conducting inter-firm exchanges. A dominant form of inter-firm governance can be referred to as a market information regime. Market information regimes arise as a way of making socially agreed upon information routinized and widely available in order to reduce market uncertainty (Anand & Peterson, 2000). Market information regimes provide a means of control for information asymmetries resulting from uncertainties in actions and intentions by competitors or trade partners (Heimer, 1985). Market information regimes make others' actions more predictable, but in markets with powerful externalities such as a rapid rate of technological advance, they can become an obstacle as they routinize information that rapidly obsolesces or is otherwise overcome by events. Under these

circumstances, larger companies often reduce their uncertainty by obligating another supply chain member to bear it (Heimer, 1985). Managers at the individual firm level cannot guarantee their exchange partners will continue to be the best trading partner into the future, and striking the right balance of commitment and flexibility in a relationship is a critical strategic decision. This translates into a problem of bounded rationality for the managers.

Evolution of interfirm collaboration implies change in firm relationships. This research effort refers to the selective force on supply chain relationships as transience. In order to measure transience in the simulation, a collaboration index was developed which kept track of the degree of permanence or loyalty of relationships in the supply chain network. Transience is defined as the inability to predict who exchange partners will be over time. High transience makes predicting who will be the future exchange partners for a given firm more difficult. As described subsequently, transience was assessed by maintaining a col-

laboration index which kept track of the degree of permanence or loyalty of relationships in the supply chain network.

Retention

Retention is defined as the continued existence of the same firms in a network and serves as the basis of stability in a supply chain network. Destabilizing effects that reduced longevity include a rapid pace of technology, volatility resulting from competition, mortality of partner firms, and switching of exchange partners. Retention is defined as the perpetuation of existing firms in the supply chain network and is measured as longevity of the individual firms and assessed using survival analysis.

Variation

Variation is the appearance of new combinations of firms that produce and distribute a final product co-exist in the supply chain network. Increased variation implies increased complexity of the supply chain network as both new firms and different forms of inter-firm governance rise and fall until more effective and efficient forms appear and are replicated. The extreme example of a supply chain network with low complexity is a single vertically integrated supply chain serving the entire end market. Increasingly complex supply chain networks exhibit more varieties of firms and wide variation in governance mechanisms between firms.

Complex adaptive systems theory describes increasingly complex networks as more expensive and fragile to maintain, but their diversity

of structures provides greater robustness to environmental fluctuations. The simulation investigated the resilience of more complex networks in heterogeneous environments characterized by a rapid rate of technological advance.

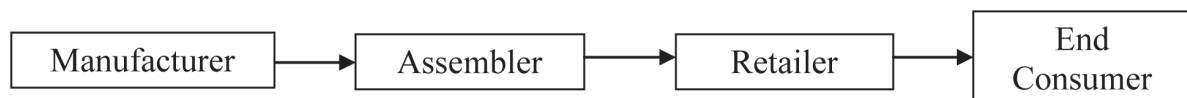
FRAMEWORK AND RESEARCH METHOD

This section describes the methodology, experimental design, model validation and verification, and the statistical analysis. The supply chain modeled consists of a manufacturer who originates most of the product innovations, an assembler, and a retailer who serves the end market (see Figure 3). The methodological roadmap provided by Davis, et al. (2007), while analogous to roadmaps provided in other simulation texts (Banks, II, & Nelson, 1999; Law & Kelton, 2000; Maisel & Gnugnoli, 1972), is tailored to the application of simulation to theory building and extension (Table 1). The introduction presented step 1 which identified the research question as, “How does interfirm collaboration evolve in a supply chain

Table 1. Theory building roadmap

| Step |
|--|
| 1. Begin with a research question |
| 2. Identify simple theory |
| 3. Choose a simulation approach |
| 4. Create computational representation |
| 5. Verify computational representation |
| 6. Experiment to build novel theory |
| 7. Validate with empirical data |

Figure 3. Basic supply chain



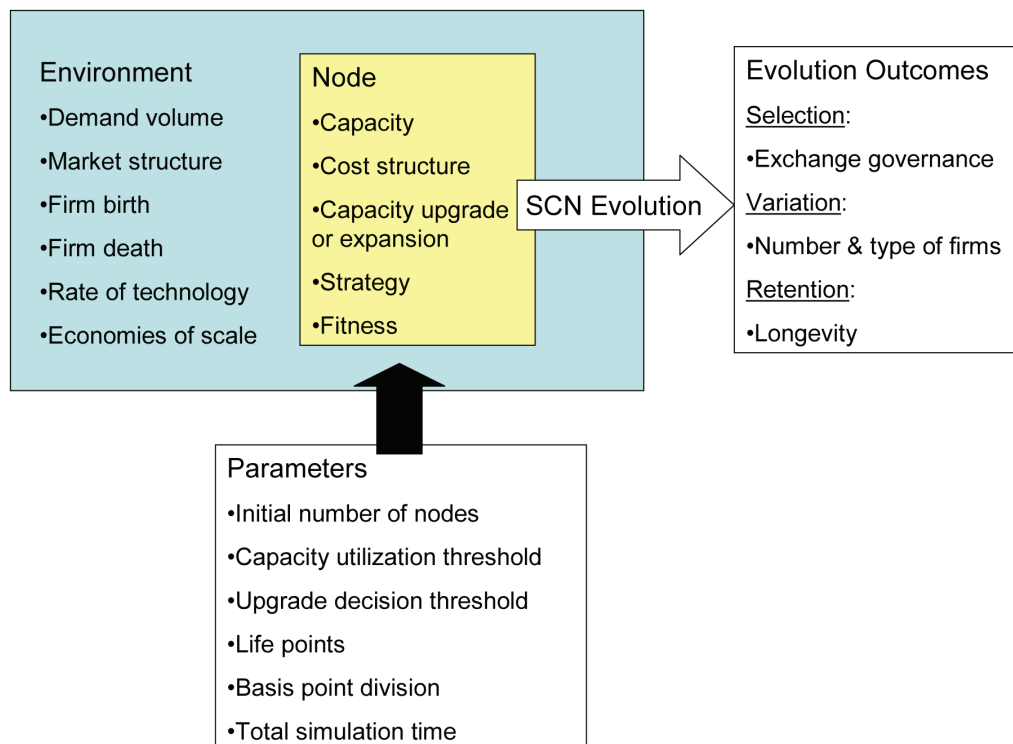
network under different product-market conditions?” Step 2, identification of “simple theory,” appears as a literature review of transaction cost analysis, complex adaptive systems, and organizational evolution theories. Steps 3 through 5 are described in the methods section. The outcomes of Step 6 appear in the results section. Step 7 consists of empirical validation and is beyond the scope of this paper; empirical validation appears as an area of future research.

Figure 4 presents the simulation framework (for a more complete description of the simulation model, see Appendix A). It synthesizes the interrelationships of the simulation variables in order to extend TCA theory into a dynamic network environment by using the CAS paradigm. A brief description of the predicted relationships follows.

Simulation Approach

Simulation models have studied supply chains as complex adaptive systems using the systems dynamics approach (Akkermans, 2001; Kim, 2003; Lin, Huang, & Lin, 2002; Parunak, 1998; Pathak, 2005). Past researchers have used an agent-based approach to study how markets consisting of semi-autonomous entities self-organize in a way that characterizes complex adaptive systems. The systems dynamics approach to simulation was used. It is useful when research focuses on the influence of causal relationships among constructs on the behavior of the system (Davis, et al., 2007) and allows the researcher to specify several simple processes with circular causality—such as lower price leading to higher sales,

Figure 4. Simulation framework



which provides positive feedback to lower price again. These processes of circular causality also intersect with other constructs. For example, lower prices may result from increased economies of scale. The simple theories underlying the modeling framework dictate the sources of stochasticity in the modeled system.

Experimental Design

A full factorial experimental design was implemented with a 2 x 3 x 2 experimental design consisting of two levels of capacity cost (high vs. low), three levels of consumer end markets (heterogeneous or homogeneous with high and low price sensitivity), and two levels of rate of technological change (rapid vs. slow), with a total of 12 experiments. In order to achieve an adequate sample size for each experiment, an n of 30 simulations runs was selected, making for a total of 360 samples.

Exogenous Factors

The exogenous factors in the simulation were the per unit cost, demand curve, capacity utilization threshold, capacity upgrade decision threshold, starting life points (for firm “health”), and the rate at which firm health degrades or improves in the face of poor or strong performance.

Per unit cost was the outcome of economies of scale and transaction costs. Inefficient use of capacity caused firms to die off. Increasing capacity utilization increased firm health and opportunity to increase capacity. Health was indicated by life points assigned to each firm. Exceptional capacity utilization increased life points. Low capacity utilization reduced life points and also reduced the likelihood of increasing capacity. When life points reached zero, the company was marked inactive to indicate that it had “died.” Companies also gained production expertise over time as reflected by lowering cost per unit as a function of experience tied to company age.

Unfulfilled demand spawned the process of firm birth. A new firm formed when there was enough unfulfilled demand to support it. As the result of a demand curve with rapid early growth, many births appeared early in the simulation. When each company was created it started at the average capacity of other firms of the same type and would elect either a high quality or a low quality strategy. High quality strategy meant harvesting higher prices but lower production and lower optimum economy of scale; low quality strategy meant the converse. When confronted with a small price differential for high and low quality products, consumers preferred the high quality product. Prices for both high and low quality products decreased linearly over time, but price for low quality products decreased more rapidly. As the quality differential between the two classes of products diminished, more customers will prefer savings over a high quality product.

Demand recreated the product life cycle with volume following a normal curve, with rapid demand growth followed by decline. A stochastic element was implemented to emulate random demand fluctuation. The simulation started with a dozen firms at each level of the supply chain. At the beginning these firms practiced exclusive relationships with one buyer and one supplier. Growing demand prompted the appearance of new firms; when demand diminished, firms were forced out of business.

Dependent Variables

Retention was measured as the longevity, in simulation time steps, of individual firms, and analyzed via survival analysis, a specialized form of The dependent variable was the collaboration index, as previously described in detail.

The collaboration index was a scaled variable (from 0 to 1) that described the exchange behavior for a given company in terms of how exclusive the relationships are that the company maintains with its buyers or suppliers. If $E(x,y)$ represented

the total number of units sold by company x to company y , E was approximately the product of the number of exchanges that occurred and the number of units sold per exchange (x times y). If I_i represented the collaboration index, then the collaboration index was calculated as:

$$I_i = \frac{\sum_{j=1}^n E(x_i, y_j)^2}{\left(\sum_{j=1}^n E(x_i, y_j) \right)^2}$$

where n is the number of companies j with whom company i does business.

The collaboration index provides a single measure of both the magnitude and duration of the relationship between company x and buyers or suppliers y . This means that a manufacturer would only have one collaboration index for all of its relationships with its downstream buyers, but assemblers had separate collaboration indices for their suppliers and their buyers.

This formulation for a collaboration index had the interesting property that for n equal companies that company x did business with, the collaboration index would be $1/n$. This may be demonstrated by assuming that for n equal companies that all had the units exchanged per combination of (i, j) ,

$$I_i = \frac{\sum_{j=1}^n b^2}{\left(\sum_{j=1}^n b \right)^2} = \frac{nb^2}{(nb)^2} = \frac{nb^2}{n^2b^2} = \frac{1}{n}$$

The reciprocal of the collaboration index had the interesting property of equaling the approximate number of companies that were company x 's primary suppliers or buyers. In other words, a simple calculation that estimates a "virtual number of companies" that company i does business with may be calculated by simply taking $1/I_i$.

