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Relationship Learning

With

Key Customers

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ABSTRACT

In this dissertation I argue that a group consciousness exists in organizations and even in relationships between organizations. This group consciousness is capable of thinking and learning. It guides actions, considers consequences, and interprets outcomes. A limitation of organizational learning theory is that it usually views the firm as an autonomous unit. Firms are not autonomous. They are imbedded in a myriad of interconnections where boundaries between firm and network are blurred. For inter-firm learning this distinction is critical. Focusing on the autonomous firm implicitly focuses research on what firms learn *from* each other. I take a relational approach to capture how firms learn *with* each other. My unit of analysis is the buyer-seller dyad and I call this relationship learning.

My empirical context is industrial buyer-seller relationships. Based on 26 interviews across 13 dyads in combination with the relevant literature, we defined relationship learning and developed a conceptual model (Selnes and Sallis 1999, p. 10). This dissertation refines and extends that work and offers an empirical test of the model. The central variables that drive relationship learning are:

1. Collaborative objectives.
2. Trust.
3. Environmental uncertainty.
4. Structural complexity.
5. Asset specificity.

These variables are generally considered to have a positive influence on relationship learning. However, the interaction of collaborative objectives and trust has a dark side. First, there is the risk of opportunism where the parties may take advantage of trust and exploit each other (Hamel 1991). Second, a high level of trust is usually accompanied by strong positive emotions and liking (Jones and George 1998). In such atmospheres it is unlikely that negative or critical information will be exchanged because it may endanger the good atmosphere of

the relationship, thus the benefit of constructive conflict is lost (Eisenhardt, Kahwajy, and Bourgeois 1997). Third, as commitment increases, value systems converge to the extent where the parties may develop a common identity (Gaertner, Dovidio, and Bachman 1996). This group-think (Janis 1989) may hinder the creative processes found in more heterogeneous groups. This means that as trust increases it will interact with collaborative objectives to actually reduce relationship learning.

To test the model I combined the multitrait-multimethod (MTMM) matrix approach (Campbell and Fiske 1959), modeled as a covariance structure (Jöreskog 1974), with Bagozzi and Edwards' (1998) general approach for representing constructs in organizational research through applying structural equation modeling at varying levels of aggregation. Stepwise aggregation provides justification for either aggregating, or not aggregating measures and constructs. I used a combination of structural equation modeling and two-stage least squares regression. The findings support what Heide and John (1994) contend, that key informants can in fact be used to measure particular inter-organizational constructs that are a collective property of a higher order construct.

The findings also support the positive direct effects of the variables, and more importantly, they support the negative interaction effect between collaborative objectives and trust. That the interaction comes out as a negative effect relative to relationship learning is, I believe, a surrogate-warning signal for isomorphism. Institutional theory holds that organizational adaptation is a function of isomorphic pressure (Martinez 1999). In lieu of a better plan, institutions conform to the status quo in their environments. Assuming relationships to be quasi-organizations (Håkansson and Snehota 1995), they are subject to institutional pressures. They gain legitimacy through playing the game as others do. Conformity supplants thinking!

ACKNOWLEDGEMENTS

When I am teaching strategy I try to help the students understand the role of chance in determining outcomes. Planning is good, but at times I wonder for what. Perhaps it helps people like me to think we control our fates. Was this doctorate part of a great plan? Certainly not mine. It started because I was lost in Suva, Fiji. My plan was to ask a pretty blonde girl for directions. The plan somehow got extended, and here I am. So the person who played the most pivotal role is the blonde girl, Charlotta. Her and our two sons, Max and Theo (both planned), are my inspiration in life.

The next pivotal turn came because of the worst instructor I ever had, whom I guess I should thank (but who remains nameless), because he made me so angry that I complained to the Dean, Fred Selnes. Somehow Fred saw through my anger and recognized a good candidate for an academic career. Fred is the person who opened the doors, got me the funding, and provided the ideas and encouragement. His drive and the countless hours of discussion are a large part of what got me here.

In the early stages I would sit in my office wondering, "What now, do I actually get paid to do this?" Then I met Line Lervik Olsen who shared my thoughts. We both expected that at any time someone would come in the door and say, "It's over now, you have to leave." Nobody ever did. Line and I helped each other (I hope) navigate the world of Lisrel.

Then my friend Håvard Hansen became my office-mate. When I would bring Max to the office Håvard was tremendous about taking care of him while I got some work done. Then I clued in that babies attract girls, so Håvard derived some side-benefits. In addition to the dissertation, Håvard helped me a lot with my teaching. He provided excellent advice (he's very talented), and is a great subject for discussion. When teaching methodology I advise my students to (unlike Håvard)

always order self-stick envelopes when sending out a large number of questionnaires. Håvard's tongue has a reputation of its own.

As things got going, other doctoral students became good friends. Ragnhild Silkoset would hold my hand after office parties and assure me I'm not insane. Bendik Samuelsen would attempt to explain structural equation modeling to me and make me feel insane. Arne-Morten Ulvnes would crawl bleary-eyed from his office after 24 hours straight of pondering transaction cost economics, and I would think he's insane. These three have such sharp intellects, much to the benefit of my dissertation.

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Lotta's family has been tremendous. They manage to make a strange man in a strange land feel at home. Between us I think we have kept a vineyard in business somewhere in France. They make life fun. My family has also been great. I'm not an easy person to live with and I've done my share of apparently crazy things. They stick by me no matter what. The distance may be great but they are always close in my heart.

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1. INTRODUCTION

“People do not get married or divorced, commit murder or suicide, or lay down their lives for freedom upon detailed cognitive analysis of the pros and cons of their actions (Zajonc 1980, p. 172).”

Firms, like people, do not always consider the ramifications of actions. To say they never consider ramifications, I believe, is wrong. In this dissertation I argue that a group consciousness exists in organizations and even in relationships between organizations. This group consciousness is capable of thinking and learning. It guides actions, considers consequences, and interprets outcomes. These postulates in themselves are not radical. There is an abundance of research on organizational learning where firms are thought to have theories of action (Argyris and Schön 1978), organizational knowledge structures (Lyles 1988), shared mental models (Senge 1990), or organizational cognition (Walsh 1995) to name a few. Whatever the label, these collective knowledge structures impose meaning on the organizational environment. They simplify interpretation of stimuli by furnishing a basis for evaluating information.

A limitation of organizational learning theory is that it usually views the firm as an autonomous unit. Firms are not autonomous. They are imbedded in a myriad of interconnections where boundaries between firm and network are blurred (Håkansson and Snehota 1995). For inter-firm learning this distinction is critical. Focusing on the autonomous firm implicitly focuses the research on what firms learn *from* each other. While perfectly valid, it provides a limited picture of firms learning *with* each other. My starting point, then, is to take a dyadic approach to inter-organizational learning to capture what transpires between firms. This may not capture the full complexity of the network, however, it will show the learning

in relationships while retaining the degree of simplicity needed for a meaningful analysis and interpretation of results within the limitations of current statistical techniques.

Focusing on learning between firms implies relationships can learn. How? An inter-organizational relationship is like an intangible, amorphous fog; it lacks form and shape. It exists in another dimension separate from the organizations that constitute it. Despite this, relationships have many attributes in common with organizations. Consider a marketing channel. In most cases, products reach the market through channels of intermediate actors. Raw materials are transformed, combined, distributed, and consumed. There are producers, wholesalers, retailers, and so on. Exchange between firms in marketing channels usually takes place in series over time, thus the relationships are durable. There is a mutually oriented interdependence of outcomes that none of the channel members can produce alone (Håkansson and Snehota 1995, p. 25), thus performance is a function of conscious vertical coordination between actors (Buvik and John 2000). To facilitate this, channel members adapt to each other and the entire channel adapts based on some common understanding and focus (Lukas, Hult, and Ferrell 1996). If the outcome is valuable and idiosyncratic, it may provide competitive advantage (Barney 1991). The relationships may be formally constituted through legal agreements (MacNeil 1980), or socially constituted through shared perceptions of their existence (Granovetter 1985). The relationships have a history and an anticipated future (Axelrod 1984), and they attain a unique identity separate from their members (Van de Ven 1976, p. 25). In sum, relationships are like quasi-organizations (Håkansson and Snehota 1995). Accepting this and accepting that organizations can learn, it is plausible, then, that relationships can learn as well.

Within the growing literature on inter-organizational learning is the contention that learning is taking place in or across relationships between organizations. It involves building common understandings at the intersection between actors (Lukas et al. 1996); it is reliant on intent, openness, and receptivity (Hamel 1991);

it is a function of values and processes (Larsson, Bengtsson, Henriksson, and Sparks 1998); and it is a valuable resource that can lead to superior performance (Dyer and Singh 1998). What lacks is a formalized, empirically tested definition of a construct of inter-organizational learning. Within the cognitive tradition, Selnes and Sallis (1999) followed Lukas, Hult, and Ferrell's (1996) suggestion to develop a relationship learning construct in line with the process definition of the market orientation construct (e.g. Kohli and Jaworski 1990), combined with Huber's (1991) argumentation that organizational learning affects the potential for behavior change. My aim here is to further develop the definition of relationship learning and empirically test it.

To meaningfully test the relationship learning construct it need be imbedded in a context. Strictly speaking, firms can learn *from* each other across relationships, however, learning *with* each other presupposes some degree of collaborative objectives. Take relationship memory as an example. Unlike organizational memory, relationship memory spans the boundaries of organizations. The parties develop idiosyncratic relationship memories that capture the common history of the relationship. For example, in joint R&D projects disseminated information becomes imbedded (memorized) at different places in the relationship like individuals, databases, documents, and so on. If an individual in one organization does not possess a particular piece of information generated in the relationship, but knows it exists in the other organization, they can access (remember) it across the relationship. In this way the learning (and remembering) has elements that are both internal and external to the respective organizations, yet are captured within the context of the relationship. Without the objective to collaborate, relational parties suffer amnesia due to a lack of access to stored knowledge across the relationship.

In organizations, managers presumably have the authority to impose learning strategies. They can at least strive to create an environment conducive to learning. This is not the case in relationships. Collaboration is contingent upon a mutual orientation between parties. Autonomous firms cannot mandate mutuality and

collaborative objectives, thus they cannot impose relationship learning on another firm. This is a bit like the adage, “You can lead a horse to water, but you can’t make it drink.” A powerful firm can impose its will over a weaker trading partner (lead it to water), however, in lieu of the mutual objective to collaborate and learn together, it cannot make the weaker partner drink.

Consistent with the literature on learning in inter-organizational relationships (e.g. Dodgson 1993b; Hamel 1991), is the argument that collaboration enhances learning. Powell, Koput, and Smith-Doerr (1996) identified two perspectives on collaboration and learning.

The classical economic perspective on collaboration, largely dominated by transaction cost economics, involves reconciling risk versus return. Reliance on external partners involves risk primarily because actors are assumed to be opportunistic. When environmental uncertainty is high and investments in nontransferable specific assets are high, risk is high. Transaction cost economics suggests that in such situations the most efficient way to govern transactions is to internalize them within the organization. Current transaction cost thinking expands the original discrete boundary choice between markets and hierarchies to include hybrid forms like collaboration where direct ownership is substituted with formal (e.g. contracts) and informal (e.g. norms of information sharing and trust) control mechanisms in relationships (Rindfleisch and Heide 1997).

The transaction cost approach has at least two problems related to collaboration and relationship learning. First, the classical rigid governance form envisaged in transaction cost economics is not very conducive to learning because formal agreements are static, whereas learning is dynamic (Powell et al. 1996). Second, it focuses attention on individual organizations that learn from each other in a competitive race to learn (Larsson, Bengtsson, Henriksson, and Sparks 1998). For example, Hamel (1991) laid the groundwork for a theory of inter-organizational learning. He proposed that *intent* (collaborative versus competitive), *receptivity*

(ability to absorb knowledge), and *transparency* (openness with information) are key determinants of inter-organizational learning. He warns, however, that failure to out-learn one's partner could render a firm first dependent, then redundant within the relationship. This suggests a strategy of competitive intent with high receptivity but low transparency. Such a strategy would inhibit the relationship and undermine collaborative learning, and despite the inter-organizational setting it places emphasis on the individual firm.

An alternative perspective is found in the economic sociology literature, specifically in network theory (e.g. Granovetter 1985). A central thesis of network theory is that economic behavior is imbedded in social relations. Seen this way, collaboration and learning are social construction processes (Powell et al. 1996). Relationships and collaboration emerge through exchange between parties (Johanson and Mattsson 1987), and as a result of the social exchange the parties may come to trust each other (Håkansson and Johanson 1988). Trust is the antithesis of opportunism and is an important concept in the network approach (Johanson and Mattsson 1987). Effective learning between partners depends on a climate of trust ingrained in organizational modes of behavior, and supported by the belief in the mutual benefits of collaboration throughout the organization (Dodgson 1993b).

At face value, the network theory approach to collaboration fits well with the concept of relationship learning. Collaboration, trust, and relationship learning are intuitively attractive as positive reinforcing forces in cycles of learning. Doz (1996) proposed that a set of initial conditions either facilitated or hampered inter-firm learning in alliances. As alliances evolve the parties go through cycles of evaluation, revision of the initial conditions, and learning. The alliance cycles will either spiral up towards success or down towards failure. Evaluation either leads to growing trust or growing suspicions. Suspicion will undermine the potential for success, while trust will support it. Trust, then, supports relationship learning and collaboration, however, what of the cost?

A manifestation of trust is adaptation (Hallén, Johansen, and Seyed-Mohamed 1991). In the course of a relationship the parties demonstrate trust as they adapt to each other and influence each other toward adaptation. The systems strive to fit each other and isomorphism sets in, exposing the dark side of trust. The once separate systems become too homogenous. Neither part offers unique perspectives or novel ideas because they are the same. Trust breeds complacency. Neither party questions the other and they get locked into patterns of doing things. In sum, they act without thinking. Assuming thinking to be an integral part of learning, trust carries a potentially high cost.

1.1 RESEARCH OBJECTIVES AND CONTRIBUTION

This research is in response to criticism that organizational learning theory focuses too much on the individual firm locked in a learning race (Larsson, Bengtsson, Henriksson, and Sparks 1998). Thus far I have established my fundamental article of faith: inter-organizational relationships are cognitive entities capable of learning. My focus is on dyadic learning processes. The setting is the vertical relationship between buyers and sellers in the marketing channel. My premise is that relationship learning is distinct from organizational learning with respect to mutuality, which entails such things as relationship memory and collaborative objectives. Trust plays a dual role by both facilitating and impeding relationship learning.

I rely heavily on inter-organizational theory (e.g. transaction cost economics, network theory, resource-based theory, and agency theory) for describing relationship formation and the motivation for relationship learning. Organizational learning theory underpins development of the relationship learning construct.

My objectives are to (1) further develop the relationship learning construct, (2) relate it to existing inter-organizational theory, (3) operationalize the constructs as perceptual measures, and (4) conduct an empirical test of the model. Through this

my theoretical contribution is to empirically demonstrate that relationships can indeed learn and that trust carries a potentially high cost that is largely unrecognized in the extant literature. I highlight the hazard of isomorphism and the complacency it breeds.