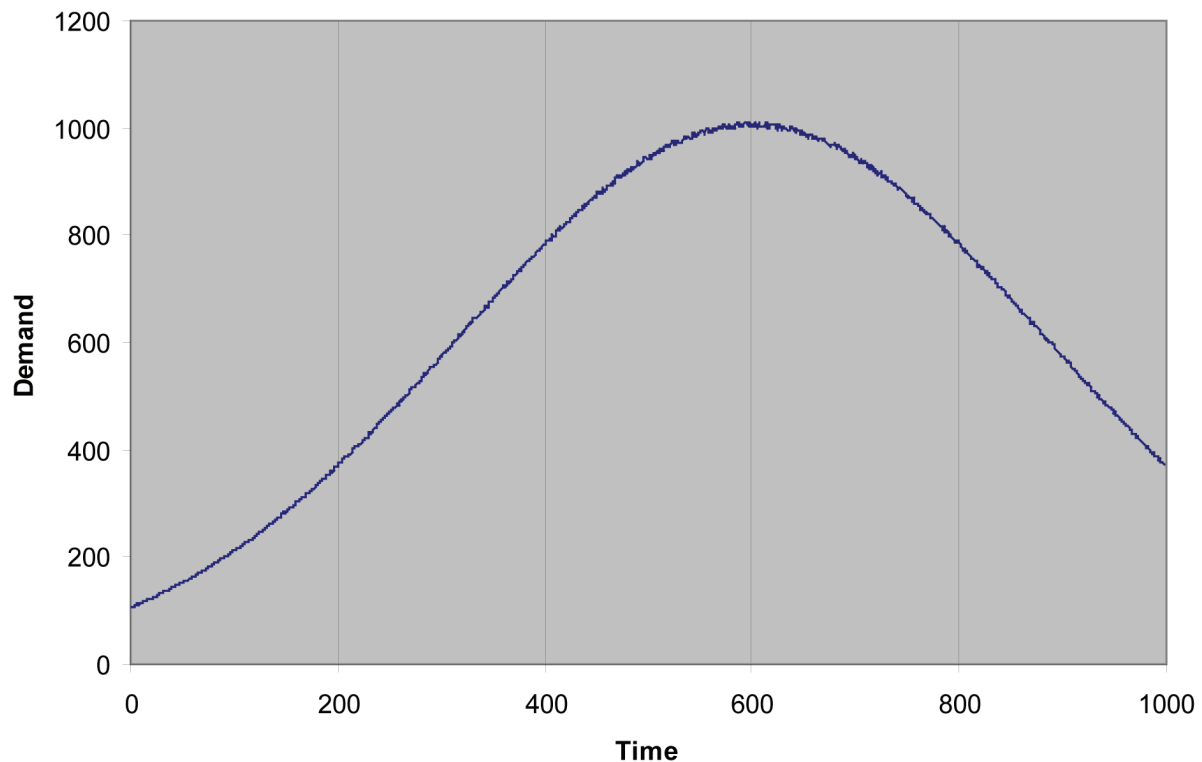
Time-series analysis was used to assess the processes of evolution of exchange governance (Pathak, 2005; Surana, et al., 2005). In this section, analyses of the experimental results are presented in several stages with regard to their evolutionary implications. Thirty runs of 1,000 time steps were made of each of the 12 experimental scenarios. The resulting 3,600,000 data points (300,000 per experiment) provided a rich dataset for analysis.

Proportional time series analysis assessed transience as reflected by the evolution of interfirm relationships using the collaboration index. First, the simulation was divided into 5 time steps of 200 demand cycles each based upon the stages of the product life cycle (Figure 5). Operationalization of selection was based on changes to the collaboration index. Using PROC GLM in SAS, simple univariate analysis created 95% confidence intervals of the collaboration index at each time step. Binary encoding based upon statistically significant changes to the collaboration index between successive time periods was the basis for classifying as unstable, with a 1 indicating that a statistically significant change had occurred from one time step to the next and a 0 indicating that no statistically significant change to the collaboration index had occurred. Then a technique frequently applied to this type of analysis (Fokianos & Kedem, 2003)—Agresti's (1990) multinomial logit model—was used to analyze the series of encoded 1's and 0's.

RESULTS

In this section, analyses of the experimental results are presented in several stages with regard to their evolutionary implications. Thirty runs of 1,000 time steps were made of each of the 12 experimental scenarios. The resulting 3,600,000 data points (300,000 per experiment) provided a rich dataset for analysis.

Figure 5. Demand volume curve



First, time series analysis provide insight into processes of variation, describing types of firms and strategies that propagated in the different supply chain network scenarios. Second, general linear models and survival analysis of firm longevity were used to assess retention of firms under different experimental conditions. Third, proportional time series analysis assessed selection as reflected by the evolution of interfirm relationships using the collaboration index.

Variation

Analysis of variation was conducted by use of differencing and generalized linear modeling (GLM). Differencing was a special case of time series analysis based on the difference in the number of firms between the current and the previous time steps (i.e., a positive difference indicates an

increase in the number of firms). Differencing commonly appears as a way of focusing on change in time series analysis of non-stationary processes (Granger & Newbold, 1977; Nelson, 1973). The GLM procedure in SAS version 9.1 was used to model the differencing scores as the dependent variable with time and strategy as the independent variables individually for each experiment except the homogeneous high price scenarios in which no low price firms were spawned. All the GLM models returned significant overall F-scores. Table 2 displays the parameter estimates and their significance for manufacturers, assemblers, and retailers across all 12 experiments. Time cycles were divided by 1000 to put it closer to the same relative scale as the average differences.

A significant parameter estimate for time indicates that differences increased over time—either the number of firms increased at first than

Table 2. Variation analysis results

| Experiment | Parameter | Manufacturers | | Assemblers | | Retailers | |
|------------|---------------|---------------|---------|------------|---------|-----------|---------|
| | | Estimate | Pr > t | Estimate | Pr > t | Estimate | Pr > t |
| 1 | Time | -0.0112 | 0.0066 | -0.0275 | <.0001 | -0.0315 | <.0001 |
| | Strategy | 0.0246 | <.0001 | -0.0119 | <.0001 | 0.0176 | <.0001 |
| | Time*Strategy | -0.0681 | <.0001 | | | -0.0602 | <.0001 |
| 2 | Time | -0.0096 | 0.0185 | -0.0272 | <.0001 | -0.0290 | <.0001 |
| | Strategy | 0.0232 | <.0001 | -0.0136 | <.0001 | 0.0146 | 0.0015 |
| | Time*Strategy | -0.0699 | <.0001 | | | -0.0673 | <.0001 |
| 3 | Time | -0.0259 | <.0001 | -0.0412 | <.0001 | -0.0379 | <.0001 |
| | Strategy | 0.0213 | <.0001 | -0.0121 | <.0001 | 0.0194 | <.0001 |
| | Time*Strategy | -0.0618 | <.0001 | | | -0.0638 | <.0001 |
| 4 | Time | -0.0215 | <.0001 | -0.0388 | <.0001 | -0.0353 | <.0001 |
| | Strategy | 0.0222 | <.0001 | -0.0141 | <.0001 | 0.0163 | 0.0013 |
| | Time*Strategy | -0.0696 | <.0001 | | | -0.0710 | <.0001 |
| 5 | Time | -0.0978 | <.0001 | -0.0453 | <.0001 | -0.1151 | <.0001 |
| 6 | Time | -0.0986 | <.0001 | -0.0386 | <.0001 | -0.1240 | <.0001 |
| 7 | Time | -0.1134 | <.0001 | -0.0615 | <.0001 | -0.1259 | <.0001 |
| 8 | Time | -0.1094 | <.0001 | -0.0508 | <.0001 | -0.1348 | <.0001 |
| 9 | Time | -0.0400 | <.0001 | -0.0319 | <.0001 | -0.0636 | <.0001 |
| | Strategy | -0.0115 | <.0001 | -0.0126 | <.0001 | -0.0163 | <.0001 |
| 10 | Time | -0.0356 | <.0001 | -0.0304 | <.0001 | -0.0627 | <.0001 |
| | Strategy | -0.0135 | <.0001 | -0.0148 | <.0001 | -0.0222 | <.0001 |
| 11 | Time | -0.0534 | <.0001 | -0.0471 | <.0001 | -0.0703 | <.0001 |
| | Strategy | -0.0120 | <.0001 | -0.0130 | <.0001 | -0.0157 | <.0001 |
| 12 | Time | -0.0496 | <.0001 | -0.0439 | <.0001 | -0.0710 | <.0001 |
| | Strategy | -0.0136 | <.0001 | -0.0152 | <.0001 | -0.0216 | <.0001 |

decreased over time (negative parameter estimate), or it decreased at first then increased (positive parameter estimate). A zero (statistically non-significant) time estimate indicated that there was no trend in the differencing over time—in other words, neither proliferation nor diminishment occurs systematically. In this last situation, a trend of variation was not occurring, compared to the situation of a significant parameter estimate indicating that a trend of variation was occurring. Overall, variation appears to depend strongly on end market conditions. Presentation of experimental results are grouped by end market scenarios.

Heterogeneous Demand (Experiments 1 through 4)

Analysis of the parameter estimation results of the variation analysis for manufacturers and retailers revealed statistically significant parameter estimates for time, strategy and the interaction term. Additionally, for both manufacturers and retailers, the parameter estimates for all four experiments were negative for the effect of time while they were positive for the effect of strategy. A negative slope on the time estimate indicated that the number of firms grow then decrease until it becomes negative, at which point firms begin dying out. The positive strategy parameter estimates indicated that the differencing for the high price firms cross zero

later than for low price firms—initial population growth was faster for high price firms, but so was later population decline.

The interactive effect was significant and negative for manufacturers and retailers for all four experiments. High price firms experience relatively greater negative population growth over the course of the simulation compared to low price firms. Overall, this paints a picture for heterogeneous end markets prompting growth early in the simulation for both low and high price firms. After demand peaks, the number of both high and low price firms declined, but much more so for high price firms. The magnitude of the parameter estimates indicated by the slopes of the differences from time step to time step, and thus were commensurate with the amount of growth then decline. Since manufacturers and retailers each had the same starting populations, the greater parameter estimates suggested that retailers propagated to a higher population than manufacturers before rapidly dying out.

Assemblers had statistically significant negative parameter estimates for time and strategy, but once the interaction term was added strategy lost its significance. These results describe a life cycle for assemblers of initial growth that eventually diminish in keeping with the pattern of demand growth and shrinkage. High price assemblers gradually declined in population over the course of the simulation, the population of low price manufacturers gradually increased to serve the burgeoning low price market. The lack of significance for the interaction term indicated that assembler population does not have a significant growth-then-decline like manufacturers and retailers—instead, the total population of assemblers remained relatively steady as the population of high price assemblers declined while low price assemblers proliferated.

Homogeneous High Demand (Experiments 5 through 8)

All four experiments with a homogeneous high price demonstrated statistically significant negative parameter estimates for time for all three firm types. This indicated that all firms profligate rapidly at first with a steady decline in the rate of population growth followed by an increasing loss in population from time step to time step. The parameter estimates indicated the greatest variation (magnitude) for retailers and the least for assemblers. Assemblers apparently enjoy some benefit from being in the middle of the supply chain—retailers face the brunt of variability in demand, and manufacturers were impacted by variation in the success of their products, but assemblers feel these effects only secondarily. Since the population of manufacturers and retailers buffers the volatility of end market demand, assemblers only have to respond to their buyer and supplier markets.

Homogeneous Low Demand (Experiments 9 through 12)

For all firm types in all four experiments with a homogeneous low price demand setting, significant negative parameter estimates resulted for time and strategy. Introducing the interactive term reduced the overall R-square and resulted in a non-significant strategy coefficient. Based on this evidence, the simpler model was retained.

The parameter estimates for retailers exhibited the greatest magnitude for both time and strategy. This revealed that retailers exhibit the greatest increase at the beginning followed by greater declines in numbers of retailers. The negative value for strategy indicated that as high strategy firms begin to decline in numbers, low strategy firms increase in numbers. This relationship was relatively stronger for retailers than it was for manufacturers and retailers. The lack of a significant interaction term indicated that the increasing

rate of population growth for low price firms does not change during the course of the simulation.

Retention

Since the supply chain network under study evolved over time, retention was assessed using parametric survival analysis since it specifically measured the time-dependence (Harrell, 2001). SAS 9.1 was used to conduct all retention analyses. Survival analysis addresses the positively skewed distribution of time to occurrence of an event and supplies a probability of surviving past a given time, which was often more useful than an expected lifespan. Analytical results of firm longevity are summarized in Table 3.

Rate of Technological Advance

Under conditions of rapid technological advancement manufacturers and assemblers displayed 11% and 12% reductions in longevity, respectively. Markets characterized by rapid technological advancement also reduced retailer longevity by a statistically significant but small (<3%) amount; otherwise rate of technological advance demonstrated no significant effect on retailers. These results followed intuitive expectations since manufacturer production capacity served as the starting point for technological advances in the supply chain, and assemblers relied on a small number of manufacturers. Assemblers choosing poorly found their suppliers going out of business. The

Table 3. Longevity parameter estimates by experiment

| Market | RTA | EOS | Experiment | Manufacturer | | Assembler | | Retailer | |
|------------------|------|------|------------|--------------|--------------|-----------|--------------|----------|--------------|
| | | | | Strategy | Max Capacity | Strategy | Max Capacity | Strategy | Max Capacity |
| Heterogeneous | Fast | Fast | 1 | 0.7024 | 0.0035 | 0.1291 | 0.0029 | 0.1715 | 0.0159 |
| | | | | <.0001 | <.0001 | 0.0384 | <.0001 | 0.0021 | <.0001 |
| | Slow | Fast | 2 | 0.7517 | 0.0048 | 0.0026 | 0.0255 | -0.3849 | -0.0718 |
| | | | | <.0001 | <.0001 | 0.9705 | <.0001 | <.0001 | <.0001 |
| Homogeneous High | Fast | Fast | 5 | . | 0.0226 | . | 0.0073 | . | -0.0106 |
| | | | | . | <.0001 | . | <.0001 | . | <.0001 |
| | Slow | Fast | 7 | . | 0.0235 | . | 0.0039 | . | 0.0116 |
| | | | | . | <.0001 | . | <.0001 | . | 0.0006 |
| Homogeneous Low | Fast | Fast | 9 | 0.7938 | 0.0046 | 0.328 | 0.0046 | 0.032 | 0.0205 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | 0.336 | <.0001 |
| | Slow | Fast | 11 | 0.6604 | 0.013 | 0.2464 | 0.0042 | 0.1081 | 0.0279 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| Homogeneous Low | Fast | Fast | 10 | 0.6796 | 0.004 | 0.4256 | 0.0217 | -0.4116 | -0.0328 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| | Slow | Fast | 11 | 0.6604 | 0.013 | 0.2464 | 0.0042 | 0.1081 | 0.0279 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |
| Homogeneous Low | Fast | Fast | 12 | 0.839 | 0.0172 | 0.0622 | 0.0044 | -0.3391 | -0.021 |
| | | | | <.0001 | <.0001 | 0.0901 | <.0001 | <.0001 | 0.0013 |
| | Slow | Fast | 11 | 0.6604 | 0.013 | 0.2464 | 0.0042 | 0.1081 | 0.0279 |
| | | | | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 | <.0001 |

strength of relationship with manufacturers and retailers also contributed to assembler longevity. As discussed subsequently, retailer longevity was more influenced by economies of scale.

For manufacturers price strategy (high vs. low quality product) exhibited a strong influence on longevity regardless of the rate of technological advance, with manufacturers following the high price strategy displaying significantly greater longevity. Assemblers following a high price strategy under conditions of fast rate of technological advance and homogeneous, low price end markets exhibited 39% and 53% greater longevity, respectively, than low price assemblers in response to fast and slow increases to economies of scale. This counterintuitive result was the outcome of intense inter-firm competition among low-price strategy firms prompted by rapid growth in that market; stagnant growth of the high end market resulted in stable conditions that allowed high end assemblers to persist. Under conditions of slow rate of technological advance and growth of economies of scale, the slow pace of change made for a relatively small difference in longevity for high vs. low price strategy assemblers. Assemblers lived longer in environments with homogeneous pools of suppliers and buyers; if existing manufacturers and retailers switched assemblers or went out of business, assemblers benefited from having more substitutes available.

Economies of Scale

Rapidly growing economies of scale prompted statistically significant increases to longevity for all three firm types with 9%, 7.5%, and 18.7% greater longevity, respectively, for manufacturers, assemblers, and retailers. Under conditions of rapid demand growth and rapidly increasing economies of scale, larger companies achieved lower production costs and the additional stability resulting from serving larger market shares. Retailers that invested in greater capacity also

benefited from additional demand stability of having larger market share.

Analysis of the individual experimental results, economies of scale had a similar positive effect on longevity for manufacturers across all experimental conditions. For assemblers, the high price strategy related positively to increased longevity for the heterogeneous end market when the rate of increase of economies of scale was high (longevity for these assemblers was 13-14% greater); this effect was even greater for the homogeneous low price end market with a fast rate of technological advance (where high price assemblers lived 53% longer). Parametric regression results were statistically non-significant for assemblers in both a homogeneous low price end and heterogeneous markets with a slow rate of technological advance.

Economies of scale exhibited a strong effect on retailers. For heterogeneous and homogeneous, low price markets, conditions of fast-paced increase of economies of scale increased longevity of retailers following a high price strategy (from 11-29%). The exception was under conditions of a homogeneous low price end market with a fast rate of technological advance, results of which did not achieve statistical significance. Slowly increasing economies of scale factor provoked the opposite effect, reducing longevity of high price retailers by 29-34% compared to low-price retailers serving either heterogeneous or homogeneous low price end markets. Compared to low price retailers, the high price retailers failed to establish a stable pool of end market demand to survive fluctuations and competition. These results reflect the real-life consequence of economies of scale where under the right conditions large retailers quickly drive small retailers out of business.

Selection

When examining the results of the experiments, it was important to keep in mind that all experiments started with 10 firms at each level of the supply

chain, each with one-on-one, exclusive relationships with suppliers and customers, and all firms dedicated to serving the high end market. Results are discussed for each end market condition.

Analysis of the evolutionary process of selection was implemented with binary encoding. The thousand time cycle duration of the simulation was divided into 5 time steps of 200 demand cycles each. Simple univariate analysis (via PROC GLM in SAS) was used to create 95% confidence intervals of the collaboration index for each time

step. Successive time steps were assessed for significant changes to the collaboration index, with a 1 encoding indicating that a statistically significant change had occurred from one time step to the next; a 0 indicated no significant time change had occurred, and therefore evolution of the exchange relationships had remained stable. The series of 1's and 0's were then analyzed using a multinomial logit model defined by Agresti (1990) and frequently used for this type of analysis (Fokianos & Kedem, 2003). Table 4 presents a

Table 4. Significant trends in inter-firm collaboration

| | | PLC Transition to: | | | |
|--|------------------|--------------------|----------|---------------|--------------|
| | Pricing Strategy | Growth | Maturity | Early Decline | Late Decline |
| Manufacturer-to-Assembler | | | | | |
| Heterogeneous End Market | Low | 0 | - | 0 | 0 |
| | High | 0 | 0 | 0 | 0 |
| Homogeneous Low Price End Market | Low | + | - | - | - |
| | High | 0 | 0 | 0 | 0 |
| Assembler-to-Manufacturer | | | | | |
| Heterogeneous End Market | Low | + | + | 0 | - |
| | High | 0 | 0 | 0 | 0 |
| Rate of Technology Advance with a Heterogeneous End Market | Low | + | + | - | - |
| | High | 0 | 0 | 0 | 0 |
| Homogeneous Low Price End Market | Low | + | - | 0 | - |
| | High | - | - | - | 0 |
| Assembler-to-Retailer | | | | | |
| Heterogeneous End Market | Low | - | - | - | + |
| | High | - | - | - | 0 |
| Homogeneous Low Price End Market | Low | - | - | - | + |
| | High | - | - | - | 0 |
| Retailer-to-Assembler | | | | | |
| Heterogeneous End Market | Low | + | + | - | - |
| | High | 0 | 0 | 0 | 0 |
| Rate of Technology Advance with a Heterogeneous End Market | Low | - | + | 0 | 0 |
| | High | 0 | 0 | 0 | 0 |
| Homogeneous Low Price End Market | Low | + | - | 0 | - |
| | High | - | - | - | 0 |

simplified depiction of the trends in inter-firm collaboration for each of the exchange relationship perspectives between manufacturers, assemblers, and retailers. Inter-firm collaborations evolved differently depending on the level in the supply chain, the product price strategy, and the rate of technological advance. Only variables that demonstrated statistically significant effects appear in Table 4; complete results appear in Appendix B.

Heterogeneous End Market

High price strategy perpetuated strong inter-firm collaborations across most interfirm exchanges throughout the demand life cycle. A shrinking high end market meant a shrinking pool of high end businesses with whom to conduct exchanges; surviving firms were those with a history of strong collaboration. The exception was the assembler-to-retailer relationship, which exhibited trend of diminishing collaboration throughout the demand life cycle until leveling off at late decline. This contrasts with unchanging retailer-to-assembler collaboration, indicating that even as assemblers expanded market opportunities, retailers stayed with established suppliers.

The rapid growth of a low end market prompted much more evolution of inter-firm collaboration for companies following the low price strategy with a slow pace of technological advance. Low price manufacturers exhibited a decline in collaboration during the transition to rapid growth, but thereafter remained unchanged. Low price assemblers exhibited little change in the collaboration index throughout the life of the simulation for their relationships with manufacturers. On the sell-side, low price assemblers appear to expand their markets as indicated by a declining collaboration index throughout most of simulation until late decline, when collaboration intensifies with the remaining retailers. Retailers on the other hand exhibited increasing collaboration as demand progressed to the growth and maturity stages, and then declining collaboration during the stages of

declining demand. Retailers were forced to prolong supplier relationships when demand outstripped supply, but were more likely to switch suppliers as increasingly price sensitive customers declined in number relative to available supply.

High rate of technological advance exhibited a significant effect only for the buying side of interfirm relationships for low price companies. Assembler-to-manufacturer relationships demonstrated increased collaboration into both the growth and maturity stages, with declining collaboration thereafter. During the first half of the simulation, manufacturing capacity trailed end market demand, leading assemblers to leverage collaborative relationships to ensure a source of supply. Retailer-to-assembler collaboration initially declined as demand entered the growth phase, then increased during maturity, remaining level thereafter. In conjunction with the analysis on variation and retention, this indicates that under conditions of rapid technological advance that low price retailers at first struggled to find enough sources of supply to satisfy demand, with surviving retailers strengthening the relationships discovered during the growth phase which offered the benefit of reduced prices to the end consumer.

Homogeneous Low Price Demand

Homogeneous low price end market demand led to the same evolutionary path for interfirm collaboration for three out of four of supply chain relationships which exhibited declining collaboration throughout the simulation until remaining steady during the transition from early to late decline. High price manufacturers were the exception to this pattern as they exhibited unchanged collaboration indices throughout the demand life cycle.

Low price supply chains exhibited different evolutionary trajectories depending generally on whether firms are selling or buying. Manufacturers initially increased collaboration with assemblers, and then decreased collaboration for the rest of the demand life cycle. Assemblers decreased

collaboration with retailers until the late decline stage when the collaboration index increased. On the sell-side, low price assemblers exhibited decreasing collaboration with retailers through growth, maturity, and early decline followed by an increase to collaboration during late decline. Low price companies exhibited a common pattern of evolution for buying side collaboration. Assembler-to-manufacturer and retailer-to-assembler collaboration increased during the growth phase, then decreased at maturity and remained steady until decreasing again at late decline.

Homogeneous High Price Demand

The experimental conditions of homogeneous, high end market demand prompted the appearance of additional numbers of firms to satisfy growing demand, but failed to prompt evolution of interfirm collaboration, as would be expected under conditions of low environmental pressure. Firms appear to maintain their exclusive ties, and the greater expense of expanding or upgrading capacity for high end product meant a slower pace of growth at the firm level; it also meant that aggregate production capacity continuously lagged end market demand. Firms maintained exclusive relationships under this setting largely due to the lack of available trading partners with unclaimed output, and lack of competitive pressures meant low mortality rates.

IMPLICATIONS FOR THE ROLE OF KNOWLEDGE IN SUPPLY CHAIN NETWORKS

Business literature may be re-orienting toward a dominant logic founded on collaboration and knowledge as the sources of competitive advantage (Vargo and Lusch, 2004a; Inkpen and Tsang, 2005; Grant and Baden-Fuller, 2004; McEvily and Chakravarthy, 2002; Kogut, 2000). For example,

in marketing Service-Dominant Logic (Vargo and Lusch, 2004b) posits that knowledge, and the knowledge processes surrounding products and product management, are key sources of competitive advantage (Lusch and Vargo, 2006; Vargo and Lusch, 2004a). In essence, rather than focus on its physical properties and features, the product embodies the knowledge and collaborative abilities of all those who contributed to its creation. Furthermore, "...knowledge as the basis for competitive advantage can be extended to the entire supply chain" (Vargo and Lusch, 2004b, p. 9). In this view, knowledge exchange underlies successful organizational and collaborative forms.

But not all knowledge is the same, and different forms of collaboration will interact to affect the value and outcomes of inter-organizational knowledge management. What follows are propositions regarding how the evolution of inter-organizational collaboration will affect or be affected by the different roles of knowledge in the supply chain: knowledge generation, knowledge sharing, and knowledge implementation (Gravier, et., 2008). Some empirical research supports these propositions, but in the absence of a predictive theory for the role of knowledge in inter-organizational supply chains, it is hoped that these propositions can provide some insights or guide future research.