The practical implications are tightly coupled to current issues in marketing. Emphasis on tighter more responsive vertical coordination in marketing channels is increasing. Trends like relationship marketing and market orientation underscore the importance of inter-organizational research in learning. The increasingly popular oxymoron “mass customization” in the relationship marketing literature (e.g. Sheth and Parvatiyar 2000) is contingent upon learning about every customer’s needs and preferences. In the market orientation literature there is a direct link to relationship learning. Slater and Narver (1995) argue that a market orientation provides strong norms for learning from customers and competitors, however, appropriate organizational structures and processes for higher-order learning must compliment it. They refer directly to the organizational learning literature, specifically Argyris' (1977) double-loop learning.

In the organizational learning literature it is widely accepted that learning takes place on different levels related to the magnitude of change in the collective knowledge structures. Argyris and Schön (1978; 1996) described levels of learning

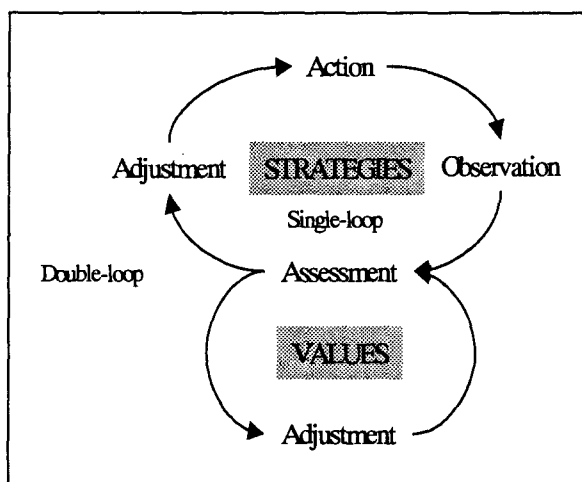


Figure 1.1, Learning Loops

as learning loops. Adjusting strategies in response to observed outcomes while the organization carries on with its present policies or achieving its present objectives is single-loop learning. Double-loop learning occurs when adjustment involves the modification of an organization’s underlying norms, policies, and

objectives.

The magnitude or level of learning is increasingly important. The half-life of useable market knowledge is shrinking in the face of compressed life cycles, fragmenting markets, proliferating media and distribution channels (Day 1994b), and hypercompetition (Volberda 1996), thus firms need to learn faster and be innovative. An avenue to this is higher-level learning. McKee (1992, p. 235) observed that product innovation requires two types of learning for two types of product innovation. *Incremental innovation* like product adaptation requires very focused expertise and *incremental learning*, while *generative innovation* like developing new products requires more radical thinking and *generative learning*. March (1991) captured this thinking in his exploitation and exploration dichotomy. Exploitation is about extending existing competencies within a familiar frame of reference, whereas exploration is about experimenting with new alternatives that challenge the status quo way of thinking.

Perhaps the best way to challenge the status quo is to contrast it with alternatives. On one hand, organizations may function well in an isolated environment free from disruptive disturbances. However, for long-term viability external stimuli are imperative. Sources of innovation do not reside exclusively within firms (Powell, Koput, and Smith-Doerr 1996) and novel ideas often come from outside firm boundaries (Cohen and Levinthal 1990). Managed properly, relationship learning should provide alternative perspectives that generate novel ideas. It can stimulate the firm to reconsider current practices and enable the firm to achieve higher-order learning (Lyles 1988). In sum, relationship learning may be a valuable resource for competitive advantage in so far as it contributes to developing non-substitutable, fast learning, difficult to imitate links between collaborating parties (Dyer and Singh 1998).

1.2 OUTLINE OF THE DISSERTATION

The dissertation is organized as follows. I spend considerable effort in chapter two explaining and positioning the relationship learning definition. It lies at the heart of the research and represents the single greatest theoretical contribution of the research. In chapter three I argue for the variables in the relationship learning model and offer hypotheses as to their effects. This is based on the qualitative portion of the study. Chapter four is divided between describing the qualitative methodology used in developing the model and the quantitative methodology used for testing it. I entirely devote chapter five to measure validation because it represents an important methodological contribution of the research. Chapter six presents the analysis and results of the hypothesis test. The discussion in chapter seven summarizes the theoretical and methodological contributions of the research, then I offer practical implications and ideas for future research.

In the appendices I show the interview guide used in the qualitative research, and the questionnaire used to collect the quantitative data. I also show my SPSS syntax for exporting the data to Preliis as well as the two-stage least squares syntax. This is followed by the Preliis syntax and Lisrel syntax used to validate the measurement model and structural model. Only final models are shown. While on one hand this may seem excessive, it leaves a clear trail for the validation of my research as well as for replicating the procedures.

2. RELATIONSHIP LEARNING DEFINED

“Physical concepts are free creations of the human mind, and are not, however it may seem, uniquely determined by the external world. In our endeavor to understand reality we are somewhat like a man trying to understand the mechanics of a closed watch. He sees the face and the moving hands, even hears it tick, but he has no way of opening the case. If he is ingenious he may form some picture of a mechanism which could be responsible for all the things he observes, but he may never be quite sure his picture is the only one which could explain his observations. He will never be able to compare his picture with the real mechanism and he cannot even imagine the possibility of the meaning of such a comparison (Einstein and Infeld 1938, p. 31).”

For me, the essence of what Einstein and Infeld are saying in the opening citation is that we all have a unique perspective on reality. This has bearing on the following discussion of how to define relationship learning. Any research, consciously or unconsciously, is grounded in the basic assumptions of the researcher (cf. Zaltman, Pinson, and Angelmar 1973, p. 10). Despite our efforts for objectivity in science, we are intrinsically subjective beings. Some researchers strive to overcome this by holding as closely as possible to empirical observability. In effect, they restrict their interpretation of a closed watch to what they observe without speculating as to the mechanism. However, as Hunt observes, “Restricting ‘knowing’ to ‘knowing with certainty’ is not just being prudently conservative or cautious. Rather, because it denies even the possibility that we can learn or ‘know’ on the grounds of accumulated experience, such a restriction amounts to nothing less than nihilism (1993, p. 83).”

Based on the field interviews and a review of the relevant literature, in this chapter I argue for and propose a definition of relationship learning. My starting point is previous work by Selnes and Sallis (1999). My intent here is to expand the discussion and in so doing hopefully sharpen the argumentation. My rationale is that while there is a plethora of work on organizational learning theory, contributions to inter-organizational learning theory are somewhat scant. Beyond the “it has not yet been done” argument, I believe this to be a worthy endeavor because of key differences between the constructs. Relationship learning is unique to organizational learning because of the mutuality element it relies on collaborative objectives, information processing across organizational boundaries, and relationship memory that is a function of the interaction between parties.

I begin by explaining how I believe learning takes place in and between organizations. I then describe two dichotomies that I perceive in the literature: the behavioral-cognitive dichotomy (cf. Fiol and Lyles 1985, p. 806; Huber 1991, p. 89; Shrivastava 1983, p. 8) and the values-process dichotomy (e.g. Hamel 1991; Lukas, Hult, and Ferrell 1996). In so doing I position this research. Finally, I describe the elements that together constitute the definition of relationship learning.

2.1 HOW DO ORGANIZATIONS LEARN?

In the early 1960s the metaphor of the organization as an organism in symbiotic existence with its environment gained popularity as an alternative perspective to the formalized mechanistic view that served management. (e.g. Burns and Stalker 1961; Lawrence and Lorsch 1967; Woodward 1965). In the mechanistic view, knowledge and thinking was concentrated at the top of the firm, and communication flowed from the top down as instructions for specialized workers in a clearly defined hierarchy. In the organic view, when problems cannot be broken down by management and distributed to specialist roles in the hierarchy, individuals must think for themselves in light of the tasks of the firm as a whole. Rather than management being the brain of the organization, the entire

organization is the brain. In such an organic structure, as a group, individuals endow an organization with its culture, behaviors, goals, and other characteristics not attributable to any one individual. While it is arguable that the organization is nothing without the people, it is also plausible that the group synergy is greater than the sum of the individuals (Powell et al. 1996, p. 116). Herein lies the collective consciousness of the organization.

Accepting the possibility of group consciousness infers the viability of organizational learning (e.g. Argyris and Schön 1978; Cyert and March 1963; Hedberg 1981). Consider the behavior of firms. They consciously adjust when they enter or exit a market, restructure, or change operating procedures. Assuming the adjustments are not by random chance, they must be based on previously learned knowledge. It is arguable that one or a very few people who manage the organization decide upon these changes, therefore, it is not the organization that learns but those few people. However, from a broader perspective, the decision-makers receive much of their stimuli through channels in the organization. These channels learn what information to pass on and what information to filter out, and which decisions to take at their particular level and which decisions to refer further up the channel. As the channels become long and numerous, as characterized by large organizations, and decision pressure rises in unstable environments, it becomes increasingly important that information be properly filtered and acted on. It is logical that the leader of a large organization cannot possibly make every decision that takes place within the organization. The position of this dissertation is that even in a two-person organization, as soon as either person begins to act out of consideration for the other person's position within the organization, a collective consciousness is born and organizational learning is possible.

Symbiosis is the mutually beneficial coexistence of two or more organisms (Sykes 1978, p. 923). Many if not all organizations exist symbiotically in relationships with other organizations (cf. Håkansson and Johanson 1988; Starbuck 1992; Thorelli 1986). Broadly, an inter-organizational relationship is a mutual

orientation of at least two organizations toward each other (Johanson and Mattsson 1987), wherein interaction norms are established. If norms are shared expectations about behavior (Heide and John 1992, p. 34), then a core element of relational exchange is a norm of reciprocity (Oliver 1990, p. 244). This implies mutual knowledge about each other, awareness of each other's interests, and willingness to pay attention to them. It also means that organizational actions are constrained and determined by relationships with other organizations (Granovetter 1985). Therefore, just like with the collective consciousness in organizations, as soon as there are norms of reciprocity in an inter-organizational relationship, a collective consciousness between organizations is born and relationship learning is possible.

2.2 THE BEHAVIORAL-COGNITIVE DICHOTOMY

In simplistic terms, behaviorists see the learning entity as a black box into which they do not peer. Their focus is to examine the change in probabilities of certain behaviors (responses) given certain stimuli. Behaviorist theories have in many ways been eclipsed by more recent cognitive theories that consider the contents of the black box. Cognitive theorists take into account information processing and problem solving rooted in collective knowledge structures. It is a misnomer, however, to consider the cognitive approach as superior to, or as a replacement for behavioral theories, rather, the two approaches while distinct in many ways are arguably complementary (cf. Inkpen and Crossan 1995; Kim 1993; Lukas et al. 1996).

As will come clear, my position with this research reflects the cognitive tradition and I favor a process definition. The following discussion is relevant because I see the alternatives, behaviorism and values, as greatly contributing to my understanding of relationship learning.

2.2.1 BEHAVIORAL THEORIES

Levitt and March define organizational learning as, “Encoding inferences from history into routines that guide behavior (1988, p. 320).” Their definition is premised on three fundamentals:

- Action stems from legitimacy rather than intention or consideration of consequences.
- Action is based on history rather than anticipation of the future.
- Action is target oriented.

From these fundamentals it can be inferred that organizations only think to the extent that they search existing routines to determine the most legitimate action. Search for existing routines is both a function of available options and the ability to identify them as options. This, in turn, is a function of how often a routine is used, how recently it was used, and its proximity to the searcher. Unused routines or routines distant to the searcher are not very accessible and risk being forgotten. When there is no routine, organizations revert to trial-and-error experimentation (Levitt and March 1988, p. 328).

As uncertainty in the organizational environment grows, the likelihood of not finding a match will also grow. In such an environment organizations must spend a great deal of time in trial and error experimentation. It also means that because actions are directed responses to specific stimuli, without a trigger there would be no action or thinking. The ramifications are that organizations are backward looking; they do not consider hypothetical reactions to disturbances; and they do not possess the capacity to consider, “What if ...?”

I find it tough to imagine such a complete lack of conjecture. In a collective sense, if the group does not know what to do it simply experiments to find a successful routine. Lacking the ability of conjecture means that any untried action is presumably as likely as any other. What then is the purpose of strategy? Of course

this is an exaggeration and behaviorists would claim that firms will continually try to adaptively improve. Nevertheless, I believe that the behavioral approach tells only part of the story and I contend that so long as there is collective strategy in organizations there is at least a shadow of conjecture and thus cognition.

A clue to the behaviorist penchant for history dependent adaptation may be found in the seminal work of Cyert and March (1963; 1992). In developing their behavioral theory of the firm they state that one of their major research commitments is to, “*Link models of the firm as closely as possible to empirical observations of both the decision output and the process structure of actual business organizations (1992, p. 2).*” A directly observable model is the paramount goal of objective science. Their definition of organizational learning reflects this:

“Organizations learn: to assume that organizations go through the same processes of learning as do individual human beings seems unnecessarily naive, but organizations exhibit (as do other social institutions) adaptive behavior over time (Cyert and March 1963, p. 171).”

Observable behavioral change, however, is arguably only a manifestation of learning rather than learning itself. For instance, through learning, an entity may not change its behavior because it learns that the optimal course of action is inaction. There is no observable change, and therefore no observable learning, however, learning has taken place.

Cyert and March assume an adaptive system to have the following properties:

1. “There exist a number of states of the system. At any point in time, the system in some sense “prefers” some of these states to others.

2. There exists an external source of disturbance or shock to the system. These shocks cannot be controlled.
3. There exists a number of decision variables internal to the system. These variables are manipulated according to some decision rules.
4. Each combination of external shocks and decision variables in the system changes the state of the system. Thus, given an existing state, an external shock, and a decision, the next state is determined.
5. Any decision rule that leads to a preferred state at one point is more likely to be used in the future than it was in the past; any decision rule that leads to a non-preferred state at one point is less likely to be used in the future than it was in the past (1992, pp. 117-118).”

This stepwise conceptualization of organizational learning conjures a rational decision-tree-like process. While valid and relevant, it captures only part of the learning phenomenon. It lacks a dimension for conjecture by relying solely on history, and it is tied to observability thus denying the option of inaction.

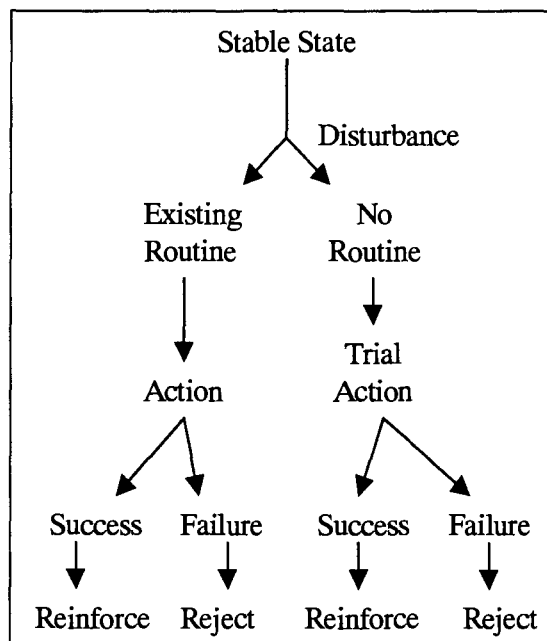


Figure 2.1, Decision Tree

2.2.2 COGNITIVE THEORIES

Cognitive theories dominate the organizational learning field, as evidenced by the rich diversity of literature. Cognitive theorists generally agree that an entity learns through processing information that leads to a change in the state of knowledge.