Much of the literature included derives from the work in strategic alliances, which is rooted in the premise that firms collaborate in order to access the knowledge and competences of other firms. But not all accessions of knowledge are created equal. Hamel distinguished "internalizing" as opposed to merely "accessing" knowledge endemic to another firm (Hamel, 1991). Real-life challenges to inter-organizational collaborations lead to a "collaborative membrane" that acts as a filter between organizations in alliances. The collaborative membrane can profoundly influence the magnitude, content, and direction of inter-organizational knowledge flows. In effect, the collaborative membrane defines the collaborative

relationship that exists between alliance (and supply chain) members. Based upon these insights, inter-organizational interaction falls into one of two approaches to inter-organizational interaction: collaboration (“internalizing” knowledge) or modularization (“accessing” knowledge). The underlying premise rests on the assumption that the role that inter-organizational knowledge plays determines the degree of collaboration or modularity in the supply chain (see Figure 6).

Collaboration

Kahn’s (1996) research into integration equated “collaboration” with continuous interaction, often informal in nature, most often without clearly defined structure. Collaboration attains collective goals via resource sharing and a common vision. Collaboration would represent the outcomes of long-term relationships characterized by trust and many interactions (a high collaboration index in the previously described simulation) Collaboration buffers volatility for firms in highly unstable environments, which enhances the opportunity to learn-by-doing (Sorenson, 2003). Collaboration characterizes well-functioning alliances but also many high-performing supply chains whose firms depend upon each other and interact frequently and

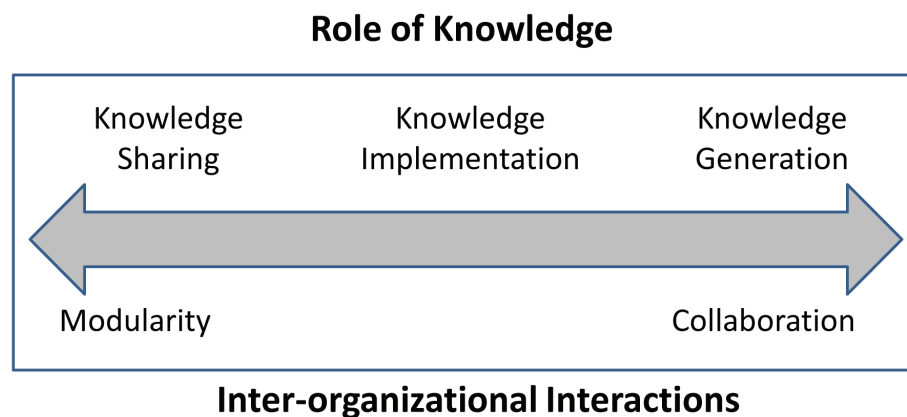
effectively. Supply chain integration approaches such as vested outsourcing (Vitasek, 2011) and performance-based logistics (Randall, et al., 2010) increase collaboration.

Collaboration benefits supply chains with operations characterized by more complex interactions. Products involving optimization of highly interdependent or complex interdependencies of design and manufacture, or diverse design choices (such as a microprocessor), tend to benefit more from collaboration.

Modularity

Modularity represents a strong focus on the individuality of each firm and less inter-operational dependence (represented by lower levels of the collaboration index in this study’s simulation). Traditional contract-based outsourcing represent one possible outcome of modular supply chains, although modularity also includes discrete organizational nodes or clusters held together by standards of member performance and conformance to design rules (Langlois, 2002). Modular supply chain architectures lower transaction costs while preserving the independent identities of the firms (Kahn, 1996). For many supply chains, modularity offers benefits over collaborations as

Figure 6. Role of knowledge in determining degree of interfirm collaboration



it allows redundant parallel operations by several network members, thereby improving speed and efficiency (Ethiraj and Levinthal, 2004). Compared to a collaborative supply chain with sole sourcing or a reduced supplier base, modularity has the potential to reduce idle time, prompting more completed work in the same amount of time compared to situations where the same operations are all conducted by one or a small number of firms.

Modularity most benefits supply chains that provide modular products with limited diversity that have independent markets for each of the modules; such markets also benefit from the recombinant possibilities endemic to these supply chains.

Computer memory represents one supply chain that benefits from modularity. Computer memory has many applications in a variety of electronic products, both for consumers and as components for more complex assemblies such as automobiles or aircraft. On the other hand, supply chains that require frequent or complex interactions, such as testing and integrating new product innovations, bring to light the difficulties of optimizing highly interdependent processes in a modular network (Ethiraj and Levinthal, 2004).

Knowledge Generation

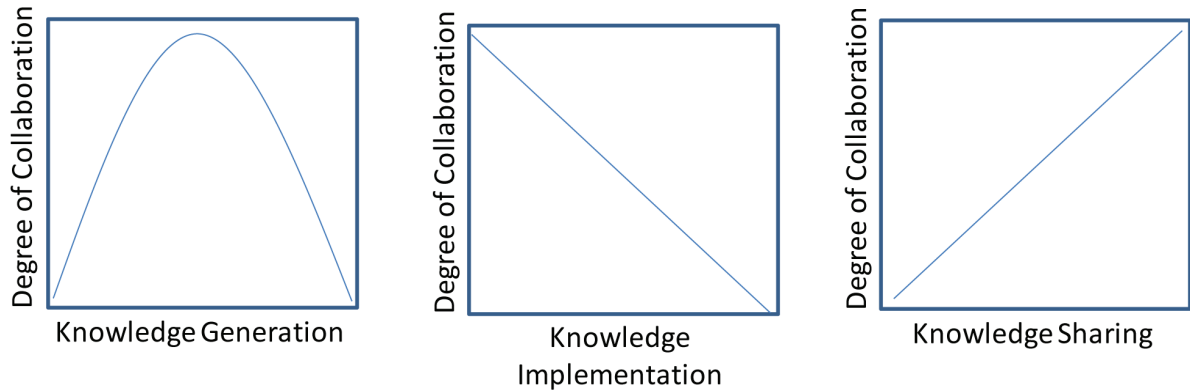
In keeping with the knowledge problem-solving perspective of the knowledge-based theory of the firm (Nickerson and Zenger, 2004), and also with the information acquisition views of Rindfleisch and Moorman (2001), knowledge generation focuses on the acquisition of information that pertains directly to the development of new products or services. Knowledge generation in its various guises such as new product development and process innovation has a well-established record for boosting firm performance (c.f., Sethi et al., 2001; Kohli and Jaworski, 1993). Research has also found evidence of knowledge generation's effectiveness at developing new products in the

inter-organizational context (Rindfleisch and Moorman, 2001; Sivadas and Dwyer, 2000; Im and Workman, 2004).

Inter-organizational knowledge generation could benefit from either modular or collaborative knowledge exchanges. For example, alliances have been called "...the most important source of new ideas and information that result in performance-enhancing technology and innovations" (Dyer and Singh, 1998, p. 665). Evidence indicates that close inter-organizational collaborations in alliances bolsters innovation generation (Roy et al., 2004; Nielsen, 2005). However, intra-firm technological and strategic flexibility capabilities may limit the benefits of inter-organizational collaborations (Zhou and Wu, 2010). Specifically, at the intra-firm level, technological capability can create "lock-in" or path dependencies. An inverted-U relationship appears to define technological capability's influence on innovation (Zhou and Wu, 2010), with too little technological capability resulting in a firm incapable of taking advantage of opportunities, and too much technological capability impeding adaptability. This evidence jibes with this study's simulation findings. The collaboration index increased most in situations of intense innovation and diminishing profit margins—two powerful real-life motivators to collaborate innovatively. Among the requirements for successful intra-organizational innovativeness are flexibility and departures from planned objectives; both of these factors destabilize close relationships (Sivadas and Dwyer, 2000). These observations lead to the following proposition (see Figure 7):

P1: The degree of knowledge generation will demonstrate a U-shaped relationship with inter-organizational knowledge exchanges, with the highest need for knowledge generation leading to optimal rather than maximal levels of collaboration.

Figure 7. Graphical representation of the proposed relationships between role of knowledge and supply chain collaboration



This proposition implies that the most innovative knowledge-exchanges will not be the closest collaborations, nor the arm's-length transactions, but rather the hybrid forms that blend the benefits of each of the extremes, especially the flexibility to change partners if necessary. In keeping with the simulation's findings, recent empirical work tends to support that close collaborations disintegrate less often from their failures and more often from the desirability of finding other partners (Greve, et al., 2012). On the surface, this proposition appears to fly in the face of common wisdom, but the high failure rate for strategic alliances implies that at worst close collaborations are useful only so long as they serve a purpose, and at best the benchmark organizations strive to enter alternative inter-organizational relationships that provide the benefits of alliances while minimizing impacts on flexibility.

Knowledge Sharing

Knowledge sharing leverages information systems and other to support sharing resources, competencies, personnel and other knowledge resources already possessed by at least one alliance member but not by at least one other (Baker and Sinkula, 1999; Kohli and Jaworski, 1993).

Also known as knowledge transfer or interfirm learning, knowledge sharing refers to the extent that organizations are able to access each other's established know-how and critical information (Appleyard, 1996).

Distinct from knowledge generation, knowledge sharing merely accesses knowledge rather than internalizing it across the inter-organizational collaborative membrane (Hamel, 1991). Knowledge sharing of course generally occurs in many instances of organizational learning and other forms of knowledge generation (Roper and Crone, 2003; Appleyard, 1996). However, as a process, knowledge sharing represents the antithesis of knowledge generation, focusing on information sharing rather than mutual learning and creation of new knowledge (Rindfleisch and Moorman, 2001; Dyer and Singh, 1998).

Knowledge sharing often consists of horizontal alliances seeking to reduce environmental uncertainty (Bucklin and Sengupta, 1993). One example is SEMATECH, a group of semiconductor manufacturing firms that shares information for the purposes of setting standards and tracking industry trends. The semiconductor firms also notoriously guard their secrets with regard to innovations to both process and product.

Research has linked the sharing of knowledge at the organization level with higher short-term financial benefit (Moorman and Miner, 1997). Sharing complementary knowledge resources on supplier or customer markets can prove beneficial and may lead to competitive advantage; indeed, that knowledge sharing may constitute the primary advantage that firms accrue through alliances and close collaborations (Grant and Baden-Fuller, 2004). Toyota's production supply chain is often cited as an example of a knowledge sharing network (Dyer and Nobeoka, 2000).

Importantly, one study has found that knowledge sharing can have different effects on innovation depending on the breadth vs. depth of knowledge. Firms with a broad knowledge base tend not to benefit as much from external knowledge sharing, whereas firms with a deep knowledge base tend to benefit from sharing information externally (Zhou and Li, 2012). This follows the insights from this study's simulation that revealed that collaborations tend to be asymmetric, with firms such as retailers and assemblers with little need to innovate tending to collaborate more. On the other hand, firms such as manufacturers that need to innovate a lot tend not to collaborate outside of their boundaries. This and the previous observations lead to the following proposition:

P2: The degree of knowledge sharing will demonstrate an increasing relationship with inter-organizational knowledge exchanges, with more knowledge sharing leading to more collaboration.

Knowledge Implementation

The implicit and explicit costs associated with Generating and sharing knowledge generates certain costs and require varying levels of commitment and action on the part of the participating organizations. In order to avoid these costs or commitments, organizations may exercise the option to delegate certain activities to another

organization (Kogut and Zander, 1992). Firms that elect to divest themselves of a non-core competence are putting knowledge implementation to use (Prahalad and Hamel, 1990). In supply chains, logistics knowledge frequently falls into the role of knowledge implementation, as evidenced by the rise of third party (3PL) and fourth party (4PL) logistics providers. As an example of knowledge exchanges occurring purely to allow another organization implement what they know how to do best, the latest evidence indicates that 3PL providers often coordinate not just logistics but all supply chain functions, allowing firms to focus on their core competences (Zacharia, et al., 2011). Firms avoid knowledge sharing with a logistics partner because of the volume of information that must be shared on package contents, origins, destinations, truck license number, air cargo flight numbers, shipping costs, hazardous material routing and the like, which generally requires that expensive information systems be developed for activities that occur outside of the firm. 3PLs and other logistics service providers function as "turnkey" service providers.

Knowledge implementation benefits both parties most when their knowledge requirements are relatively self-sufficient and independent. Firms add value when they implement or execute specialized knowledge, processes, and capabilities. The complexities of modern products and services often rely on recombinatorial capabilities with many components in a way that often becomes exceedingly complex; increasingly, firms rely on outside specialists to make subcomponents or provide specialty services as housing all production under one roof has become not just intractably complex but economically untenable. Just imagine trying to manage all the manufacturing for a common and relatively simple consumer product such as a cell phone, which involves more than 18 subassemblies (not including software) and a minimum of a dozen manufacturers across at least seven countries—and this list does not include many manufacturers nor any ancillary service

providers (such as 3PLs) (*Economist*, 2011). More complex supply chains such as for automobile, pharmaceutical, medical equipment, and aircraft quickly become much more complicated.

Knowledge implementation benefit inter-organizational networks by enhancing execution or consolidating common knowledge and expertise in order to pool risk and reduce investment in additional production capacity or processes (Roper and Crone, 2003). Knowledge implementation focuses on efficiency rather than creating or accessing knowledge. The outcome is compartmentalized knowledge in the supply chain, but done in such a way that certain processes and services are readily provided, as required.

Knowledge implementation embodies the strategic blending of the unique capabilities of each organization in the network (Kogut and Zander, 1992). Creating new inter-organizational outcomes depends on mixing and matching firms, and the reliance on architectural capabilities at the interfirm level (Henderson and Cockburn, 1994). For example, Microsoft produces its eponymous office software for both Apple and the PC market. Despite the importance of the software to the usability of their final products, neither Apple nor Dell need to interact heavily with Microsoft; rather they simply purchase Microsoft's finished product and related services "ready to go." By facilitating economies of scale and compartmentalized competence, knowledge implementation enables leveraging the broader capabilities throughout the supply chain.

In the context of the earlier presented simulation, under experimental treatments of rapidly expanding markets collaboration declined rapidly, especially under scenarios of low price elasticity. Low price elasticity meant little incentive to innovate or collaborate, and with a rapidly growing market firms shopped from any source in order to meet demand. These insights lead to the following proposition:

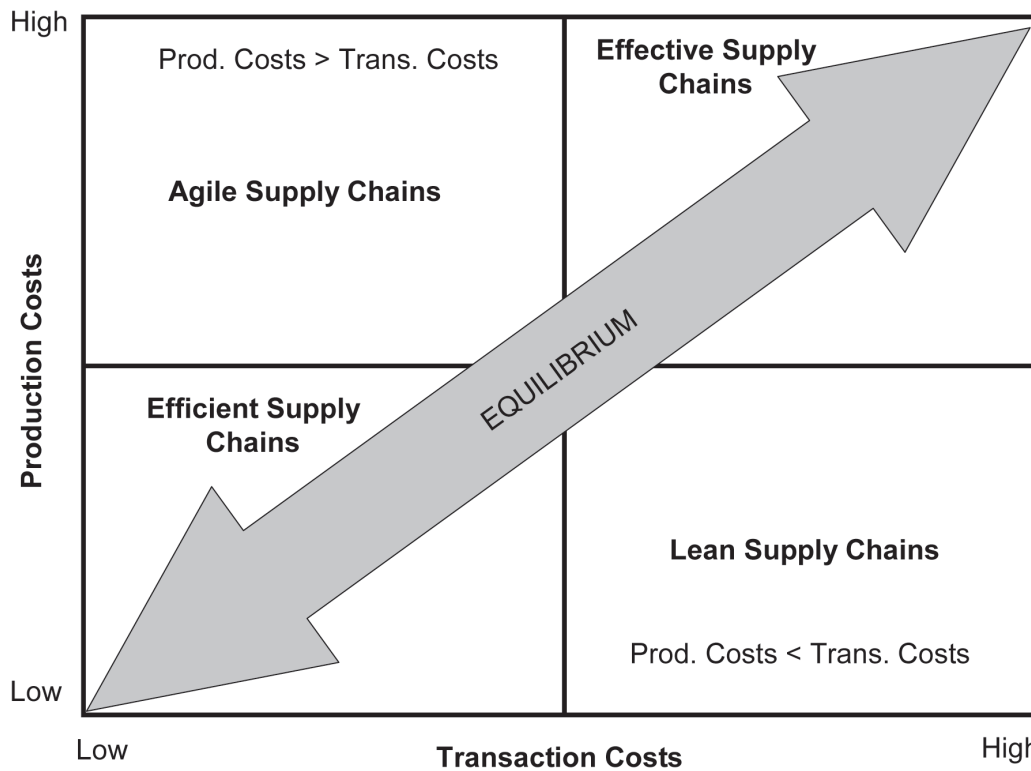
P3: The degree of knowledge implementation will demonstrate a negative relationship with inter-organizational knowledge exchanges, with more reliance on knowledge implementation leading to less collaboration.

CONCLUSION

Assessing the role that knowledge plays in the supply chain holds promise for deepening scholarly understanding and practitioner management of supply chain evolution. Viewing supply chains as inter-organizational networks characterized by dynamism, adaptability, and knowledge-based exchanges allows some ability to predict patterns of collaboration, and could also explain why the "integration prescription" provides such mixed outcomes.

Past research has highlighted the importance of balancing transaction and production costs in accordance with Coase's original conceptualization of TCE (Gravier and Farris, 2012). The imbalance or balance of production vs. transaction costs may explain which supply chain strategies prove most effective or evolve out of a given set of circumstances (see Figure 8). If knowledge-based exchanges do indeed form the basis of supply chain evolution, then measuring the amount of knowledge inherent to the supply chain, as well as the ability of the supply chain to communicate knowledge efficiently, become important predictors of supply chain performance. Information theory's entropy provides precisely such a measure. Entropy—usually embodied by Shannon's entropy—measures the amount of information content; additionally, the measurement also shows the absolute limit to the amount of information that can be carried in a given channel (Shannon, 1948). As such, entropy holds the promise to measure the maximum complexity that a given supply chain can reasonably manage. Current ef-

Figure 8. Using production and transaction costs to predict supply chain designs



forts to measure entropy and apply it as a means of managing inter-organizational processes and operations demonstrate promise (c.f., Gravier and Kelly, 2012; Liu and Zhang, 2011). Assessing entropy would enable managers to assess whether collaboration and integration are on an upward or downward trend, and to assess trends against the propositions presented in this study in order to predict outcomes or explain shortcomings and success. Researchers could also apply the entropy measure to test this study's propositions for empirical validity.

With regard to changing paradigms in supply chain and inter-organizational knowledge management research, the dominant paradigm resting on an essentially static or steady state suffers shortcomings in a world characterized by increasing change. In order to escape from a reactive ap-

proach, organizations need tools to anticipate dynamic trends. Rather than "agile" supply chains, organizations should evolve into adaptive networks whose members maintain enough autonomy to respond to their environments. Rather than providing prescriptive mandates for managing entire networks of firms—a process that can be slow and limits firm agility—more and more researchers are suggesting that the right inter-organizational architecture to allowed to "emerge" so that supply chains effectively manage themselves. Empirical evidence hints that inter-organizational information technology and information sharing lead to improved supply chain performance outcomes, especially in situations where the firms work together over time and can evolve solutions (Prajogo and Olhager, 2012). Of course, it does appear that individual firms must first master

integration within their own boundaries before they can effectively integrate with other firms (Huo, 2012), so this insight has as many implications for internal as it does for external decision-making and strategizing.

As a last thought, this research effort suggests that certain roles of knowledge can actually reduce integration and collaboration, while others may increase them. Managers and researchers should consider investing more resources to investigating methods that combine the benefits of both highly collaborative and modular supply chain networks. Research suggests that a dual network structure may provide the benefits of both close collaboration and flexibility. Capaldo's (2007) propositions suggest that a strong network near the hub of value creation with a weaker network to carry out distribution and other functions that do not add directly to the core value proposition may provide the best structure for certain supply chains. This suggests a boundary analogous to the customer decoupling point but instead of materials flows or customer information determining the "push-pull" boundary, the amount and type of collaboration determines a collaborative intensity boundary. From a theoretical standpoint, a collaborative intensity boundary offers a more pro-active approach to supply chain design since determining deficiencies and abundances in collaborative intensity ideally should precede material flows or movement of customer information. Adopting a collaborative intensity perspective of supply chain networks finds support in the interfirm problem-solving research that also found that complex problems (slower rate of technological advance) favored integrated (highly collaborative) interfirm boundaries, whereas simpler problems that were well structured favored lower levels of integration (Macher, 2006).

REFERENCES

- Abel, T. (1998). Complex adaptive systems, evolutionism, and ecology within anthropology: Interdisciplinary research for understanding cultural and ecological dynamics. *Georgia Journal of Ecological Anthropology*, 2, 6–29. doi:10.5038/2162-4593.2.1.1
- Agresti, A. (1990). *Categorical data analysis*. New York: John Wiley and Sons.
- Akkermans, H. (2001). *Emergent supply networks: System dynamics simulation of adaptive supply agents*. Paper presented at the 34th Hawaii International Conference on System Sciences. Hawaii, HI.
- Alchian, A. A., & Demsetz, H. (1972). Production, information costs, and economic organization. *The American Economic Review*, 62(5), 777–795.
- Anand, N., & Peterson, R. A. (2000). When market information constitutes fields: Sensemaking of markets in the commercial music industry. *Organization Science*, 11(3), 270–284. doi:10.1287/orsc.11.3.270.12502
- Anderson, P. (1999). Complexity theory and organization science. *Organization Science*, 10(3), 216–232. doi:10.1287/orsc.10.3.216
- Appleyard, M. M. (1996). How does knowledge flow? Interfirm patterns in the semiconductor industry. *Strategic Management Journal*, 17, 137–154.
- Baker, W. E., & Sinkula, J. M. (1999). The synergistic effect of market orientation and learning orientation on organizational performance. *Journal of the Academy of Marketing Science*, 27(4), 411–427. doi:10.1177/0092070399274002

- Banks, J. S. C. II, & Nelson, B. L. (1999). *Discrete-event system simulation* (2nd ed.). Upper Saddle River, NJ: Prentice Hall.
- Bendoly, E., Bharadwaj, J., & Bharadwaj, S. (2012). Complementary drivers of new product development performance: Cross-functional coordination, information system capability, and intelligence quality. *Production and Operations Management*, 21(4), 653–667. doi:10.1111/j.1937-5956.2011.01299.x
- Bettis, R. A., & Prahalad, C. K. (1995). The dominant logic: Retrospective extension. *Strategic Management Journal*, 16(1), 5–14. doi:10.1002/smj.4250160104
- Bourlakis, M., Maglaris, G., & Fotopoulos, C. (2012). Creating a best value supply chain? Empirical evidence from the Greek food chain. *International Journal of Logistics Management*, 23(3), 360–382. doi:10.1108/09574091211289228
- Bucklin, L. P., & Sengupta, S. (1993). Organizing successful co-marketing alliances. *Journal of Marketing*, 57(2), 32–46. doi:10.2307/1252025
- Bureau, U. S. C. (2005). *Survey of plant capacity*. Author.
- Capaldo, A. (2007). Network structure and innovation: the leveraging of a dual network as a distinctive relational capability. *Strategic Management Journal*, 28(6), 585. doi:10.1002/smj.621
- Chesbrough, H. W., & Teece, D. J. (1996). When is virtual virtuous? Organizing for innovation. *Harvard Business Review*, 74(1), 65–73.
- Chiva-Gomez, R. (2003). The facilitating factors for organizational learning: Bringing ideas from complex adaptive systems. *Knowledge and Process Management*, 10(2), 99–114. doi:10.1002/kpm.168
- Choi, T. Y., Dooley, K. J., & Rungtusanatham, M. (2001). Supply networks and complex adaptive systems: Control versus emergence. *Journal of Operations Management*, 19, 351–366. doi:10.1016/S0272-6963(00)00068-1
- Coase, R. H. (1937). The nature of the firm. *Economica*, 4(16), 386–405. doi:10.1111/j.1468-0335.1937.tb00002.x
- Daugherty, P. J., Ellinger, A. E., & Gustin, C. M. (1996). Integrated logistics: Achieving logistics performance improvements. *Supply Chain Management*, 1(3), 25–33. doi:10.1108/13598549610155297
- David, R. J., & Han, S.-K. (2004). A systematic assessment of the empirical support for transaction cost economics. *Strategic Management Journal*, 25, 39–58. doi:10.1002/smj.359
- Davis, J. P., Bingham, C. B., & Eisenhardt, K. M. (2007). Developing theory through simulation methods. *Academy of Management Review*, 32(2), 480–499. doi:10.5465/AMR.2007.24351453
- Deitrich, M. (2012). *Transaction cost economics and beyond: Toward a new economics of the firm*. London: Routledge.
- Dooley, K. J. (1997). A complex adaptive systems model of organization change. *Nonlinear Dynamics Psychology and Life Sciences*, 1(1), 69–97. doi:10.1023/A:1022375910940
- Droge, C., Vickery, S. K., & Jacobs, M. A. (2012). Does supply chain integration mediate the relationships between product/process strategy and service performance? An empirical study. *International Journal of Production Economics*, 137(2), 250–262. doi:10.1016/j.ijpe.2012.02.005

Dyer, J. H., & Nobeoka, K. (2002). Creating and managing a high-performance knowledge-sharing network: The Toyota case. *Strategic Management Journal*, 21(3), 345–367. doi:10.1002/(SICI)1097-0266(200003)21:3<345::AID-SMJ96>3.0.CO;2-N

Dyer, J. H., & Singh, H. (1998). The relational view: Cooperative strategy and sources of inter-organizational competitive advantage. *Academy of Management Review*, 23(4), 660–679.