Responses are not simply a matter of probabilities, but rather, they are a function of information search (both in memory and externally) and reasoning (Shrivastava 1983, p. 8). Beyond information processing they disagree. Cognitive theorists striving for objectivity accept that learning involves cognitive change, however, they define organizational learning in such a way as to require behavioral change and thus observability (e.g. Argyris and Schön 1978; Dodgson 1993a; Senge 1990). For example, Argyris and Schön (1996) define organizational learning as:

“Organizational learning occurs when individuals within an organization experience a problematic situation and inquire into it on the organization’s behalf. They experience a surprising mismatch between expected and actual results of action and respond to that mismatch through a process of thought and further action that leads them to modify their images of the organization or their understandings of organizational phenomena and to restructure their activities so as to bring outcomes and expectations into line, thereby changing organizational theory-in-use (1996, p. 16).”

Again, observable change is arguably only a manifestation of learning rather than learning itself. Learning can take place and not precipitate any observable behavior. Limiting a learning definition to observable, quantifiable phenomena greatly inhibits its scope.

Organizational learning researchers who accept a greater degree of subjectivity and distance themselves from strict observability recognize that learning can affect the potential to change behavior (e.g. Huber 1991, p. 89; Huber 1996, p. 822; Sinkula 1994, p. 36; Slater and Narver 1995, p. 63). In other words, if an organization learns something, it may choose not to change behavior based on the new knowledge. For example, Slater and Narver define organizational learning as:

“At its most basic level, organizational learning is the development of new knowledge or insights that have the potential to influence behavior (1995, p. 63).”

This definition reflects a cognitive approach and allows for the *potential* change of behavior, thus not requiring observable behavior change.

2.2.3 RECONCILING BEHAVIOR AND COGNITION

Fiol and Lyles define organizational adaptation as, “The ability to make incremental adjustments as a result of environmental changes, goal structure changes, or other changes (1985, p. 811).” and organizational learning as, “The development of insights, knowledge, and associations between past actions, the effectiveness of those actions, and future actions.” By so doing they attempt to resolve the behavioral-cognitive debate by defining behavioral learning as adaptation and cognitive learning as possessing the ability for conjecture. In other words, organizational learning transcends time. Unconscious adaptation, as it were, is not organizational learning because it lacks the past-future association. Therefore, Fiol and Lyles (1985) reject the premise of the behaviorist approach to organizational learning by re-labeling it as organizational adaptation.

My difficulty with accepting Fiol and Lyles' (1985) reasoning is that when an organization detects some sort of environmental change and makes a conscious adjustment, be it incremental or not, it is arguable that the organization is learning at a shallow level rather than a deep level (cf. Argyris and Schön 1996; Slater and Narver 1994). Arguably, Fiol and Lyles' (1985) definition of adaptation is simply single-loop learning, that is, changing strategies or actions without revising the underlying values (Argyris and Schön 1996, p. 21). Fiol and Lyles, however, state that, “Within the category of cognition development it is possible to identify a hierarchy based on the level of insight and association building. Two general levels are referred to as lower- and higher-level learning (1985, p. 807).” Thus, they do not consider behavioral learning as associated with lower level learning, it

is a separate construct, and the way they resolve the debate is to add another dimension.

Fiol and Lyles (1985) liberally quote and concur with Hedberg (1981) in developing their definitions, yet even they point out the ambiguity in Hedberg's reasoning when he postulates that in one form of learning, "Behavior requires no understanding (1985, p. 805)." Hedberg states that, "It is misleading to equate learning with adaptation (1981, p. 3)," which implies that his opinion corresponds with that of Fiol and Lyles (1985). Yet in the very next sentence he says, "Organizational learning includes both the processes by which organizations adjust themselves defensively to reality and the processes by which knowledge is used offensively to improve the fits between organizations and their environments (1981, p. 3)." He does not clarify the difference between adaptation and adjustment, although it may be inferred that adjustment involves a greater degree of conscious thought than adaptation. This, however, begs the question of when does adaptation become adjustment?

Mahoney (1995) attempts to synthesize resources-based theory with learning theories (both cognitive and behavioral) based on the premise that, "Core competencies are a function of the tacit understanding, skills, and resources that a firm accumulates over time (1995, p. 92)." Organizational learning is thus an avenue to develop key resources, which in turn contribute to sustainable competitive advantage. He loosely follows the definition that organizational learning is a process whereby shared understandings change, although he borrows from many perspectives across the cognitive-behavioral dichotomy, therefore, he is not committed to any specific position. Rather, he sees the positions as complementary.

Inkpen and Crossan (1995) also see cognitive and behavioral learning as complementary. They develop a conceptual framework for studying organizational learning and apply it to learning in joint ventures. They employ it at the individual,

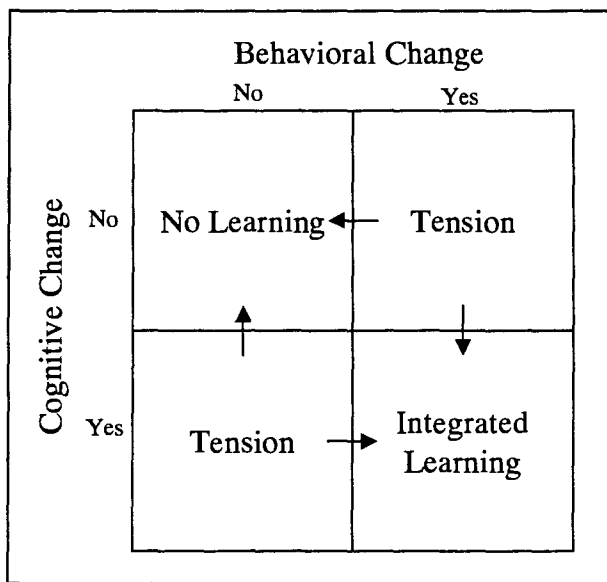


Figure 2.2, Behavioral and Cognitive Learning
(Adapted from Inkpen and Crossan 1995, p. 599)

group, and organizational levels, although their reasoning does not exclude the inter-organizational level as well. The axes dimensions on their framework are behavioral change (observable) and cognitive change (unobservable). Rather than consider the two in strict opposition, however, they argue that, "Cognition and behavior are so tightly intertwined that it is

counter-productive to define learning as change in either one or the other. ... Different types of learning will depend on whether there is cognitive and/or behavioral change (Inkpen and Crossan 1995, p. 599)." This implies that learning can involve adjusting only behavior, only cognition, or both. However, when only one is adjusted, cognitive dissonance arises because of the tension between the mismatch of cognition and behavior, therefore, ultimately they will both be adjusted to attain a balance.

My position is that behavioral and cognitive learning are simply different manifestations of the same phenomenon. While there is no clear consensus on a definition of learning, most writers agree that there are both cognitive and behavioral elements (Child and Faulkner 1998, p. 283). Although the behavioral approach is somewhat distinct from the cognitive approach, it is complimentary rather than contradictory. When it comes to defining relationship learning I favor the cognitive tradition. Placing too much emphasis on observability risks greatly constricting a learning definition. I choose to risk measurement error at the gain of

capturing a more realistic glimpse of the phenomenon. I judge this as preferable to knowingly measuring only a part of it.

2.3 THE VALUES-PROCESS DICHOTOMY

Like market orientation, relationship learning can be defined as either a process or a set of values. Kohli and Jaworski (1990) and Narver and Slater (1990) provided the first attempts to define market orientation as a process including information acquisition, dissemination, and organizational responsiveness. Deshpandé, Farley, and Webster (1993) followed by defining it as a set of values that put organizational stakeholders first.

2.3.1 RELATIONSHIP LEARNING VALUES

A value is an enduring belief that some mode of conduct or end-state is preferable to its opposite, and it guides actions, attitudes, judgments, and comparisons in specific situations (Rokeach 1973). Given its guiding function, a value will set the stage for how something will be approached.

Hamel (1991) provided the foundation for a considerable amount of the recent work on inter-organizational learning. He proposed a set of key determinants of inter-organizational learning: *intent* (collaborative versus competitive), *receptivity* (ability to absorb knowledge), and *transparency* (openness with information).

Despite that he states he is providing insight into the process of knowledge acquisition, my view is that Hamel's determinants are largely a function of values in so far as his key determinants describe approaches to modes of conduct.

Hamel's research setting encompassed relationships between American and Japanese automobile manufactures. Intent, receptivity, and transparency in the relationships reflect values captured in racism, egoism, nationalism, and so on. He quotes a Japanese manager as saying, "We had the attitude of students, and our Western partners the attitude of teachers (1991, p. 96)." Thus, the Japanese receptivity took advantage of American openness. The Japanese intent was to learn, the American intent (though most likely not conscious) was to teach.

2.3.2 RELATIONSHIP LEARNING PROCESSES

Lukas, Hult, and Ferrell (1996) develop a theoretical model of the antecedents and consequences of organizational learning in marketing channels. They propose that while organizational learning occurs within individual organizations, it is a function of the interaction between channel members. They discuss developing a relationship learning construct in line with the market orientation construct (e.g. Kohli and Jaworski 1990), consistent with Sinkula (1994) and Slater and Narver (1995), encompassing information acquisition, dissemination, and shared interpretation. Their fundamental proposition is that organizational learning in marketing channels is a *process* of understanding and gaining new insights.

Many researchers agree that organizational learning involves some kind of information processing (e.g. Day 1994a; Lukas et al. 1996; Shrivastava 1983; Sinkula 1994; Slater and Narver 1995). Huber (1991) suggests four distinct organizational learning constructs:

“Knowledge acquisition is the process by which knowledge is obtained. *Information distribution* is the process by which information from different sources is shared and thereby leads to new information or understanding. *Information interpretation* is the process by which distributed information is given one or more commonly understood interpretations. *Organizational memory* is the means by which knowledge is stored for future use (1991, p. 90).”

The common thread through the constructs is their process nature, and collectively they are referred to as information processing (Sinkula, Baker, and Noordewier 1997, p. 308). The information processing perspective assumes that “An entity learns if, through its processing of information, the range or likelihood of its potential behaviors is changed (Huber 1991, p. 89).” Information processing in relationships is about reducing ambiguity between multiple, often conflicting interpretations.

2.3.3 RECONCILING VALUES AND PROCESSES

Clearly, relationship learning can be defined as either values or processes. They are intrinsically intertwined so that both impact relationship learning. A distinction that can be made is that values are at the root of attitudes. An attitude is held by an entity and is directed at something (Fishbein 1980), while the process is more a function of the interplay between the entities. Because my focus is on the interactional dyadic dimensions of relationship learning I will concentrate on processes. A weakness in this is that I measure the magnitude of the process, but this says nothing directly about the quality. Alternatively, I could attempt to measure outcomes and thus capture more of the quality element. Outcomes, however, often occur substantially distant in time from the learning episode and are thus attributed to spurious relationships with other events (Levitt and March 1988, p. 325).

2.4 RELATIONSHIP LEARNING: A COGNITIVE PROCESS

I treat information processing in a relationship as encompassing information sharing, mutual interpretation, and memory integration. In the relationship context information sharing captures both elements of acquisition and distribution.

2.4.1 INFORMATION SHARING

Information at its most primary level is a stimulus that could cause a shift in expectations or evaluations (Driver and Streufert 1966, p. 272). For organizations the stimulus can be internal like detecting errors (Argyris and Schön 1978, p. 2), or external like feedback from other organizations (Levitt and March 1988, p. 319) or environmental changes (Fiol and Lyles 1985, p. 811; Hedberg 1981, p. 9). In the context of relationship learning I limit myself to information sharing between two organizations. Other information may impact relationship learning, however, it is exogenous to the construct. That is, it influences the process but is not directly influenced by the process (von Krogh and Roos 1996, p. 125).

Information sharing implies some minimal degree of collaborative effort from both parties, distinguishing it from information acquisition that entails only the effort of one party. Respondents in the field interviews saw it as impacting learning.

“Mostly we learn through communication. This is exactly the point we are trying to make with our customers. ... We want them to refer to us when they are developing new products or if they are making changes. We are trying to find contact points, regional and worldwide who will work with us. ... This is something we are really working with, that is, to gain a mutual understanding with our customers for how we operate.”

The amount and type of information will influence relationship learning, as will the media and the way the information flow is organized. Organizations can suffer information under-load or overload, and similar to just-in-time delivery, they need the right information at the right place at the right time.

The type of information will impact its transfer because information often contains knowledge. Two types of knowledge are widely recognized: migratory and tacit. Relative to tacit knowledge, migratory knowledge can relatively easily and quickly be moved because it can be articulated and encoded in a formula, a design, a manual, a book, or a piece of machinery, or because one person is capable of knowing it (Badaracco 1991, p. 35). So long as you have access to the manual or the expert, you have the knowledge. Tacit knowledge is much more difficult to transfer because it is captured in the norms, attitudes, information flows, and decision processes of particular relationships among individuals and groups (Badaracco 1991, p. 79).

Media refers to how information is transferred and has two dimensions: the variety of cues it can provide and the rapidity of feedback (Daft and Huber 1987). Cues are more likely related to interpretation, while rapidity will affect the amount of information sharing.

Information flow refers to how the relationship between parties is organized. The most relevant dimension is how many contact points exist between the two firms. For example, in the specialty chemicals industry there were several contact points at all levels of the organization. In most cases information was transferred between the two relevant people who were involved. That is, the person who needed the information in one company and the person who held the information in the other company interacted directly. By contrast, in the farmed salmon industry information flow was usually funneled through sales people and purchasing agents. There was very little interaction between firms across other functions. This is likely related to product complexity and the type of information necessitated in the exchange (Metcalf, Frear, and Krishnan 1990, p. 29). In the farmed salmon industry the product is relatively standardized, thus the sales and purchasing people have the basic knowledge needed for the meaningful transfer of information. In the specialty chemicals industry, however, the products are complex and customized such that sales and purchasing people may lack the knowledge for a meaningful dialogue that is more relevant between, for example, two chemical engineers.

2.4.2 INTERPRETATION

Interpretation is the process of giving meaning to information (Daft and Weick 1984). In relationships every message is in actuality two messages, the sender's and the receiver's (MacNeil 1980, p. 9). Necessarily, there must be some degree of mutual interpretation for relationship learning to occur.

Ring and Van De Ven (1994) suggest that in the developmental processes of inter-organizational relationships the parties informally and formally negotiate their joint expectations. They commit to the relationship through formal agreements and psychological contracts, and they execute their commitments. Throughout the cyclical process they continually assess the efficiency and equity of the relationship. Crucial to the success of the relationship process is sense making. Through sense making the parties clarify their identity in relation to each other and

if the relationship is successful they gradually build mutual interpretations. Over time, personal relationships supplement formal relationships, psychological contracts supplement formal contracts, and formal contracts begin to mirror implicit understandings.

Contact across the relationship is the primary mechanism for building mutual interpretation. In the field interviews we found that most interactions between the two parties were related to solving some sort of operational problem, and thus were addressed in operational kinds of meetings or simply on the telephone. Hedberg (1981, p. 16) concurs with this when he identifies how organizational learning is triggered. He suggests that while people and opportunities can trigger organizational learning, it is more typically triggered by problems.

There were also many examples where the parties met face-to-face at organized information-forums, such as customer visits and trade shows, in order to build an understanding for each other. Cross-functional teams in customer visit programs have been suggested as a mechanism for creating learning arenas (McQuarrie 1993, p. 23). Meeting face-to-face is important for the level of information ambiguity because media vary in their capability to convey meaning, therefore, as ambiguity increases it demands richer media (Wathne, Roos, and von Krogh 1996, p. 62).

2.4.3 MEMORY INTEGRATION

“In its most basic sense, organizational memory refers to stored information from the organization’s history that can be brought to bear on present decisions (Walsh and Ungson 1991, p. 61).” I extrapolate this concept to relationships. This presupposes that the organizations in a relationship build a common interpretation of information that is then stored in memory, and that the information is retrievable at a later point in time (McKee 1992, p. 233). Common interpretation is fundamental to relationship memory because information is often context specific,

therefore, retrieving it out of context may render it unrecognizable or unusable (Starbuck 1992, p. 722).

Memory is retained at the individual, organizational, and relational level. Individuals retain information based on their direct experiences and observations, stored in their memories as cognition (Lee, Courtney, and O'Keefe 1992, p. 27; Walsh 1995, p. 281). Unlike individual memory, organizational and relationship memory is decentralized (Moorman and Miner 1997, p. 92), and unlike organizational memory, relationship memory spans the boundaries of organizations. Relationship memories are captured in the shared beliefs, values, assumptions, norms, and behaviors that transcend the organizational boundaries and are captured in the relationship. It transcends personnel turnover and the passage of time through systems of socialization and control (Levitt and March 1988, p. 326).

Lukas, Hult, and Ferrell (1996) divide organizational memory into four "bins" that they label: physical capital, organizational formations, social capital, and organizational culture. Accepting that relationships are formally (MacNeil 1980) and socially (Granovetter 1985) constituted, that they have histories and futures (Axelrod 1984), and that they become quasi-organizations (Håkansson and Snehota 1995), allows me to extrapolate Lukas et al.'s (1996) conceptualization to the relational level.

The physical capital bin represents retention in computers, documents, individuals, and so on that transcend organizational boundaries (Håkansson and Johanson 1988, p. 369). It is the easiest to access and understand, and is thus very useful in facilitating decisions and aiding in problem solving (Quinn, Anderson, and Finkelstein 1996, p. 74). For example, in joint R&D projects disseminated information becomes imbedded (memorized) at different places in the relationship like individuals, databases, documents, and so on. If an individual in one organization does not possess a particular piece of information generated in the

relationship, but they know it exists in the other organization, they can access (remember) it across the relationship. In this way the learning (and remembering) has elements that are both internal and external to the respective organizations, yet are captured within the context of the relationship. From the field interviews, it came through very clearly that this bin is a function of input quality (memorization). Input quality relates to routines for input and information dissemination. In one organization there was no incentive or encouragement to input information into electronic databases. On the sales staff only one person had developed a database and it was highly personalized, thus it was not openly accessible to other sales staff. This type of dysfunctional memory would propagate what Day (1994b, p. 23) refers to as organizational amnesia. That is, an organization fails to know what it knows.

Relational formations are such things as relational structure, routines, processes, and so on. By changing the formations, the relationship is recording what it has learned. For example, standard operating procedures are inherited between organizations to achieve fit, and in so doing the relationship is recording what is learned. The field interviews revealed several relationship-domain specific behavioral routines that were adjusted or customized across relationships, such as logistic systems and production processes.

Social capital represents the network of ties between individuals within and outside of the organization. Burt (1997) describes social capital as “credit slips” a person can use in time of need. Respondents in the field interviews said that when faced with a problem they often referred to their personal network of contacts for a solution, and that the network transcended organizational boundaries. Håkansson and Johanson (1988, p. 369) also observed that personal networks transcend the boundaries of the organizations.

Relationship culture is the most opaque of the four bins in that it is largely tacit (Garud and Nayyar 1994, p. 375). It represents the norms and values captured in

the relationship and while evolving, it transcends time thus functioning as a repository for memory. Along with social capital, organizational culture is very difficult for competitors to imitate and thus from a resource perspective can be a unique source of competitive advantage (Barney 1991).

2.5 DEFINITION

Based on the preceding discussion, the following definition of relationship learning is offered:

A supplier and a customer learn in a relationship to the degree that information is *shared* among the two parties, the information is jointly *interpreted*, and then *integrated* into relationship-domain specific memory that will change the range or likelihood of *potential* relationship-domain specific behavior (Selnes and Sallis 1999, p. 10).

3. A MODEL OF RELATIONSHIP LEARNING

“As far as the laws of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality (Einstein 1923, p. 28).”

Under what conditions does relationship learning occur? This refers to the environmental, organizational, and inter-organizational conditions that induce relationship learning. To identify these conditions we (Selnes and Sallis 1999) conducted 26 interviews across 13 industrial buyer-seller relationships and reviewed the literature on inter-organizational relationships, organizational learning, and inter-organizational learning. This chapter integrates our findings with the literature to propose what drives relationship learning.

My argumentation so far has been premised on two firms that learn with each other in a collaborative relationship based on some sort of mutual orientation. However, simply because firms collaborate in a relationship does not mean they learn together. They may, for example, collaborate to utilize unused factory capacity, achieve economies of scale, or gain access to capital (Child and Faulkner 1998). These factors motivate a marriage of convenience where learning in the relationship is not a goal, although it may be a byproduct where the firms get knowledge *from* each other. Given my premise of a mutual orientation where firms learn *with* each other, I posit that a collaborative objective that includes learning is the most fundamental variable to motivate relationship learning. This is consistent with the literature on inter-organizational relationships and learning (Dodgson 1993b; Hamel 1991).

There are many perspectives on motives for firms to collaborate (cf. Child and Faulkner 1998), I refer to Kogut (1988) who generalizes to three: the transaction cost motive, the strategic-behavior motive, and the organizational learning motive.

From a transaction cost perspective (e.g. Williamson 1981), in situations of high environmental uncertainty and high investments in nontransferable relationship specific assets, internalizing transactions minimizes costs. Current transaction cost thinking expands the original discrete boundary choice between markets and hierarchies to include hybrid forms like collaboration where direct ownership is substituted with formal (e.g. contracts) and informal (e.g. norms of information sharing and trust) control mechanisms in relationships (Rindfleisch and Heide 1997).

Transaction cost economics focuses on governance problems and the conditions under which the cost of conducting economic exchange in a market may exceed the cost of organizing the exchange within a firm (Rindfleisch and Heide 1997). A key assumption of transaction cost economics is that actors are opportunistic to the extent of being self-interest seeking with guile (Williamson 1981, p. 554).

However, if business transactions take place in series is it wise to exploit your trading partner? Axelrod's, "Shadow of the future (1984, p. 113)", succinctly captures the essence of why trading partners are unlikely to be inclined to opportunism. The future matters because both buyer and seller are able to punish each other in subsequent interactions (Haugland and Grønhaug 1996), and the reputation for being a valued trading partner can be a valuable asset (Powell et al. 1996). Recent transaction cost theory recognizes trust, the antithesis of opportunism, as an informal control mechanism (Rindfleisch and Heide 1997, p. 48). Network theory (e.g. Håkansson and Johanson 1988; Johanson and Mattsson 1987) holds that trust is an important variable in business relationships. Generally speaking, trust is a critical variable in any collaborative relationship (cf. Child and Faulkner 1998), therefore, I posit that it is an important variable for relationship learning.

Borrowing from transaction cost economics, I posit that environmental uncertainty will also motivate relationship learning. Environmental uncertainty is operationalized two ways in transaction cost economics (Rindfleisch and Heide 1997, p. 42). Most often it is treated as one-dimensional in that it focuses only on the unpredictability of the environment (e.g. Heide and John 1990; Noordewier, John, and Nevin 1990). The other is two-dimensional, distinguishing between volatility and complexity (Klein, Frazier, and Roth 1990, p. 199). Volatility creates uncertainty through constraining rationality (Williamson 1975). Rational decisions are difficult or impossible under quickly changing conditions. Complexity constrains rationality because problem solving becomes difficult or impossible (Spence and Brucks 1997). For relationship learning both dimensions are important. Environmental uncertainty will be used to explain the volatility of the environment whereas structural complexity will be used to describe the complexity within the relationship.

Again borrowing from transaction cost economics, I posit that asset specificity will also motivate relationship learning. Williamson identifies three types of asset specificity: site specificity, physical asset specificity, and human asset specificity. Human asset specificity is, "... learning by doing (1981, p. 555)," meaning accumulating know-how in long-term relationships. It locks the partners into the relationship by introducing switching costs and can be developed through further learning. Accumulating specialized knowledge in a relationship can lead to competitive advantage (Dyer and Singh 1998, p. 662; Grønhaug 1996, p. 219).

From the strategic behavior perspective (e.g. Porter 1985), when complementary assets create synergies that allow for competitive advantage, firms will be motivated to collaborate. In contrast to transaction cost economics, rather than minimizing costs the motive is to gain advantage. This is related to resource-based theory where combining valuable, idiosyncratic resources can create competitive

advantage (Barney 1991), and the relational view (e.g. Dyer and Singh 1998) where these combinations can take place across organizational boundaries.

With the third motive, organizational learning, firms are motivated to collaborate in order to transfer knowledge, especially tacit knowledge (Fiol and Lyles 1985). Because tacit knowledge is not explicitly codifiable, it is only transferable through working together (Child and Faulkner 1998, p. 66). This is related to the concept of grafting whereby one organization grafts another organization into its structure, thus creating a knowledge pool. Huber (1991, p. 97) suggests that as the pressure to learn faster increases, grafting will increase as a fast way to acquire knowledge.

To summarize, the principal antecedent variables for relationship learning are:

6. Collaborative objectives.
7. Trust.
8. Environmental uncertainty.
9. Structural complexity.
10. Asset specificity.

3.1 COLLABORATIVE OBJECTIVES

Relationship learning happens when there is a commonality of interests based on a mutual orientation where firms are aware of each other's interests and prepared to pay attention to them (Heide 1994). Reciprocity is a core element of this kind of relational exchange (Oliver 1990, p. 244), contributing to a balance in social relations, promoting predictability and shared expectations (Bagozzi 1995, p. 276). To reflect this I propose that firms have collaborative objectives that encompass a reciprocal commonality of interests manifested in joint goals. This is more restrictive than simple collaboration that can take place for other reasons where goals may be divergent.

Collaborative objectives enhance learning in inter-organizational relationships (Badaracco 1991; Dodgson 1993b; Hamel, Doz, and Prahalad 1989). Firms often collaborate as a means for creating knowledge or accessing knowledge that resides outside firm boundaries (Huber 1991; Prahalad and Hamel 1990). Joint goals legitimate collaboration between parties (Scott 1987, p. 32), and facilitate relationship formation (Doz 1996, p. 69; Ring and Van De Ven 1994, p. 97). The scope of joint goals will influence how and the degree to which the two parties will collaborate (Borys and Jemison 1989, p. 237; Sheth and Parvatiyar 1992, p. 76). A narrow scope may encompass such things as providing for reliable deliveries, while a broad scope may include more complex objectives like improving key processes, developing new products, developing new markets, and so on. It follows that the more ambitious the joint goals in a relationship, the more reasons there should be to learn (Hamel 1991; Powell et al. 1996).

H₁: Collaborative objectives are positively related to relationship learning.

3.2 TRUST

The management and sociology literatures recognize two separate views of trust, one is based on confidence in predictability and the other is based on confidence in goodwill (Ring and Van De Ven 1994, p. 93). Anderson and Narus define trust in working relationships as, “The firm’s belief that another company will perform actions that will result in positive outcomes for the firm, as well as not take unexpected actions that would result in negative outcomes for the firm (1990, p. 45).” During the field interviews it became quite clear that in many working relationships the parties trusted each other in a very calculative way. They trusted the consistency of each other’s actions, yet this did not necessarily entail considering positive or negative outcomes, at least not to the extent that it changed actions. They did not appreciate opportunism in the sense of self-interest seeking with guile (e.g. Williamson 1981), however, they did appreciate that each

organization needs to prioritize its own interests, which at times means making decisions that will have negative consequences for the other party. For example, one respondent in the field interviews told of how his supplier closed an unprofitable supply plant in his region, necessitating transporting supply from a more distant plant, thus increasing his expenses. He did not like it, but it did not affect the level of trust because he understood and agreed with the supplier's rationale. Therefore, regarding relationship learning, trust is conceptualized as the confidence one party has in an exchange partner's reliability and integrity (Morgan and Hunt 1994, p. 23). This parallels Moorman, Deshpandé, and Zaltman (1993, p. 82) and Selnes (1998, p. 309) by reflecting confidence and expectations as opposed to more restrictive definitions that encompass goodwill as an additional element of trust (e.g. Ring and Van De Ven 1992, p. 488).

Doney and Cannon (1997, p. 35) observed that trust in buyer-seller relationships exists at both the inter-organizational and the interpersonal levels. At the inter-organizational level, trust operates as a governance mechanism (Bradach and Eccles 1989, p. 104), reduces conflict, enhances satisfaction (Anderson and Narus 1990, p. 45), and is closely connected to commitment to the relationship (Morgan and Hunt 1994, p. 22; Selnes 1998, p. 310). At the interpersonal level between the two organizations, trust facilitates effectiveness of persuasion and communication processes (Doney and Cannon 1997, p. 41). Results from the field interviews support this. When questioned about the difference between inter-organizational trust and interpersonal trust, one customer commented, "I would extrapolate that and say, well, the more you trust the people, the more personal relationships you have with people from your suppliers, the more that you're in a position to learn something from them. Probably they are more open-minded and are willing to give you information, whereas, on a company level it's more an abstract relationship rather than something personal."

Zaheer, McEvily, and Perrone (1998, p. 142) propose a model of how interpersonal and inter-organizational trust are related. While they propose that

individuals can trust individuals in other organizations and they can also trust the organization itself, organizations are incapable of trusting. This differs fundamentally from the position of this dissertation because to accept that organizations can learn also implies that organizations can trust. As two organizations interact and trust builds, routines will be established between the organizations that may be characterized as manifestations of trust (Dodgson 1993b, p. 84) In the same sense that routines are memories of organizational learning (Cyert and March 1992, p. 119), and further organizational learning may result in changing these routines, relationship learning to trust may also change the inter-organizational routines. Zaheer et al. (1998, p. 144) refer to this as inter-organizational norms that are recreated in interpersonal trust orientations. Heide and John define norms as, "Expectations about behavior that are at least partially shared by a group of decision makers (1992, p. 34)." Accepting this definition of norms makes it plausible that an inter-organizational norm of trust can in actuality be considered as inter-organizational trust as opposed to simply a person in one organization trusting another organization. For present purposes trust is treated as a single dimension because the levels of trust reinforce each other with respect to relationship learning. Lack of one does not negate the positive influence of the other.