Economist (2011). *Slicing an apple*. Retrieved on June 24, 2013, from <http://www.economist.com/blogs/dailychart/2011/08/apple-and-samsungs-symbiotic-relationship>

Eisenhardt, K., & Tabrizi, B. N. (1995). Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly*, 40(1). doi:10.2307/2393701

Ethiraj, S. K., & Levinthal, D. (2004). Modularity and innovation in complex systems. *Management Science*, 50(2), 159–173. doi:10.1287/mnsc.1030.0145

Fabbe-Costes, N., & Jahre, M. (2008). Supply chain integration and performance: A review of the evidence. *International Journal of Logistics Management*, 19(2), 130–154. doi:10.1108/09574090810895933

Fokianos, K., & Kedem, B. (2003). Regression theory for categorical time series. *Statistical Science*, 18(3), 357–376. doi:10.1214/ss/1076102425

Forrester, J. W. (1958). Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review*, 37–66.

Forrester, J. W. (1961). *Industrial dynamics*. Cambridge, MA: MIT Press.

Frohlich, M. T., & Westbrook, R. (2001). Arcs of integration: An international study of supply chain strategies. *Journal of Operations Management*, 19(2), 185–200. doi:10.1016/S0272-6963(00)00055-3

Garicano, L., & Kaplan, S. N. (2001). The effects of business-to-business e-commerce on transaction costs. *The Journal of Industrial Economics*, 49(4), 463. doi:10.1111/1467-6451.00158

Gligor, D. M., & Holcomb, M. C. (2012). Understanding the role of logistics capabilities in achieving supply chain agility: A systematic literature review. *Supply Chain Management: An International Journal*, 17(4), 438–453. doi:10.1108/13598541211246594

Goldstone, R. L., & Sakamoto, Y. (2003). The transfer of abstract principles governing complex adaptive systems. *Cognitive Psychology*, 46(4), 414–466. doi:10.1016/S0010-0285(02)00519-4 PMID:12809681

Granger, C. W. J., & Newbold, P. (1977). *Forecasting economic time series*. New York: Academic Press.

Grant, R. M., & Baden-Fuller, C. (2004). A knowledge accessing theory of strategic alliances. *Journal of Management Studies*, 41(1), 61–84. doi:10.1111/j.1467-6486.2004.00421.x

Gravier, M. J., & Farris, M. T. (2012). Integrative vs. disintegrative forces in the evolution of supply chain networks. *International Journal of Knowledge-Based Organizations*, 2(3), 1–32. doi:10.4018/ijkbo.2012070101

Gravier, M. J., & Kelly, B. (2011). Measuring the cost of complexity in supply chains: Comparison of weighted entropy and the bullwhip effect index. In *Modelling value*. Berlin: Springer. doi:10.1007/978-3-7908-2747-7_13

- Gravier, M. J., Randall, W. S., & Strutton, D. (2008). Investigating the role of knowledge in alliance performance. *Journal of Knowledge Management*, 12(4), 117–130. doi:10.1108/13673270810884291
- Greve, H. R., Mitsunashi, H., & Baum, J. A. C. (2012). Greener pastures: Outside options and strategic alliance withdrawal. *Organization Science*, 24(1), 79–98. doi:10.1287/orsc.1110.0733
- Gustin, C. M., Daugherty, P. J., & Stank, T. P. (1995). The effects of information availability on logistics integration. *Journal of Business Logistics*, 16(1), 1–21.
- Hamel, G. (1991). Competition for competence and interpartner learning within international strategic alliances. *Strategic Management Journal*, 12(S1), 83–103. doi:10.1002/smj.4250120908
- Harrell, F. E. (2001). *Regression modeling strategies: With applications to linear models, logistic regression, and survival analysis*. New York: Springer-Verlag.
- Heide, J. B. (1994). Interorganizational governance in marketing channels. *Journal of Marketing*, 58(1), 71–85. doi:10.2307/1252252
- Heimer, C. A. (1985). Allocating information costs in a negotiated information order: Interorganizational constraints on decision making in Norwegian oil insurance. *Administrative Science Quarterly*, 30(3), 395–417. doi:10.2307/2392671
- Henderson, R., & Cockburn, I. (1994). Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal*, 15(S1), 63–84. doi:10.1002/smj.4250150906
- Hobbs, J. E. (1996). A transaction cost approach to supply chain management. *Supply Chain Management*, 1(2), 15–27. doi:10.1108/13598549610155260
- Hofman, D., & Aronow, S. (2012). *The Gartner supply chain top 25 for 2012*. Stamford, CT: Gartner, Inc.
- Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Reading, MA: Addison-Wesley Publishing Company.
- Holland, J. H., & Miller, J. H. (1991). Artificial adaptive agents in economic theory. *The American Economic Review*, 81(2), 365–370.
- Holme, P., Kim, B. J., Yoon, C. N., & Han, S. K. (2002). Attack vulnerability of complex networks. *Physical Review E: Statistical, Nonlinear, and Soft Matter Physics*, 65(5), 1–15. doi:10.1103/PhysRevE.65.056109
- Hunt, S. D., & Morgan, R. M. (1995). The comparative advantage theory of competition. *Journal of Marketing*, 59(2), 1–15. doi:10.2307/1252069
- Huo, B. (2012). The impact of supply chain integration on company performance: An organizational capability perspective. *Supply Chain Management: An International Journal*, 17(6), 596–610. doi:10.1108/13598541211269210
- Ilachinski, A. (2000). Irreducible semi-autonomous adaptive combat (ISAAC), an artificial-life approach to land combat. *Military Operations Research*, 5(3), 29–46. doi:10.5711/morj.5.3.29
- Im, S., & Workman, J. P. (2004). Market orientation, creativity, and new product performance in high-technology firms. *Journal of Marketing*, 68(2), 114–132. doi:10.1509/jmkg.68.2.114.27788
- Inkpen, A. C., & Tsang, E. W. K. (2005). Social capital, networks, and knowledge transfer. *Journal of the Academy of Marketing Science*, 30(1), 146–165.

- Jayaram, J., & Pathak, S. (2013). A holistic view of knowledge integration in collaborative supply chains. *International Journal of Production Research*, 51(7), 1958–1972. doi:10.1080/00207543.2012.700130
- Jonsson, P., & Mattsson, S.-A. (2012). The value of sharing information in supply chains. *International Journal of Physical Distribution and Logistics Management*, 43(4), 282–299.
- Joshi, A. W., & Campbell, A. J. (2003). Effect of environmental dynamism on relational governance in manufacturer-supplier relationships: A contingency framework and an empirical test. *Journal of the Academy of Marketing Science*, 31(2), 176–188. doi:10.1177/0092070302250901
- Kahn, K. B. (1996). Interdepartmental integration: A definition with implications for product development performance. *Journal of Product Innovation Management*, 13(2), 137–151. doi:10.1016/0737-6782(95)00110-7
- Kim, S. W. (2003). *An investigation of information technology investments on buyer-supplier relationship and supply chain dynamics*. East Lansing, MI: Michigan State University.
- Kirby, S. (2000). Syntax without natural selection: How compositionality emerges from vocabulary in a population of learners. In *The evolutionary emergence of language: Social function and the origins of linguistic form* (pp. 185–215). Academic Press. doi:10.1017/CBO9780511606441.019
- Kogut, B. (2000). The network as knowledge: Generative rules and the emergence of structure. *Strategic Management Journal*, 21(3), 405–425. doi:10.1002/(SICI)1097-0266(200003)21:3<405::AID-SMJ103>3.0.CO;2-5
- Kogut, Z., & Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Science*, 3(3), 383–397. doi:10.1287/orsc.3.3.383
- Kohli, A. K., & Jaworski, B. J. (1993). Market orientation: The construct, research propositions, and managerial implications. *Journal of Marketing*, 54(2), 1–18. doi:10.2307/1251866
- Langlois, R. N. (2002). Modularity in technology and organization. *Journal of Economic Behavior & Organization*, 49(1), 19–37. doi:10.1016/S0167-2681(02)00056-2
- Law, A. M., & Kelton, W. D. (2000). *Simulation modeling and analysis* (3rd ed.). New York: McGraw-Hill Higher Education.
- Lee, H. L., Padmanabhan, V., & Whang, S. (1997a). The bullwhip effect in supply chains. *Sloan Management Review*, 38(3), 93–102.
- Lee, H. L., Padmanabhan, V., & Whang, S. (1997b). Information distortion in a supply chain: The bullwhip effect. *Management Science*, 43(4), 546–558. doi:10.1287/mnsc.43.4.546
- Leiblein, M. J. (2003). The choice of organizational governance form and performance: Predictions from transaction cost, resource-based, and real options theories. *Journal of Management*, 29(6), 937–961.
- Limburg, K. E., O'Neill, R. V., Costanza, R., & Farber, S. (2002). Complex systems and valuation. *Ecological Economics*, 41(3), 409–420. doi:10.1016/S0921-8009(02)00090-3
- Lin, F.-R., Huang, S.-H., & Lin, S.-C. (2002). Effects of information sharing on supply chain performance in electronic commerce. *IEEE Transactions on Engineering Management*, 49(3), 258–268. doi:10.1109/TEM.2002.803388
- Liu, P., & Zhang, X. (2011). Research on the supplier selection of a supply chain based on entropy weight and improved ELECTRE-III method. *International Journal of Production Research*, 3(1), 637–646. doi:10.1080/00207540903490171

- Lummus, R. R., & Vokurka, R. J. (1999). Managing the demand chain through managing the information flow: Capturing 'moments of information'. *Production and Inventory Management Journal*, 40(1), 16–20.
- Macher, J. T. (2006). Technological development and the boundaries of the firm: A knowledge-based examination in semiconductor manufacturing. *Management Science*, 52(6), 826–843. doi:10.1287/mnsc.1060.0511
- Maisel, H., & Gnugnoli, G. (1972). *Simulation of discrete stochastic systems*. Chicago: Science Research Associates, Inc.
- Markose, S. M. (2005). Computability and evolutionary complexity: Markets as complex adaptive systems (CAS). *The Economic Journal*, 115(504), F159. doi:10.1111/j.1468-0297.2005.01000.x
- McElroy, M. W. (2000). Integrating complexity theory, knowledge management and organizational learning. *Journal of Knowledge Management*, 4(3), 195–203. doi:10.1108/13673270010377652
- McEvily, S. K., & Chakravarthy, B. (2002). The persistence of knowledge-based advantage: An empirical test for product performance and technological knowledge. *Strategic Management Journal*, 23(4), 285–305. doi:10.1002/smj.223
- McNamara, G., Vaaler, P. M., & Devers, C. (2003). Same as it ever was: The search for evidence of increasing hypercompetition. *Strategic Management Journal*, 24(3), 261–278. doi:10.1002/smj.295
- Mena, C., Humphries, A., & Choi, T. Y. (2013). Toward a theory of multi-tier supply chain management. *Journal of Supply Chain Management*, 49(2), 58–77. doi:10.1111/jscm.12003
- Moorman, C., & Miner, A. S. (1997). The impact of organizational memory on new product performance and creativity. *JMR, Journal of Marketing Research*, 34(1), 91–106. doi:10.2307/3152067
- Morel, B., & Ramanujam, R. (1999). Through the looking glass of complexity: The dynamics of organizations as adaptive and evolving systems. *Organization Science*, 10(3), 278–293. doi:10.1287/orsc.10.3.278
- Narasimhan, R., & Jayaram, J. (1998). Causal linkages in supply chain management: An exploratory study of North American manufacturing firms. *Decision Sciences*, 29(3), 579–605. doi:10.1111/j.1540-5915.1998.tb01355.x
- Nelson, C. R. (1973). *Applied time series analysis for managerial forecasting*. San Francisco: Holden-Day, Inc.
- Nickerson, J. A., & Zenger, T. R. (2004). A knowledge-based theory of the firm—The problem-solving perspective. *Organization Science*, 15(6), 617–632. doi:10.1287/orsc.1040.0093
- Nielsen, B. B. (2005). The role of knowledge embeddedness in the creation of synergies in strategic alliances. *Journal of Business Research*, 58(9), 1194–1204. doi:10.1016/j.jbusres.2004.05.001
- Ouchi, W. G. (1979). A conceptual framework for the design of organizational control mechanisms. *Management Science*, 25(9), 833–848. doi:10.1287/mnsc.25.9.833
- Parunak, H. V. D. (1998). *The DASCh experience: How to model a supply chain*. Retrieved from <http://www.erim.org/~vparunak/iccs98.pdf>
- Pathak, S. D. (2005). *An investigative framework for studying the growth and evolution of complex supply networks*. Nashville, TN: Vanderbilt University.
- Pettit, T. J., Croxton, K. L., & Fiksel, J. (2012). Ensuring supply chain resilience: Development and implementation of an assessment tool. *Journal of Business Logistics*, 34(1), 46–76. doi:10.1111/jbl.12009