When the parties in an exchange trust that they will not be harmed, exploited, or put at risk by the action of the other party, they are more likely to share information (e.g. Morgan and Hunt 1994) and to forsake short-term gains at the expense of the other party (Axelrod 1984). Some researchers go so far as to say that mutual trust is a condition for relationship learning (Child and Faulkner 1998, p. 292). A climate of inter-organizational trust supplants interpersonal trust that is susceptible to personnel turnover or personality clashes between individuals across the inter-organizational relationship (Dodgson 1993b). Based on this I hypothesize that:

H₂: Trust is positively related to relationship learning.

3.3 THE INTERACTION EFFECT

It is generally acknowledged that trust facilitates collaborative behavior in customer-supplier relationships (Das and Teng 1998; Dwyer, Schurr, and Oh 1987), and likewise, collaborative behavior facilitates trust (Håkansson and Johanson 1988). Thus, there is a reciprocal relationship between collaborative objectives and trust. This interaction between the variables is where we perceive a hidden cost, which can be illustrated by looking at the relationship between trust and control.

Trust and control play a balancing act in a relationship. As the relationship between two organizations develops, calculative trust, based on explicit control mechanisms and credible information, gives way to relational trust (Rousseau, Sitkin, Burt, and Camerer 1998), thereby reducing transaction costs (Nooteboom, Berger, and Noorderhaven 1997, p. 313). Because trust potentially reduces costs it is attractive to develop, although it is seldom the only control mechanism. Using the analogy that organizations are like oceans, explicit control mechanisms retain a role as life jackets in lieu of exclusive reliance on trust (Ring and Van De Ven 1994, p. 96). In one dyad from the field interviews, the two parties had developed a partnering contract in order to secure that sensitive information would not be distributed to outsiders, and that all records of sensitive information would be destroyed if the collaboration were terminated. While not restricting information sharing, the contract acted as a life jacket against opportunism in the event of relationship dissolution.

Control mechanisms, while perhaps bolstering trust can also reduce it (Das and Teng 1998, p. 501). They can give the impression of distrust, which in turn may lead to further control mechanisms, which creates more distrust, and so on in a negative cycle. Furthermore, control mechanisms can propagate rigidity in response to problems where flexibility may be a better solution (Rousseau et al.

1998, p. 400). Conversely, control mechanisms provide feedback as to the trustworthiness of the other party, thereby contributing to building trust. Das and Teng (1998, p. 501) explain this inconsistency by dividing control mechanisms into formal control and social control. Formal control refers to explicit rules, procedures, and contracts, whereas social control relies on values and norms. Formal control mechanisms imply distrust, whereas social control mechanisms do not explicitly limit behavior, thereby instilling trust. The chemical buyers from the field interviews said that they rarely tested products from the suppliers, relying on reputation as a control mechanism. It was understood (social norm) that for a supplier to do anything but supply the specified product would be foolish.

Whatever the case, there is a tendency to relinquish formal control as trust develops in a relationship. This is where the potential cost comes in. First, there is the risk of opportunism where the parties may take advantage of trust and exploit each other (Hamel 1991). Second, a high level of trust is usually accompanied with strong positive emotions and liking (Jones and George 1998). In such atmospheres it is unlikely that negative or critical information will be exchanged because it may endanger the good atmosphere of the relationship, thus the benefit of constructive conflict is lost (Eisenhardt, Kahwajy, and Bourgeois 1997). Third, as commitment increases, value systems converge to the extent where the parties may develop a common identity (Gaertner, Dovidio, and Bachman 1996). This group-think (Janis 1989) may hinder the creative processes found in more heterogeneous groups. The ramification is that as trust increases it may interact with collaborative objectives to actually reduce relationship learning. Therefore, I hypothesize that:

H₃: The interaction of trust with collaborative objectives is negatively related to relationship learning.

3.4 ENVIRONMENTAL UNCERTAINTY

Assuming firms are not self-sufficient, resource dependency theory suggests that firms will seek to reduce environmental uncertainty through establishing formal and semi-formal links with other firms (Heide 1994). The greater the environmental uncertainty, the greater the need for inter-firm collaboration and relationship learning (Dodgson 1993b, p.79). Firms are motivated to learn together to gain some control over the uncertainty or to buffer the consequences (Jap 1999, p. 464). In the field interviews and literature review three core elements of environmental uncertainty surfaced: (1) external competition, (2) external shocks, and (3) technological complexity.

3.4.1 EXTERNAL COMPETITION

In both the literature (e.g. Hallén, Johansen, and Seyed-Mohamed 1991, p. 84) and field interviews, increasing competition in the market was cited as one of the major drivers of relationship learning. Globalization of markets through cross-border trade agreements such as the WTO, EU, and NAFTA, and improving communication and transportation technologies are opening up previously protected markets (Levitt 1983, p. 92; Ohmae 1989, p. 153). Consequently, companies are under increasing pressure to develop their learning capabilities, not only internally but in relationships as well. This is supported by results from the field interviews. In response to the increasingly competitive environment, all of the interviewed companies are experimenting with different types of learning arrangements, from loosely coupled sales agreements to tightly governed partnership contracts. As one supplier said, “The competitive situation has brought this about. There is more pressure from the end market and from our customers. We feel there is a greater need for information sharing and learning in order to gain a competitive advantage.”

3.4.2 EXTERNAL SHOCKS

Jolts and hyper-turbulence have been identified as driving organizational change (Meyer, Brooks, and Goes 1990, p. 102). Volberda (1996, p. 359) and others

discuss a shift in the organizational paradigm to hyper-competition, meaning an environment, “Fraught with uncertainty, diverse global players, rapid technological change, widespread price wars, and seemingly endless reorganization (Ilinitich, D’Aveni, and Lewin 1996, p. 211).” In the field interviews, shocks were often equated with unexpected fluctuations in demand and supply. In one case, three large customers of one supplier simultaneously started large jobs. The supplier did not have the capacity to satisfy the sudden increase in demand, causing a supply crisis for all three customers. The responsible sales agent had been maintaining an arms-length relationship with the customers, which did not facilitate the transfer of what turned out to be critical information. The poor information flow had a direct negative consequence for the customer’s performance, as well as negative consequences for the relationship. All parties were motivated to form closer ties and increase relationship learning in order to avoid future shocks.

In the farmed salmon industry there were ramifications from the “mad cow” crisis. Consumer awareness of sources of food dramatically increased, making it important for retailers to be able to trace the origin of their products. Several producers and retailers implemented systems of tracability, enabling them to follow particular lots of salmon back to specific farms and even to specific hatcheries. Information flow and precision of information can be equated to relationship learning, which some salmon producers now use as a competitive tool to differentiate themselves from less organized or less integrated producers.

According to Cyert and March (1992, pp. 117-118), an organization attains some sort of preferred state. When an external disturbance or shock that is beyond the control of the organization disrupts the preferred state, the organization adjusts to attain an alternative preferred state. This reactionary view is consistent with behavioral learning because the organization relies solely on inferences from history to guide organizational action. The organization is incapable of conjecture. Consistent with the cognitive approach, relationship learning is forward-looking

which should reduce the frequency and magnitude of shocks (Slater and Narver 1995, p. 66). It will also facilitate cooperation and mutual adjustment to the unexpected (Day 1994b; Sinkula 1994).

3.4.3 TECHNOLOGICAL CHANGE

Huber (1996) suggests that technological change, which is happening at an increasing pace, is increasing environmental uncertainty and turbulence. Recognizing that no single organization can keep up with all technological changes and be excellent in every function, many organizations are focusing on developing core competencies and may discontinue developing or maintaining other capabilities (Prahalad and Hamel 1990). To compensate for lost competencies, organizations often establish relationships, and to keep pace with changes in their core competencies they pursue learning. Luckily, the same technological development that is creating the turbulence is also providing part of the solution. Technological development in information technology is allowing for the reestablishment of communication through the value-chain, effectively reconnecting producer and consumer (Sheth and Parvatiyar 1995).

Product life-cycles are growing shorter forcing companies to speed up their product and market development processes (Day 1994b, p. 9; McKee 1992, p. 233). Even simple products often require advanced technology in their production, transportation, or sale. Where technological development is moderate, as in many commodity markets, the benefits from relationship learning are likely to be low. Where development is rapid, as in telecommunications, the benefits from relationship learning are likely to be high because even small improvements in products, systems, or people will have great value. In the field interviews, every respondent gave accounts of technology related pressures to increase relationship learning. A commodity chemicals supplier said one of the main reasons they are pursuing relationship learning is to stay abreast of technological changes that could alter the market, and thus their market share. The changes could come in the form of new logistic systems or a shift to an entirely new product. In the farmed

salmon industry, some producers are relying on technological advances in smoking and filleting to produce more consistent products as well as reduce waste in processing. This is contingent, however, on consistency and quality from the fish farms right down to the retailers, thus necessitating relationship learning throughout the entire value-chain.

As competition, shocks, and technological complexity increase they contribute to environmental uncertainty, thus motivating organizations to pursue relationship learning.

H₄: Environmental uncertainty is positively related to relationship learning.

3.5 STRUCTURAL COMPLEXITY

“The structural complexity of a collectivity refers to the number of differentiated elements that must be contended with and integrated in order for an inter-organizational relationship to act as a unit (Van de Ven 1976, p. 26).” The rationale is that as the number of differentiated elements increases, the amount of required interaction increases exponentially, which contributes to complexity. I divide structural complexity into two dimensions: transaction complexity and relationship complexity. Transaction complexity relates to the product or service in the exchange, whereas, relationship complexity relates to how the exchange is organized.

3.5.1 TRANSACTION COMPLEXITY

Organizations in relationships have to exchange information in order to coordinate and plan actions (Anderson and Narus 1990). Characteristics of the products in the relationship will have a significant effect on the amount of information exchange as well as the time required in the exchange (Metcalf et al. 1990). Therefore, transaction complexity varies primarily by the technological complexity of

products as well as the number of products involved in an exchange. Absorptive capacity refers to the ability to recognize, assimilate, and apply external information, and is a function of the organization's prior related knowledge (Cohen and Levinthal 1990, p. 128). Technological complexity will challenge absorptive capacity, thus motivating relationship learning.

Low transaction complexity is exemplified by the farmed salmon industry. There is only one product with a few derivatives and although it is biological the product it is relatively simple in terms of manufacture. High transaction complexity is exemplified by the specialty chemicals industry. There are several products, all of which must be produced within very strict specifications. The technology to produce the products is usually complex, and delivery can be complex because of the often volatile nature of the products.

3.5.2 RELATIONSHIP COMPLEXITY

Relationship complexity relates to how the exchange process is organized. It varies primarily with the number of contact points and social distance between the buyer and the seller (Ford 1980, p. 344). Some relationships are organized with very few contact points, like only sales and purchasing, which translates to low complexity. As the number of contact points increases, so too does the complexity of the relationship. Social distance relates to the existence of social ties between organizations. Close social ties can act as a lubricant in the exchange relationship by providing common understanding (Heide and John 1992).

The farmed salmon industry is a good example of low relationship complexity because nearly all buyer-seller contact happens between a couple of people. While they may be geographically and culturally distant, this is buffered because the complexity of the information exchanged is low and they do not have to consider many contact points between the organizations. A high complexity relationship is exemplified by a global supplier of chemicals and a global manufacturer where several functional areas (marketing, sales, R&D, production, procurement, and

distribution) are involved from both sides of the relationship, and where both parties have several operating units around the world. One supplier described just such a relationship. “Our customer has regional and world-wide operations, and so do we. We have sales organizations and eleven production sites. We deliver to some customers from several different production sites. There are staff contacts, joint R&D contacts, and contacts at the CEO level. In other words, it is very complex for both parties to understand all of the information that is exchanged.”

As structural complexity increases, information uncertainty and ambiguity are likely to increase as well. This will most likely create problems in the relationship. As the number of serious problems grows, the parties in the relationship are likely to be more motivated to learn and thus reduce the pressure of unsolved problems (Lee et al. 1992, p. 25).

H₅: Structural complexity is positively related to relationship learning.

3.6 ASSET SPECIFICITY

Asset specificity will motivate relationship learning in several ways: as a control mechanism, as a credible commitment to the relationship, and as a reinforcement of the relationship.

Asset specificity increases risk in transactions by introducing switching costs. To the extent that assets are idiosyncratic to a relationship, switching means giving up future returns on those assets (Wathne, Biong, and Heide 2001). As the asset specificity of an exchange increases, to reduce the hazard of opportunism the trading parties will be motivated towards relational exchange (Heide 1994). As the relationship develops expectations converge, thus reducing uncertainty generated by independent parties (Williamson 1975, p. 25), acting as an implicit control mechanism (Ouchi 1979). Asset specificity in a relationship also acts as a credible

commitment to the relationship (Williamson 1981). It reassures the other party about intentions (Hallén et al. 1991), contributing to trust in the relationship. Finally, human asset specificity (Williamson 1981) as it relates to experience with tacit knowledge will facilitate communication of complex information between firms (Zander and Kogut 1995, p. 79).

H₆: Asset Specificity is positively related to relationship learning.

3.7 THEORETICAL MODEL OF RELATIONSHIP LEARNING

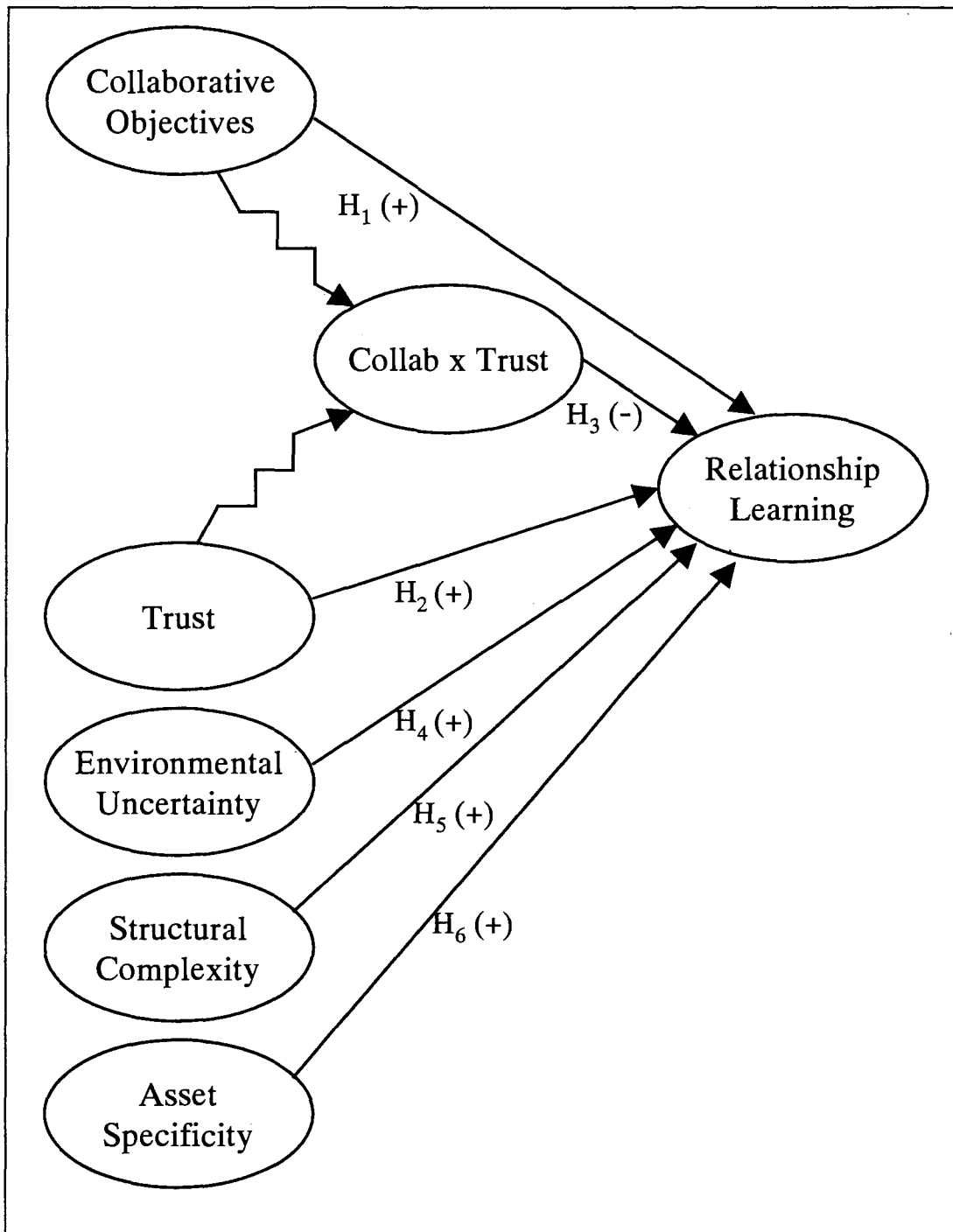


Figure 3.1, Relationship Learning Model

3.8 MODEL SUMMARY

What the model suggests are five direct effects between the independent variables (collaborative objectives, trust, environmental uncertainty, structural complexity, and asset specificity) and the dependent variable (relationship learning). While interesting, it is the hypothesized interaction effect between collaborative objectives and trust on relationship learning that is most novel within existing theory. The interaction effect modifies the positive linear effect of collaborative objectives by introducing a negative curvilinear trend. Figure 3.2a shows the hypothetical positive linear relationship between relationship learning and collaborative objectives without the interaction effect. Figure 3.2b shows the hypothetical negative curvilinear influence with the interaction effect included.

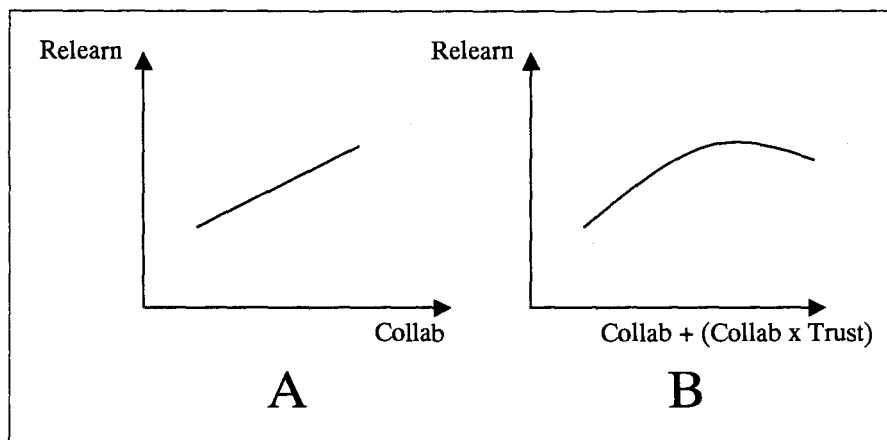


Figure 3.2, The Interaction Effect

The ramifications are that by disregarding the interaction between collaborative objectives and trust, parties to relationship learning may not be realizing its full potential.

4. METHODOLOGY

“Give a small boy a hammer, and he will find that everything needs pounding (McGrath, Martin, and Kulka 1982, p. 53).”

This chapter describes the two-step methodology used for developing and testing the relationship learning model. The reason for choosing a two-step design is the emergent state of the theory (e.g. Pine, Peppers, and Rogers 1995). There have been suggestions for how to define a relationship learning construct (e.g. Lukas et al. 1996), although nobody to my knowledge has specifically proposed or tested a definition. Different variables have been proposed as antecedent (e.g. Hamel 1991) or consequent (e.g. Kalwani and Narayandas 1995) to relationship learning, however, no proposed linkages have gained any significant degree of acceptance in the research community.

When proposing constructs, argumentation can be based on conceptual and empirical perspectives (Singh 1991). The conceptual perspective is concerned with building sound theoretical arguments for the domain of a construct and its relationship to related constructs. The empirical perspective offers estimated measures as evidence for or against the proposed constructs and relationships. The emergent state of relationship learning theory calls for conceptual development, thus it is appropriate to begin with induction (research then theory) for developing the relationship learning construct and model, then deduction (theory then research) for testing it (Zaltman, LeMasters, and Heffring 1982, p. 104). Each step can reveal findings that the other may not have made salient, and in conjunction they establish the validity (are we measuring what we want to) and reliability (are we measuring it accurately) of the research.

In describing the methodology I address dyadic measurement issues, the empirical context, sampling, and measure development.

4.1 STEP ONE: DEVELOPING THE MODEL

In step one, the objective was to attain a deeper understanding of the learning process in industrial customer-supplier relationships, with the goal of developing a testable model for step two. A logical consequence of the objective, then, was to choose an exploratory research design. An exploratory design using qualitative, inductive methodology provides ideas and insights about phenomena (Churchill 1999, p. 101). It is particularly helpful in focusing problems into testable hypotheses.

Constructs are abstractions of phenomena like learning, uncertainty, or trust (Judd, Smith, and Kidder 1991, p. 42). In theory development it is important that definitions and operationalizations of constructs be unambiguous and easily replicable as well as being broadly accepted (Calder, Phillips, and Tybout 1981, p. 201; Peter 1981, p. 135). To accomplish this, Churchill (1979) suggests specifying the domain of the construct by comparing definitions and operationalizations in previous research. Combining previous research with evidence from data enhances confidence in the constructs (Eisenhardt 1989).

Theories describe how constructs are interconnected, and constructs acquire meaning only within the context of a theory (Frankfort-Nachmias and Nachmias 1996). While relationship learning is distinct from organizational learning, it is nevertheless closely related. Organizational learning theory and inter-organizational research provide an overview of theoretically related constructs for developing the relationship learning model. A priori specification of a list of constructs is helpful because if they prove important as the theory emerges they give it empirical grounding (Eisenhardt 1989). To this end, two specific issues dominated the exploratory research:

- Construct validity – Are we measuring what we intend to?
- Nomological validity – How does relationship learning fit with other constructs to which it is theoretically related?

Construct validity is, “The degree to which a measure assesses the construct it is purported to assess (Peter 1981, p. 134).” It is closely related to reliability in that it is concerned with the accuracy of a measure (Churchill 1979), however, it extends this notion to include what is being measured. A particularly important issue with construct validity is confounding, which is when operational variables can be interpreted in terms of more than one construct (Cook and Campbell 1979).

Nomological validity is concerned with the predicted pattern of relationships between constructs (Cook and Campbell 1979), and can be thought of in terms of constructs and theories as nomological nets (Meehl 1990). Imagine a fishnet encompassing all reality; the knots represent constructs and the strands represent theories. Construct validity is concerned with the verisimilitude (truth-likeness) of the knots, while nomological validity is concerned with the verisimilitude of the strands that connect them.

4.1.1 RESEARCH CONTEXT

A heterogeneous set of buyer-seller dyads was desirable to capture the entire spectrum of learning relationships from low to high (John and Reve 1982, p. 518; Kumar, Stern, and Anderson 1993, p. 1635; Seidler 1974, p. 817). Eisenhardt (1989, p. 537) argues for this on the grounds that using polar cases renders the focal phenomenon transparently observable. This suggests theoretical sampling as a way of selecting cases on the basis of pre-specified criteria as dictated by the focal phenomenon. To this end, I selected organizations based on expected levels of relationship learning.

Allowing for the incumbent weakness of generalizing:

- The farmed salmon industry represents low learning: the product is fairly standardized and there are few contact points across the relationship. Suppliers were from the farmed salmon industry, with buyers from smokers, canneries, agents, and supermarket chains.
- The commodity chemicals industry represents medium learning: while the product is standardized, there are many more contact points across relationships, thus increasing complexity. Suppliers were commodity chemical manufacturers with buyers from the construction industry.
- The specialty chemicals industry represents high learning: it has both complex products and complex relationships. Suppliers were specialty chemical manufacturers with other more refined specialty chemical manufacturers as buyers.

The supplier organizations were contacted at the upper-management level and asked to participate in the study. Once recruited, the manager supplied a few names of people within his or her own company who were central to key-customer relationships. These people were recruited and in turn supplied the names of their key contacts in the key-customer organization. The key-customer informants were then recruited. Informants were from sales, R&D, procurement, quality control, and divisional management.

4.1.2 THE INTERVIEWS

In conjunction with the literature review, 26 interviews across 13 buyer-seller dyads were used to develop the model. Two interviewers conducted the interviews, initially together but later alone. Eisenhardt suggests that using multiple investigators, “Builds confidence in the findings and increases the likelihood of surprising findings (1989, p. 538).”

The interviews typically lasted about 60-90 minutes and were based on a prepared interview guide (see Appendix for full version). Six specific areas were discussed, although the format was very open because it was important that respondents were

free to express their beliefs on learning in the relationship. Each interview was tape-recorded and protocols were developed.

Question 1 (general learning)

This series of questions focused on how they learn, what they learn, and their perceptions of the complexity of the learning.

Question 2 (memory and processing)

The focus here was on how they perceived memory to function in the relationship and what facilitated it. Topics like information sharing, accessibility, and storage were covered.

Question 3 (driving forces and benefits)

Here we focused on what was motivating learning in the relationship and the factors that influenced the motivation. We also asked about benefits and consequences.

Question 4 (learning by the other party)

In this section we tried to capture the respondent's perceptions of how the other party in the relationship viewed learning and if they saw changes in the other party based on the learning.

Question 5 (organizational questions)

These questions were very structurally oriented covering how the relationship was organized. This included things like complexity, centralization of authority, openness, and formality.

Question 6 (suggestions)

We closed the sessions by asking how relationship learning could be improved. The point was to encourage freethinking in the respondent to bring out issues we may have missed.

4.1.3 DATA ANALYSIS

In the tradition of truly inductive grounded theory, phenomena should be allowed to emerge from the data (Glaser and Strauss 1967, p. 1; Strauss and Corbin 1990, p. 23). We used a quasi-grounded theory approach to data analysis in that as phenomena emerged we continually evaluated them against the literature. There is a reciprocal relationship between the data and the literature in that both offer ideas and both offer tests of the ideas generated from their respective opposite. We expect this iterative process to contribute to attaining high construct validity and nomological validity.

The protocols were imported into a program dedicated to analyzing qualitative data (Nudist). The structure of Nudist allows for what Strauss and Corbin (1990, p. 61) refer to as open coding. A code is an abstract label given to an excerpt of text representing the underlying meaning or theme of the text. The label usually allows for a continuum from low to high along a particular dimension. For example, in one of the interviews the respondent said, "We respect them, but often we do not trust what they say." This text unit could be labeled both "respect" and "trust". It would indicate high respect, but low trust. In the course of coding all the interviews, several other text units may also fit with these codes. When a code contains several text units it is an indication of significance to the process captured in the interviews. If a code has very few text units it may be deemed insignificant, or possibly it is appropriate to merge it with a related code. The purpose is to attain a high level of abstraction with a parsimonious approach to categorizing, resulting in a simple but effective description of the process taking place in the data.

Initially, 68 codes were derived from open coding. No associations were drawn between codes in the first round. In the second round, axial coding was conducted

whereby the initial codes were combined into a hierarchical structure in relation to each other. In many cases codes were merged when the concepts turned out to be very similar. Insignificant codes were deleted, helping to eliminate individual idiosyncrasies of key informants. The resultant hierarchy was divided into four primary dimensions; motivators, moderators, the relationship learning construct, and consequences. These were distilled down into the relationship learning construct and model.

Despite that I identify consequences, in this dissertation I limit myself to antecedents with relationship learning as the dependent variable. I have done this because at this point to include consequences would thrust the dissertation into a normative managerial domain as opposed to a descriptive theoretical domain. While in subsequent work my aim will be to further explore normative dimensions and managerial implications of the theory, given my purpose to contribute to the theoretical development of relationship learning I believe it is inappropriate here.

4.2 STEP TWO: TESTING THE MODEL

In step two the objective was to test the construct and model of relationship learning. The primary goal was to develop and refine the measurement scale. Because the model implies untested causal relationships between constructs, the logical choice was to use a causal research design. A causal design using quantitative, deductive analysis measures the degree to which a phenomenon is present (Kirk and Miller 1986), and provides evidence concerning the hypothesized cause-effect relationships (Churchill 1999 p. 140). Because of time and money constraints the causal design was carried out in a cross-sectional study, which unfortunately compromises testing the necessary condition of time-order occurrence (Churchill 1999, p. 145). Despite this it still allows for a strong test of the measurement instrument and perceptual consistency between the buyer-seller informants.

4.2.1 DYADIC MEASUREMENT

The level of a theory (e.g. individual, organizational, dyadic) concerns the target phenomenon that a researcher is trying to explain. The level of measurement and level of analysis should reflect the level of the theory (Klein, Dansereau, and Hall 1994, p. 199). Relationship learning is a dyadic level phenomenon existing between two organizations, thus the measurement and analysis should also be dyadic. Intuitively a dyadic phenomenon would require measurement from both sides (Heide and John 1994).

A complicating factor for measuring the constructs in the relationship learning model is that they are latent (i.e. not directly observable). Properties of latent constructs must be inferred indirectly from other indicators (Heide and John 1994). To facilitate this, in marketing research data is frequently collected from key informants, however, this potentially confounds the level of measurement when the level of the theory is at a higher order than the individual. To overcome this Seidler (1974, p. 817) suggests a sample of at least five key informants from each segment of the organization to which the measure applies, and that the informants should be chosen on the basis of expertise. In a dyadic setting this translates to at least five key informants from each side of the dyad, raising the dilemma of how to combine key informant reports.

Knowledgeable informants may have dissimilar opinions about the same phenomenon because of such things as different levels of expertise, their background, or their position within their organization (Kumar et al. 1993). Combining informant reports to form an average confounds separating systematic informant bias from random error in the statistical analysis, which becomes critical if the systematic informant bias accounts for a substantial proportion of the total variance (Phillips 1981). Unless perceptual agreement is established a priori, averaging responses masks possible reliability problems. Kumar et al. (1993, p. 1637) proposed a hybrid approach where prior to combining the reports, consensus is sought when key informants substantially differ. This would effectively

eliminate systematic informant bias, however, it exposes informants to conformity bias, thus simply hiding the reliability problem in a different way. As a result of these difficulties it is common to rely on single key informants (Heide and John 1994).