- Pilbeam, C., Alvarez, G., & Wilson, H. (2012). The governance of supply networks: A systematic literature review. *Supply Chain Management: An International Journal*, 17(4), 358–376. doi:10.1108/13598541211246512
- Prahalad, C. K., & Hamel, G. (1990). The core competence and the corporation. *Harvard Business Review*, 71–90.
- Prajogo, D., & Olhager, J. (2012). Supply chain integration and performance: The effects of long-term relationships, information technology and sharing, and logistics integration. *International Journal of Production Economics*, 135, 514–522. doi:10.1016/j.ijpe.2011.09.001
- Randall, W. S., Pohlen, T. L., & Hanna, J. B. (2010). Evolving a theory of performance-based logistics using insight from service-dominant logic. *Journal of Business Logistics*, 31(2), 35–61. doi:10.1002/j.2158-1592.2010.tb00142.x
- Rindfleisch, A., & Heide, J. B. (1997). Transaction cost analysis: past, present, and future applications. *Journal of Marketing*, 61(4), 30–54. doi:10.2307/1252085
- Rindfleisch, A., & Moorman, C. (2001). The acquisition and utilization of information in new product alliances: A strength-of-ties perspective. *Journal of Marketing*, 65(2), 1–18. doi:10.1509/jmkg.65.2.1.18253
- Roper, S., & Crone, M. (2003). Knowledge complementarity and coordination in the local supply chain: Some empirical evidence. *British Journal of Management*, 14(4), 339–355. doi:10.1111/j.1467-8551.2003.00383.x
- Roy, S., Sivakumar, K., & Wilkinson, I. F. (2004). Innovation generation in supply chain relationships: A conceptual model and research propositions. *Academy of Marketing Science Journal*, 32(1), 61–79. doi:10.1177/0092070303255470
- Schoenherr, T., Modib, S. B., Bentoncy, W. C., Carter, C. R., Choi, T. Y., & Larson, P. D. et al. (2011). Research opportunities in purchasing and supply management. *International Journal of Production Research*, 50(6), 4556–4579.
- Sethi, R., Smith, D. C., & Park, C. W. (2001). Cross-functional product development teams, creativity, and the innovativeness of new consumer products. *JMR, Journal of Marketing Research*, 38(1), 73–85. doi:10.1509/jmkr.38.1.73.18833
- Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27, 379–423, 623–656. doi:10.1002/j.1538-7305.1948.tb01338.x
- Sivadas, E., & Dwyer, F. R. (2000). An examination of organizational factors influencing new product success in internal and alliance-based processes. *Journal of Marketing*, 64(1), 31–49. doi:10.1509/jmkg.64.1.31.17985
- Sorenson, O. (2003). Social networks and industrial geography. *Journal of Evolutionary Economics*, 13(5), 513–527. doi:10.1007/s00191-003-0165-9
- Stank, T. P., Keller, S. B., & Closs, D. J. (2001). Performance benefits of supply chain logistical integration. *Transportation Journal*, 41(2-3), 32–46.
- Stock, G. N., Greis, N. P., & Kasarda, J. D. (1999). Logistics, strategy and structure: A conceptual framework. *International Journal of Physical Distribution & Logistics Management*, 29(4), 224–239. doi:10.1108/09600039910273948
- Surana, A., Kumara, S., Greaves, M., & Raghavan, U. N. (2005). Supply-chain networks: A complex adaptive systems perspective. *International Journal of Production Research*, 43(20), 4235–4265. doi:10.1080/00207540500142274

- Tan, K. C., Kannan, V. R., & Handfield, R. B. (1998). Supply chain management: Supplier performance and firm performance. *International Journal of Purchasing and Materials Management*, 34(3), 2–9.
- Van De Ven, A. H., & Poole, M. S. (1995). Explaining development and change in organizations. *Academy of Management Review*, 20(3), 510–540. doi:10.2307/258786
- Varadarajan, P. R., & Cunningham, M. H. (1995). Strategic alliances: A synthesis of conceptual foundations. *Journal of the Academy of Marketing Science*, 23(4), 297–300. doi:10.1177/009207039502300408
- Vargo, S. L., & Lusch, R. F. (2004a). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1), 1–17. doi:10.1509/jmkg.68.1.1.24036
- Vargo, S. L., & Lusch, R. F. (2004b). The four service marketing myths: remnants of a goods-based, manufacturing model. *Journal of Service Research*, 6(4), 324–335. doi:10.1177/1094670503262946
- Vargo, S. L., & Lusch, R. F. (2006). Service-dominant logic: reactions, reflections and refinements. *Marketing Theory*, 6(3), 281–288. doi:10.1177/1470593106066781
- Vitasek, K. (2011). *The vested outsourcing manual: A guide for creating successful business and outsourcing agreements*. New York: Palgrave-MacMillan.
- Wiggins, R. W., & Ruefli, T. W. (2005). Schumpeter's ghost: Is hypercompetition making the best of times shorter?. *Strategic Management Journal*, 26(S 887), 911.
- Williamson, O. E. (1975). *Markets and hierarchies: Analysis and antitrust implications*. New York: The Free Press.
- Williamson, O. E. (1986). *Economic organization*. New York: New York University Press.
- Williamson, O. E. (1991). Comparative economic organization: The analysis of discrete structural alternatives. *Administrative Science Quarterly*, 36(2), 269–296. doi:10.2307/2393356
- Williamson, O. E. (2008). Outsourcing: Transaction cost economics and supply chain management. *Journal of Supply Chain Management*, 44(2), 5–16. doi:10.1111/j.1745-493X.2008.00051.x
- World Economic Forum. (2013). *Enabling trade: Valuing growth opportunities*. Geneva: World Economic Forum.
- Zacharia, Z. G., Sanders, N. R., & Nix, N. W. (2011). The emerging role of the third-party logistics provider (3PL) as an orchestrator. *Journal of Business Logistics*, 32(1), 40–54. doi:10.1111/j.2158-1592.2011.01004.x
- Zhou, K. Z., & Li, C. B. (2012). How knowledge affects radical innovation: Knowledge base, market knowledge acquisition, and internal knowledge sharing. *Strategic Management Journal*, 33, 1090–1102. doi:10.1002/smj.1959
- Zhou, K. Z., & Wu, F. (2010). Technological capability, strategic flexibility, and product innovation. *Strategic Management Journal*, 31, 547–561.

ENDNOTES

- ¹ Small companies were a special case where δ was based on the current capacity (C_t) and the size of the requested upgrade (C_u). In the case that $C_t < 3$ and $C_u \leq 3C_t$, then $\delta = 1$; if $C_t < 3$ and $C_u \leq 4C_t$, then δ equaled a constant.

APPENDIX A

Key:

EOS = Economies of Scale

EMhet = End Market (heterogeneous)

EMhom = End Market (homogeneous)

RTA = Rate of Technological Advance

see Tables A1, A2, A3, A4

Table A1. Manufacturer-to-assembler selection parameter estimates by strategy

| Parameter | | Low Price Strategy | | High Price Strategy | |
|----------------|---|--------------------|------------|---------------------|------------|
| | | Estimate | Pr > ChiSq | Estimate | Pr > ChiSq |
| TimeStep | 1 | 4.96 | <.0001 | -0.35 | 0.4236 |
| | 2 | -1.19 | 0.0015 | -0.35 | 0.4236 |
| | 3 | -2.49 | <.0001 | -0.35 | 0.4236 |
| | 4 | -1.71 | <.0001 | 0.16 | 0.7035 |
| TimeStep*EOS | 1 | 0.13 | 0.7312 | 0.22 | 0.5233 |
| | 2 | 0.39 | 0.2796 | 0.10 | 0.7691 |
| | 3 | 0.36 | 0.3588 | 0.10 | 0.7691 |
| | 4 | -0.61 | 0.0658 | -0.76 | 0.0087 |
| TimeStep*EMhet | 1 | 0.35 | 0.374 | -0.24 | 0.5599 |
| | 2 | -0.93 | 0.0135 | -0.42 | 0.3242 |
| | 3 | 0.37 | 0.3566 | -0.42 | 0.3242 |
| | 4 | 0.40 | 0.2137 | 0.30 | 0.3408 |
| TimeStep*EMhom | 1 | . | . | -0.51 | 0.2272 |
| | 2 | . | . | -0.69 | 0.1128 |
| | 3 | . | . | -0.69 | 0.1128 |
| | 4 | . | . | 0.54 | 0.1439 |

Table A2. Assembler-to-manufacturer selection parameter estimates by strategy

| Parameter | | Low Price Strategy | | High Price Strategy | |
|--------------------|---|--------------------|------------|---------------------|------------|
| | | Estimate | Pr > ChiSq | Estimate | Pr > ChiSq |
| TimeStep | 1 | 1.73 | <.0001 | -1.13 | 0.0093 |
| | 2 | -1.50 | <.0001 | -1.13 | 0.0093 |
| | 3 | 0.06 | 0.7513 | -1.13 | 0.0093 |
| | 4 | -0.40 | 0.0453 | -0.24 | 0.4893 |
| TimeStep*EMhet | 1 | 2.03 | <.0001 | 0.33 | 0.4136 |
| | 2 | 0.61 | 0.0032 | -0.04 | 0.9283 |
| | 3 | -1.29 | <.0001 | -0.04 | 0.9283 |
| | 4 | -0.97 | <.0001 | -0.30 | 0.2947 |
| TimeStep*EMhom | 1 | . | . | -0.09 | 0.8273 |
| | 2 | . | . | -0.45 | 0.2896 |
| | 3 | . | . | -0.45 | 0.2896 |
| | 4 | . | . | -0.12 | 0.7428 |
| TimeStep*RTA*EMhet | 1 | -0.82 | 0.0006 | 0.25 | 0.5312 |
| | 2 | 1.27 | <.0001 | -0.11 | 0.7897 |
| | 3 | -0.19 | 0.3033 | -0.11 | 0.7897 |
| | 4 | -0.33 | 0.1123 | 0.17 | 0.6171 |

Table A3. Assembler-to-retailer selection parameter estimates by strategy

| Parameter | | Low Price Strategy | | High Price Strategy | |
|----------------|---|--------------------|------------|---------------------|------------|
| | | Estimate | Pr > ChiSq | Estimate | Pr > ChiSq |
| TimeStep | 1 | -1.16 | 0.0073 | -1.01 | 0.0195 |
| | 2 | -1.16 | 0.0073 | -1.01 | 0.0195 |
| | 3 | -1.16 | 0.0073 | -1.01 | 0.0195 |
| | 4 | 0.87 | 0.0035 | -0.05 | 0.8868 |
| TimeStep*EOS | 1 | 0.33 | 0.436 | 0.27 | 0.4147 |
| | 2 | 0.33 | 0.436 | 0.33 | 0.3392 |
| | 3 | 0.33 | 0.436 | 0.20 | 0.564 |
| | 4 | -0.95 | 0.0012 | -0.78 | 0.0031 |
| TimeStep*EMhom | 1 | . | . | -0.31 | 0.4371 |
| | 2 | . | . | -0.61 | 0.1469 |
| | 3 | . | . | -0.41 | 0.322 |
| | 4 | . | . | 0.46 | 0.1334 |

Table A4. Retailer-to-assembler selection parameter estimates by strategy

| Parameter | | Low Price Strategy | | High Price Strategy | |
|--------------------|---|--------------------|------------|---------------------|------------|
| | | Estimate | Pr > ChiSq | Estimate | Pr > ChiSq |
| TimeStep | 1 | 1.73 | <.0001 | -1.13 | 0.0093 |
| | 2 | -1.50 | <.0001 | -1.13 | 0.0093 |
| | 3 | 0.06 | 0.7513 | -1.13 | 0.0093 |
| | 4 | -0.40 | 0.0453 | -0.24 | 0.4893 |
| TimeStep*RTA | 1 | 1.48 | <.0001 | 0.04 | 0.9181 |
| | 2 | -1.21 | <.0001 | 0.04 | 0.9181 |
| | 3 | -0.03 | 0.8663 | 0.04 | 0.9181 |
| | 4 | 0.03 | 0.8948 | -0.12 | 0.7204 |
| TimeStep*EMhet | 1 | 2.03 | <.0001 | 0.33 | 0.4136 |
| | 2 | 0.61 | 0.0032 | -0.04 | 0.9283 |
| | 3 | -1.29 | <.0001 | -0.04 | 0.9283 |
| | 4 | -0.97 | <.0001 | -0.30 | 0.2947 |
| TimeStep*EMhom | 1 | . | . | -0.09 | 0.8273 |
| | 2 | . | . | -0.45 | 0.2896 |
| | 3 | . | . | -0.45 | 0.2896 |
| | 4 | . | . | -0.12 | 0.7428 |
| TimeStep*RTA*EMhet | 1 | -0.82 | 0.0006 | 0.25 | 0.5312 |
| | 2 | 1.27 | <.0001 | -0.11 | 0.7897 |
| | 3 | -0.19 | 0.3033 | -0.11 | 0.7897 |
| | 4 | -0.33 | 0.1123 | 0.17 | 0.6171 |

APPENDIX B: CREATE COMPUTATIONAL REPRESENTATION

In this section are included descriptions of variables and the equations utilized in the simulation.