In the present research one key informant per side of the dyad is used. The ramifications are not deemed serious because the focus of the measurement is on the dyad, and John and Reve (1982) showed that key informants across a wholesaler-retailer dyad can provide reliable and valid reports on concrete dyadic phenomena. I am not concerned with perceptual agreement within the respective organizations, what I care about is perceptual agreement across the dyad. Perceptual disagreement will be controlled for by partitioning the variance between respondents.

Having two key informant reports, one from each side of the dyad, still raises the dilemma of how to combine them into a dyadic measure. There is great potential for systematic differences between informants (Phillips 1981), suggesting that aggregation to form an average is inappropriate. Instead, as per Phillips (1981) and John and Reve (1982), the reports should be modeled as reflective indicators (one seller and one buyer) within a multitrait-multimethod matrix (MTMM) (Campbell and Fiske 1959), modeled as a covariance structure (Jöreskog 1974). This allows for partitioning of the variance into trait (construct of interest), method (systematic informant bias), and random error.

4.2.2 THE MEASUREMENT STRATEGY

Churchill (1979) recommends multiple measures of latent constructs. Using multiple reflective indicators for a construct entails having a sample of items tapping different nuances of the construct (Bollen and Lennox 1991). Changing out items in the sample has no effect so long as they are reflective, as opposed to formative, and equally reliable (Churchill 1979).

Evidence of construct validity comes from testing for convergence within measures and divergence between measures of theoretically related constructs. Convergent and discriminant validity can be assessed simultaneously through a multitrait-multimethod matrix (MTMM) (Campbell and Fiske 1959), which can be modeled as a covariance structure (Jöreskog 1974). In this case, the informant reports constitute the methods (the buyer is one method and the seller is another method), while the constructs, like trust or asset specificity, constitute the traits.

The model presented in figure 4.1 is in line with both Phillips (1981) and John and Reve (1982) and entails modeling the MTMM matrix as a restricted factor structure model. The lambda (λ) parameters indicate the correspondence between

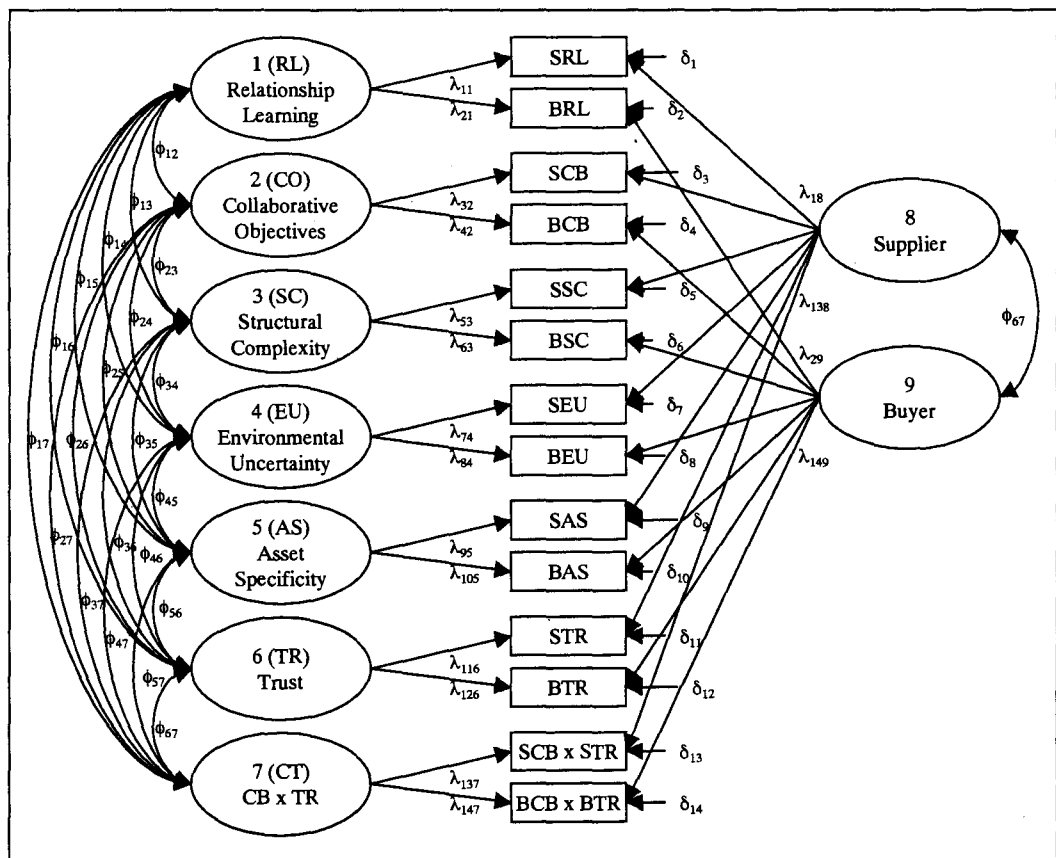


Figure 4.1, Multitrait-Multimethod Measurement Model

the measure and the trait, providing evidence of convergent validity. The phi (ϕ) parameters indicate the inter-correlation between traits, providing evidence of discriminant validity.

An additional advantage of this approach is the assessment of the reliability and validity of the dyadic measurement. The delta (δ) parameters are the error terms for the indicator variables. The square of lambda for a construct to an indicator, plus the square of lambda for its corresponding connection of an informant to the indicator, plus the delta error term accounts for the variance in an observation. The lambda for the construct to an indicator is the explained variance in the construct. The lambda for an informant to an indicator is the systematic variance idiosyncratic to that informant. Thus, the variance can be broken down into trait variance, systematic informant bias, and random error, allowing for assessment of the systematic differences between buyers and sellers reporting on the construct.

Measurement theory states (Churchill 1979): $X_O = X_T + X_S + X_R$

Where:

X_O = Observed score

X_T = True score

X_S = Systematic error

X_R = Random error

A measure is reliable if $X_R = \text{zero}$ and valid if $X_O = X_T$, thus a measure can be reliable but not valid.

The ramifications are:

- So long as random error is not excessive, the measures are reliable.
- Systematic error affects the validity of the measure; therefore, the systematic variance should also be as low as possible.

- The seller and buyer random error can be compared to ascertain who provides the most reliable measure of a given construct.
- The seller and buyer systematic variance can be compared to ascertain who provides the most valid measure of a given construct.

4.2.3 SAMPLING

High variance on the relationship learning variable was deemed the key consideration when determining the sampling frame and how to draw the sample (Kumar et al. 1993; Seidler 1974). A stratified convenience sample was drawn from databases covering Norwegian and Swedish industry. There were no statistical considerations in selecting suppliers, we simply started in Norway continuing until the selected categories were exhausted, then we turned to Sweden so as to increase the sample size. Practical limitations dictated when we stopped. Although only Norwegian and Swedish suppliers were recruited, buyers came from all over Europe. Several industries were chosen for their expected levels of relationship learning, on a spectrum of low to high. There is a weakness in generalizing for specific industries, although the goal of capturing the learning spectrum should still be accomplished. The industry labels are:

Telecommunications	Chemical producers
Food production	Office furniture
Fish wholesalers	Plastic suppliers
Fish producers	Transformer producers
Lighting equipment	Construction equipment
Fertilizer producers	Data processing
Iron works	Machinists
Ventilation equipment	Computer suppliers
Heating equipment	Electronic suppliers
Refrigeration equipment	Control instruments
Paper suppliers	Programmers
Cement producers	Machine maintenance

Table 4.1, Sampled Industries

All companies with over 50 employees in the selected industries were contacted. The size limitation was imposed to assure that respondents came from formal organizations as opposed to, for example, family operated companies where routines may be highly idiosyncratic (Weick 1965).

A desirable condition of the MTMM matrix approach is that the methods should be maximally different for the test to be strong (Campbell and Fiske 1959). In the present context the methods are the respondents from either side of the dyad, which presents a dilemma of how to select respondents. In the Phillips (1981) study, the common thread between key informants was membership to the organization and was not related to any relationship between the key informants. In fact, following the criteria set out by Campbell and Fiske (1959) regarding using different respondents as methods, he recruited informants that specifically differed as much as possible so that inter-informant agreement could not be attributed to a shared methods factor such as positional bias. This may, however, be problematic because Patchen (1961) found that measuring between organizational levels produced unreliable results, which he reasoned was at least partly due to a lack of common perspective between respondents. John and Reve's (1982) sample was made up of dyadic wholesaler-retailer relationships where the retailer sample was based on recommendations from the wholesaler. They reasoned that their sampling satisfies the maximally different methods criterion because key informants came from opposite sides of a dyad. Because John and Reve's (1982) key-informants were paired on the basis of recommendation they probably had the necessary level of common perspective suggested by Patchen (1961). In the present research we recruited key informants across the dyad based on recommendation. By doing this, the buyer and the supplier use each other and their respective organizations as reference points when completing the questionnaire.

Following the criteria set out by Campbell (1955), respondents were recruited based on their knowledge regarding the focal research issues. The supplier

organizations were contacted at the upper-management level and asked to participate in the study. Once recruited, the upper-manager was asked to supply a few names within his or her own company of people who were central to the supplier-customer relationships. Once a respondent was recruited, he or she was asked to supply names of their key contacts in a key-customer organization. A respondent in the key-customer organization was then recruited directly by the supplier. Both respondents were faxed or mailed the questionnaire.

4.2.4 QUESTIONNAIRE DEVELOPMENT

We used Churchill's (1979, pp. 67-69) approach to questionnaire development. Scales from several other relevant empirical studies were combined with new items to make one scale of 213 questions. New items were based on relevant conceptual literature, results from the field interviews, input from colleagues, and logic. Several items were deemed redundant because of excessive inter-item overlap and were, therefore, eliminated. The questionnaire was then tested on six suppliers. Comments from the suppliers and our colleagues were used to guide revisions. Several questions were revised or eliminated, and then the questionnaire was tested across 12 dyads. Analysis of the results guided final revisions, resulting in a 64-item scale.

While Phillips (1981) found dyadic measurement to be invalid and unreliable, John and Reve (1982) showed that problems were related to the types of issues being addressed. Reports were unreliable and invalid with respect to what they termed, "Dyadic sentiments". This is in contrast to, "Structural dimensions," of the relationship that are less open to interpretation by individual key informants. In other words, when measuring a higher order construct, as the dimensions about which an individual is supposed to report become more open to idiosyncratic interpretation, as with sentiments, the more likely perceptions will differ between key informants, and thus reliability and validity are weakened. Given this, it is important that survey questions reflect bilateral expectations as opposed to expectations held by the individual (Heide and John 1994).

Consistent with Dahlstrom and Nygaard (1999) and Anderson and Weitz (1992) we used a dyadic approach when developing the scales. It is broadly accepted that question wording affects responses, and that even minor changes can have profound effects on how a respondent answers (Churchill 1999). To eliminate the effect of inconsistent wording across the dyad and its incumbent error, we used parallel, generic wording such that all respondents received identical questionnaires. For example, one of the measures of information sharing was, "It is my company's policy to openly share information in this relationship."

Items were worded quite specifically as opposed to globally. For example, instead of asking respondents to respond to a global statement like, "There is a lot of information sharing between the organizations," we were more specific, "Our companies exchange information related to changes in the technology of the focal products." Patchen (1961) found that global questions can suffer from low reliability and validity as respondents think of different specifics, or weight the specifics differently when formulating answers. Asking a series of questions on different specific issues places a demand on the respondent's expertise, however, it should reduce arbitrary answers. It also allows us the freedom to generalize from the specifics rather than letting the respondent do it.

Given that testing was done in Norway, we received several comments regarding that the questionnaire was in English. It was suggested that response rates might be substantially negatively affected in the main survey. To alleviate this, the questionnaire was translated into German, French, Swedish, and Norwegian, as well as being offered in English. Translations were all based on the English original and then back-translations were made from the second language back to English. Unexpectedly, several minor flaws in the English questions were addressed as a result of this process. The questionnaires were all checked a third time by people fluent in both English and the second language. All translators and controllers had the second language as their mother tongue. They were selected

from exchange university students studying in Norway. Responses across languages were compared for significant differences by running a one-way ANOVA with language as the factor defining groups of cases and the aggregated construct measures for each side of the dyad as the dependent variables. Sellers and buyers were tested separately. No significant differences across languages were found.

4.2.5 REFLECTIVE MEASUREMENT

Reflective multi-item scales were used for all constructs. Formative indicators influence the latent variable, whereas, reflective indicators are symptoms of the latent variable (figure 4.2). Imagine you have the flu. You may have caught (formed) the flu by exposing yourself to other people with flu, neglecting to eat and sleep properly, and going out without being properly dressed. Symptoms, (reflections) may be a runny nose, fever, and headache. With reflective indicators you need a sample of items making up the multi-item scale, each tapping different nuances in the construct they represent (Bollen and Lennox 1991). This should increase reliability as measurement error decreases with more items (Anderson and Gerbing 1988).

Using the MTMM matrix approach made it particularly important to use reflective indicators because they should be significantly correlated within latent variables,

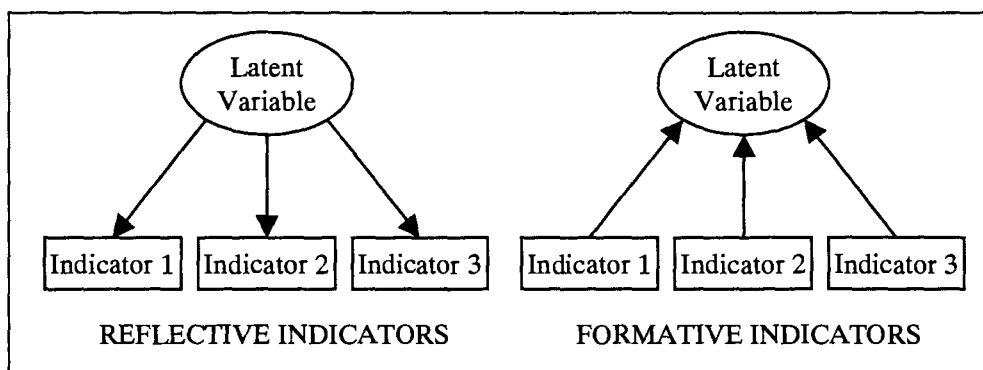


Figure 4.2, Reflective and Formative Measurement
(Adapted from Bollen and Lennox 1991, p. 306)

but not between latent variables. There is no theoretical basis for assuming formative indicators to be correlated (Bollen and Lennox 1991). The MTMM matrix is based on assessments of inter-item and inter-method correlations, and is thus dependent on reflective measures. In addition, the internal consistency of a scale can be assessed by Cronbach's Alpha, which is also dependent on reflective scales because it is determined through correlations.