Strategy

Each company used either a high quality or a low quality strategy. Companies following a high quality strategy did business exclusively with buyers and suppliers who also pursued a high quality strategy; companies following a low quality strategy similarly dealt exclusively with companies following a low quality strategy.

Life Points

Life points (λ) represented the health of the company. All companies started with the same number of life points. Companies gained or lost life points based on their capacity utilization (U). Companies making efficient use of existing capacity, as reflected by capacity utilization, were considered healthier and more resilient. *Capacity utilization* was calculated as a percent of a company's maximum capacity based on the company's sales, with the assumption that a company only produced to demand and sold all that it produced. If the capacity utilization fell below the survival threshold (θ), a life point was lost at a rate determined by a parameter called the *basis point division parameter* (β). The capacity utilization of 70% was in accordance with the recent U.S. Census Bureau plant capacity data (Bureau, 2005). Companies operating above this threshold gained a life point. Basis point division was arbitrarily set to 20; companies operating at capacity utilization between 50 and 70 lost one life point, companies operating at capacity utilization of 30-49 lose 2 life points, between 10-29 they lost 3 life points and at less than 10 they lost 4 life points. Thus a company with a long history of being successful that had fallen upon hard times would take much longer to die than a newer company or one with a history of being less successful.

Node Deaths

When a node died, all of the capacity it provided both upstream and downstream was removed from the system before calculation of node differentials (see the sub-section on *Capacity upgrades*), so any capacity lost due to node death will be supplemented by the system. The process for removing the capacity ensured that all requirements from downstream demand were balanced against capacity amongst the suppliers.

Demand Volume

Demand volume was determined by a function following a Gaussian distribution determined by the volume of peak demand (D_{\max}) with a peak demand time step (τ) and a scale factor (s). Demand also used a random factor (p) that represented the percent variance from the value determined by the demand distribution function. This is shown below where r_t is a random number between 0 and 1 and p is the specified "random" percent of variance (and which is also shown in Figure 5).

$$D_t = D_{\max} (e^{-((t-\tau)/s)^2}) (1 + r_t p)$$

Price

Price started out the same for both high and low end markets (P_s). Demand was distinguished as being either high end demand (low price sensitivity) or low end demand (high price sensitivity) as determined by the established market price in each market. As demand increased, prices dropped in a linear fashion for both markets. It was implicitly assumed that price for both high and low end products would decline as the industry matured and price for low end product would always be less, or at most equal to, the price for high end product. As prices dropped, demand for low end product increased while demand for high end product decreased. The volume of high end demand was represented as:

$$D_H = D_t \left(\frac{P_L}{P_H} \right)$$

where P_L is the market price for the low end market and P_H is the market price in the high end market. Conversely, low end demand was represented as:

$$D_L = D_t \left(1 - \frac{P_L}{P_H} \right)$$

Economies of Scale

Production facilities of each company type (i.e., high end manufacturers, low end manufacturers, assemblers, and retailers) had an optimal economy of scale (κ), which increased as the industry matured, and changed linearly over time as determined by the optimum economy of scale size factor (ω). An optimum economy of scale size factor of one reflected a static growth of economies of scale, whereas $\omega=2$ meant the economies of scale doubled over the course of the simulation.

Depending on the deviation of a plant's current capacity from the optimum economies of scale, the plant could experience economies or diseconomies of scale. The closer the current capacity was to optimal capacity, the more efficient the company. The effect of economies of scale primarily influenced the decision to increase capacity. Firms would uniformly decide to increase capacity until the optimal capacity was reached; the probability that a firm would increase capacity thereafter was reflected by a Gaussian distribution (see the section on *Capacity Upgrades*).

Technology and Capacity Upgrades

Companies faced a moving technological frontier. In order to keep up with the rate of technological change, companies would periodically upgrade their capacity. Competition amongst companies depended on having up-to-date production facilities—keeping up was assumed to be the cost of entry. The process for upgrading technology was incorporated with the process for capacity upgrades. As a result, early in the simulation companies tended to upgrade technology and capacity simultaneously, but as they reached their optimal economies of scale, technology upgrades would tend to occur without increases to capacity. The upgrade recovery time parameter (ζ) determined the pace at which plant capacity became obsolete and needed upgrading.

Upgrades also included increases to plant production capacity. The decision to upgrade depended on three factors: 1) recovery time since last upgrade, 2) relative size of upgrade, and 3) the economies of scale of the resulting upgrade. The decision to upgrade capacity occurred when the product of the three factors exceeded the company's upgrade decision threshold (υ). A brief description of each of the three factors follows:

1. **Recovery time since last upgrade (ρ):** This function was based upon the number of time steps since the last capacity upgrade. When the time since the last capacity upgrade reached the upgrade recovery time parameter ($t_U \geq \zeta$), then $\rho=1$; otherwise,

$$\rho = \frac{t_U}{\zeta}$$

2. **Relative size of upgrade (δ):** Companies tend to avoid investing in trivial amounts of capacity upgrade; instead, they wait until it is worth their while. Companies also avoid making upgrades too rapidly lest they get ahead of the market. For example, an upgrade of only one unit was unlikely to occur, while an upgrade of 50% was likely to be much more useful. This function annotated current capacity with C_t , the size of a requested upgrade with C_U , and followed a Gaussian distribution designed so a requested capacity upgrade of 50% returned $\delta = 1$ (see equation below). Very small companies (with a capacity of 1 or 2) were handled differently with a “start up factor” allowing for slightly more drastic relative growth¹.

$$\delta = e^{-\left(\frac{C_t - 2C_U}{C_t + C_U}\right)^2}$$

3. **Economy of scale of the resulting upgrade (γ):** This function led the company to uniformly increase capacity until it reached the optimum economy of scale. The result of the function depended on the company capacity at the optimum economy of scale (κ) and the company's new capacity if the upgrade was implemented ($C_t + C_U$). The economy of scale of the resulting upgrade (γ) was determined by a Gaussian distribution based on κ :

$$\gamma = 1, C_t + C_U < \kappa$$

$$\gamma = e^{-\left(\frac{(C_t + C_U) - \kappa}{\kappa}\right)^2}, C_t + C_U > \kappa$$

A decision threshold (υ) determined when an individual company make an upgrade decision. The decision threshold was constant for the entire simulation system, with individual companies making their decision to upgrade when the product of the three factors was greater than the decision threshold ($\rho\delta\gamma > \upsilon$). A product function was used for calculating the decision threshold due to advancing economies of scale, which also affected the magnitude of the relative size of the upgrade; a product function kept all

parameters to the same scale. The upgrade parameter (v) was set based upon trial and error depending corresponding with the optimum economy of scale. Upgrading capacity went through the following recursion logic:

1. Beginning at the consumer end of the supply chain, the virtual transaction cost vector was created to map transaction costs with each active company to all other active companies of the same strategy in the upstream vector.
2. The virtual transaction cost vector was ordered from lowest to highest. In the case of declining demand, the vector was sorted highest to lowest.
3. The ordered transaction cost vector was searched by the downstream node for unused capacity which could be used if available. In the face of declining demand, relationships with the highest virtual transaction costs were eliminated first.
4. If no unused capacity was available, the downstream firm requested upgrades using the ordered virtual transaction cost vector to order additional capacity from a supplier.
5. If no supplier agreed to provide enough needed capacity, a new company was created for the unmet capacity. If the increase in demand was less than half the optimal economy of scale capacity for a retailer, then the demand was left unmet.

Virtual Transaction Costs

Virtual transaction costs were used to determine the relative cost associated with a transaction. It consisted of the sum of four transaction cost factors between buyer i and supplier j : total units, current units, economy of scale, and life of company. These virtual transaction “costs” were considered by each buyer as it selected a supplier with whom to do business. This reflected the movement of demand information up the supply chain. Buyers always selected suppliers in the order of lowest to highest virtual transaction cost in keeping with the desire to seek out the most efficient relationship available, with a bias toward suppliers that were familiar. Each virtual transaction cost factor is briefly described below:

1. **Total units cost (χ_{ij}):** Total units cost resulted from the total number of units ever exchanged between two companies (h_{ij}) such that

$$\chi_{ij} = \frac{100}{100 + h_{ij}} \quad .$$

This cost began at one and decreased over time as two companies continued to do business.

2. **Current units cost (ν_{ij}):** The units exchanged in the current cycle between two companies (n_{ij}) resulted in a cost that started at one and diminished as the volume of the current transaction increased:

$$\nu_{ij} = \frac{2}{2 + n_{ij}}$$

3. **Economy of scale cost (ι_j):** This virtual transaction cost depended on the buyer's capacity in relation to its optimum economy of scale. This cost ranged from 0 (optimum) to 0.1 (least optimum) based on current capacity (C_t) and the company capacity at the optimum economy of scale (κ):

$$\iota_j = \frac{1 - e^{-\left(\frac{C_t - \kappa}{\kappa}\right)^2}}{10}$$

4. **Life of company cost (ϕ_j):** This cost started at 0.5 and diminished as the company matured and was determined by how many time steps the buyer had been active (L):

$$\phi_j = \frac{5}{10 + L}$$

MODEL VERIFICATION AND VALIDATION

Verification relied on three techniques described by Law and Kelton (2000). The first technique entailed the writing and debugging of the program in modules or sub-programs. The process started with the main program consisting of the supply chain network interacting without transaction costs or capacity decisions. Then the sub-routine for transaction costs were implemented and debugged. Absolute transaction costs were originally envisioned; however, it quickly became apparent that the relative transaction costs between firms determined the outcomes of relationships. This agreed with Coase's vision of "an outside network of relative prices and costs" (1937, p. p. 389). A virtual transaction cost interaction vector was developed based on the exchange history (number of units exchanged), the current exchange (number of units), actual vs. optimal economies of scale, and the life of the company (number of cycles the company has been active). The virtual transaction cost resulted in the expected model behavior based upon TCA theory.

Capacity decision processes were implemented using a sub-program that incorporated two aspects of the capacity upgrade decision: 1) increasing the magnitude of capacity, and 2) upgrading product ensuing from the advancing technological frontier. The capacity decision process exhibited expected behavior based upon extant production literature with production capacity increasing and decreasing as the consequence of demand in the next level of the SCN (supply chain network) as well as following the increasing economies of scale and periodic upgrades to keep up with the technological frontier.

The second verification technique engaged more than one person using a "structured walk-through of the program" (Law & Kelton, 2000, p. p. 270). One author conducted a line-by-line walk-through with a mathematician who had no formal education or experience with TCA or market governance theory in order to assess two aspects of the computer program. First, the program's relationship validity was assessed to ensure the program accurately reflected the relationships between key variables as predicted by theory. Then the walk-through scrutinized the validity of the equations to model specific relationships between the variables.

The third verification technique checked robustness or sensitivity of the simulation to a variety of input parameters. The model was run under a variety of settings to authenticate these key simulation processes:

1. TCA processes,
2. Node death and birth processes,
3. Capacity decision processes,
4. Robustness checks for the simulation model as a whole over a range of parameter settings.

In all cases, the model behaved in accordance expectations. Random demand fluctuation led to the most unstable model response once random deviance from the demand curve reached 10%. At this point, the model exhibited excessively high node mortality throughout the simulation, in turn leading to underserved markets, low collaboration index scores, and generally unstable model behavior. For the rest of the parameter settings the model proved highly robust and certainly sufficient to model any realistic supply chain scenarios