4.2.6 ORDINAL-LEVEL SCALES

In line with Heide (1994), Heide and John (1992), and Jap (1999), a seven point (ordinal) Likert-type scale was used on the first 56 questions with appropriate anchors such as Strongly Disagree (1) to Strongly Agree (7) or from Low (1) to High (7), with a category for Not Relevant (?) on all questions. While ordinal level scales are common in social science research, there are ramifications for the statistical analysis. Many estimation methods, like maximum likelihood or ordinary least squares (both of which will be used), assume normally distributed continuous variables. The distribution of ordinal variables usually differs from that of continuous variables and is often abnormal (Bollen 1989). They are often excessively asymmetric and peaked. One partial remedy is to combine individual scales to form multi-item indicators because distributions tend to average out and become more normal, but this is no guarantee. Instead, alternative estimation methods are recommended, although they are not unproblematic.

The structural equation modeling for the relationship learning data will be done in Lisrel (Jöreskog and Sörbom 1996a). Lisrel uses either a covariance matrix or correlation matrix as input. For measurement model estimation with metric (ratio level) variables, a Pearson Product Moment correlation matrix is recommended as input because it gives a standardized solution allowing for unit free comparisons of coefficients within the model (Hair, Anderson, Tatham, and Black 1998). With ordinal level data with three or more categories, however, a polychoric correlation matrix is appropriate (Anderson and Gerbing 1988) because it compensates for skewness (asymmetry) and kurtosis (peakedness) problems that are characteristic

of ordinal level data. This means that for the relationship learning data the polychoric correlation matrix would seem to be the appropriate input choice. Unfortunately, polychoric correlation matrices require using the weighted least squares (WLS) estimation method that requires very large sample sizes (into the thousands). Given that the sample size with the present data is 315 for each side of the dyad, minus cases with missing data, WLS estimation with a polychoric correlation matrix is not possible.

Olsson (1979) showed that applying confirmatory factor analysis to ordinal data may lead to incorrect conclusions when the data is highly skewed. Olsson, Foss, Troye, and Howell (2000) refined this by showing that maximum likelihood estimation is robust against kurtosis abnormality. Estimating a series of models with varying degrees of kurtosis, comparing ML, WLS, and generalized least squares (GLS) estimation methods, even at relatively extreme levels of kurtosis, ML produced reliable results. The kurtosis levels for the relationship learning data (presented in the analysis) are well within the levels used by Olsson et al. (2000). Skewness is also reasonable, therefore, any violations of the assumption of normality are deemed to be inconsequential for the relationship learning data so maximum likelihood estimation with a Pearson Product Moment correlation matrix as input was used.

4.3 THE MEASURES

Some of the measurement items are new and some are adapted from previous research. Satisfaction, dependency, and performance were measured, however, they were not used in the present analysis.

4.3.1 RELATIONSHIP LEARNING

Seventeen items were used to assess the degree of relationship learning. Seven items addressed information sharing, four interpretation, and six memory integration. Previous studies by Anderson and Narus (1990), Hedberg (1981), Heide and John (1992), Jaworski and Kohli (1993), Moorman (1995), Moorman

and Miner (1997), Noordewier et al. (1990), and Slater and Narver (1996) provided guidance in developing the items.

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?). * indicates a removed item.

INFORMATION SHARING

1. * Our companies exchange information on successful and unsuccessful experiences with products exchanged in the relationship.
2. * Our companies exchange information related to changes in end-user needs, preferences, and behavior.
3. Our companies exchange information related to changes in market structure, such as mergers, acquisitions, or partnering.
4. Our companies exchange information related to changes in the technology of the focal products.
5. * Our companies exchange information as soon as possible of any unexpected problems.
6. Our companies exchange information on changes related to our two organization's strategies and policies.
7. Our companies exchange information that is sensitive for both parties, such as financial performance and company know-how.

INTERPRETATION

1. It is common to establish joint teams to solve operational problems in the relationship.

2. It is common to establish joint teams to analyze and discuss strategic issues.
3. The atmosphere in the relationship stimulates productive discussion encompassing a variety of opinions.
4. * We have a lot of face-to-face communication in this relationship.

MEMORY INTEGRATION

1. In the relationship we frequently adjust our common understanding of end-user needs, preferences, and behavior.
2. In the relationship we frequently adjust our common understanding of trends in technology related to our business.
3. * In the relationship we frequently evaluate, and if needed adjust our routines in order-delivery processes.
4. We frequently evaluate and if needed update the formal contracts in our relationship.
5. We frequently meet face-to-face in order to refresh the personal network in this relationship.
6. We frequently evaluate, and if needed update information about the relationship stored in our electronic databases.

4.3.2 COLLABORATIVE OBJECTIVES

The scope of collaborative objectives will influence how and the degree to which the two parties will collaborate. It follows that the more ambitious the collaborative objectives in a relationship, the more reasons there should be to learn. We attempt to capture this by assessing the degree of focus on joint goals. Previous studies by Borys and Jemison (1989), Hamel (1991), Heide and John

(1992), Håkansson and Johanson (1988), and Sheth and Parvatiyar (1992) provided guidance in developing the items.

The items were measured on a seven point scale from Low (1) to High (7) with a category for Not Relevant (?).

1. To what degree do you discuss company goals with the other party in this relationship?
2. To what degree are these goals developed through joint analysis of potentials?
3. To what degree are these goals formalized in a joint agreement or contract?
4. To what degree are these goals implemented in day-to-day work?
5. To what degree have you developed measures that capture performance related to these goals?

4.3.3 TRUST

Trust of the other party was measured with eight items. These items were adapted from the scales developed by Doney and Cannon (1997), Morgan and Hunt (1994), and Zaheer, McEvily, and Perrone (1998). The first intention was to try and distinguish between three dimensions of trust. Interpersonal trust between respondents across they dyad, trust of the respondent of the other organization as a collective entity, and collective inter-organizational trust. The measures failed to discriminate between the dimensions, so in the analysis three redundant items (1, 2, and 3 below, 11, 12 and 13 in the questionnaire) were dropped leaving a five-item scale representing the general construct of trust at various levels. The eight-item scale is presented here.

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?). * indicates a removed item.

1. * I trust the contact people from the other organization.
2. * I trust that the contact people from the other organization are concerned about my well being.
3. * I believe that the other organization will consider my company's well being when making important decisions.
4. I believe the other organization will respond with understanding in the event of problems.
5. I trust that the other organization is able to fulfill contractual agreements.
6. We trust that the other organization is competent at what they are doing.
7. There is general agreement in my organization that the other organization is trustworthy.
8. There is general agreement in my organization that the contact people in the other organization are trustworthy.

4.3.4 ENVIRONMENTAL UNCERTAINTY

Previous studies by Heide and John (1990), Heide and John (1992), Huber (1996), Jaworski and Kohli (1993), Meyer, Brooks, and Goes (1990) Noordewier et al. (1990) provided guidance in developing the items.

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?). * indicates a removed item.

1. End-user needs and preferences change rapidly in our industry.
2. * The competitors in our industry frequently make several aggressive moves to capture market share.
3. Crises have caused some of our competitors to shut down or radically change the way they operate.
4. It is very difficult to forecast where the technology will be in the next 2-3 years in our industry.
5. In recent years, a large number of new product ideas have been made possible through technological breakthroughs in our industry.

4.3.5 RELATIONSHIP COMPLEXITY

Complexity of the relationship was addressed with five items we developed reflecting the number and complexity of the products and operational units involved in the relationship. Cohen and Levinthal (1990) provided guidance in developing the items.

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?). * indicates a removed item.

1. * There are several different products exchanged in our relationship.
2. These products are generally very complex.
3. * These products are highly customized for this relationship.

4. There are many operating units involved from both organizations.
5. There are many contact points between different departments or professions between the two organizations.

4.3.6 ASSET SPECIFICITY

We measured asset specificity with two items adapted from Heide and John (1990).

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

1. Our company has made significant investments dedicated to this relationship.
2. Our company has made several adaptations to accommodate the other party's technological norms and standards.

4.3.7 DEMOGRAPHIC VARIABLES

Five questions addressed the importance of the relationship and respondent competence.

1. Choose the appropriate question:
 - a) This customer represents approximately _____% of our total sales.
 - b) This supplier represents approximately _____% of our total supply.

2. What is the primary focus of your business?

Circle one

- a) Producer b) Wholesaler c) Retailer d) Service e) Other
Provider

3. How long have you personally been with your company? _____ years.

4. How long have the two companies been involved in the relationship?
_____ years.

5. How long have you personally been involved in the relationship with the other
company?

_____ years.

4.3.8 RELATIONSHIP PERFORMANCE

Previous studies by Kalwani and Narayandas (1995), Kumar, Stern, and Achrol (1992), and Noordewier et al. (1990) provided guidance in developing the items.

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

1. The relationship with the other company has resulted in lower logistics costs.
2. Flexibility to handle unforeseen fluctuations in demand has been improved because of the relationship.

3. The relationship with the other company has resulted in better product quality.
4. Synergies in joint sales and marketing efforts have been achieved because of the relationship.
5. The relationship has a positive effect on our ability to develop successful new products.
6. Investments of resources in the relationship, such as time and money, have paid off very well.
7. The relationship helps us to detect changes in end-user needs and preferences before our competitors.

4.3.9 DEPENDENCY

Two items were adapted from Heide and John (1990).

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

1. The other company can easily be replaced if the relationship was terminated.
2. Our company's systems and processes can easily be adapted to a new partner.

4.3.10 SATISFACTION

Five items were adapted from Selnes (1998).

The items were measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

1. In our company we are very satisfied with this relationship.
2. In our company we find this relationship more attractive than other relevant alternatives.
3. In our company we are highly motivated to continue this relationship.
4. In our company we are highly motivated to collaborate in this relationship.
5. In our company we talk favorably about this relationship.

4.4 SUMMARY OF MEASURES

Although I have shown measures for relationship performance, satisfaction, and dependency they were not used in the analysis. They are used for subsequent analyses with more normative implications. The next two chapters describe the analysis. Chapter 5 deals with validating the measures, chapter 6 with hypothesis testing. I divided it this way for the sake of clarity.

5. MEASURE VALIDATION

This chapter presents a detailed description of how the data was screened and prepared for hypothesis testing. I begin by describing a procedure for aggregating measures, and then move on to address the quality of the data.

5.1 REFINING MEASURES BY AGGREGATION

Bagozzi and Edwards (1998) proposed a general approach for representing constructs in organizational research through applying structural equation modeling at varying levels of aggregation. Aggregation can take place in two ways that affect construct depth or dimensionality. By depth they mean that a construct can be modeled with all of its multiple items loading individually, or the indicators can be summed (aggregated) to form sets of indicators or a single indicator. By dimensionality they mean that some constructs can be represented by multiple sub-dimensional constructs, or the sub-dimensions can be aggregated to form a single construct. Multidimensional constructs can also be examined through the use of first-order, second-order, or higher-order models (Marsh and Hocevar 1988). Thus, constructs can be represented at various levels of depth and dimensionality.

There are three reasons why aggregation may be advantageous for the present research. First, in a case like relationship learning it can simplify interpretation. By virtue of the definition, the relationship learning construct carries the meaning of its contents without needing to refer to its sub-dimensions (information sharing, interpretation, and memory integration) and their influence on the potential for behavior change. Second, summing ordinal scales effectively increases the number of categories, thus transforming the variable towards continuous from categorical (Bollen 1989, p. 438), which may help to normalize the distributions of the ordinal scales. Third, aggregation can also improve model fit because of the potentially

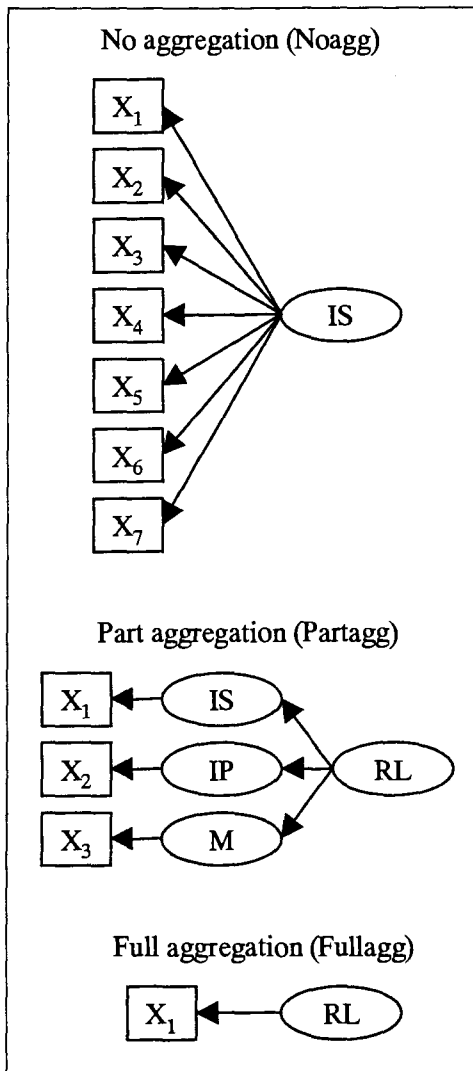


Figure 5.1, Aggregation Levels

large discrepancies between correlations of so many indicators within and between constructs, which inflates measurement error (Bagozzi and Edwards 1998).

Any aggregation is contingent upon theoretical rationale. Substantively, I have built the argument that relationship learning is three-dimensional; therefore, it is a good candidate for aggregation. From a measurement perspective I have built arguments for the reflective operational indicators for each construct in the model; therefore, aggregation of indicators is theoretically plausible. What remains is to provide statistical evidence for aggregation. However, first I will clarify terminology with reference to figure 5.1.

No aggregation (noagg) refers to modeling all indicators on all dimensions of all constructs. Part aggregation (partagg) refers to summed indicators loading on all

dimensions of all constructs. Full aggregation (fullagg) refers to summed indicators on all constructs, and the three dimensions of relationship learning aggregated to one construct with one summed indicator. The seller and buyer data are never aggregated.

5.2 INTEGRATING THE MTMM MATRIX

The aggregation procedures are integrated into the multitrait-multimethod (MTMM) matrix approach (Campbell and Fiske 1959) to jointly examine the internal consistency, convergent validity, and discriminant validity of the constructs at various levels of aggregation. I perform confirmatory factor analysis (CFA) at the noagg level to get a detailed view of the statistical properties of each indicator. In so doing I can check that indicators load significantly, converge on the correct construct, and discriminate between other constructs. Problematic items can be removed before the model is analyzed at a more aggregated level. The partagg level analysis allows me to test my rationale for aggregating the relationship learning construct. I expect the three dimensions to be highly correlated to the extent where they converge on one dimension. The fullagg level allows for the most parsimonious representation of the model.

Figure 5.2 shows an example of a MTMM noagg measurement model. The model suggests that informant reports are a function of the reality of what is being measured, the systematic bias introduced by the key-informants, and error. The basic logic of the MTMM approach is that different methods measuring the same trait should be highly correlated. In this case, the informants from each side of the dyad are modeled as separate methods measuring the same phenomenon. Two informants reporting on the same phenomenon should agree (highly correlate) if their reports are to be judged reliable and valid as composite measures (Phillips 1981). Alternatively, low correlations between informant reports can indicate expected differences in perspectives (Wathne et al. 2001). Distinct traits should not be highly correlated, as evidence of discriminant validity.

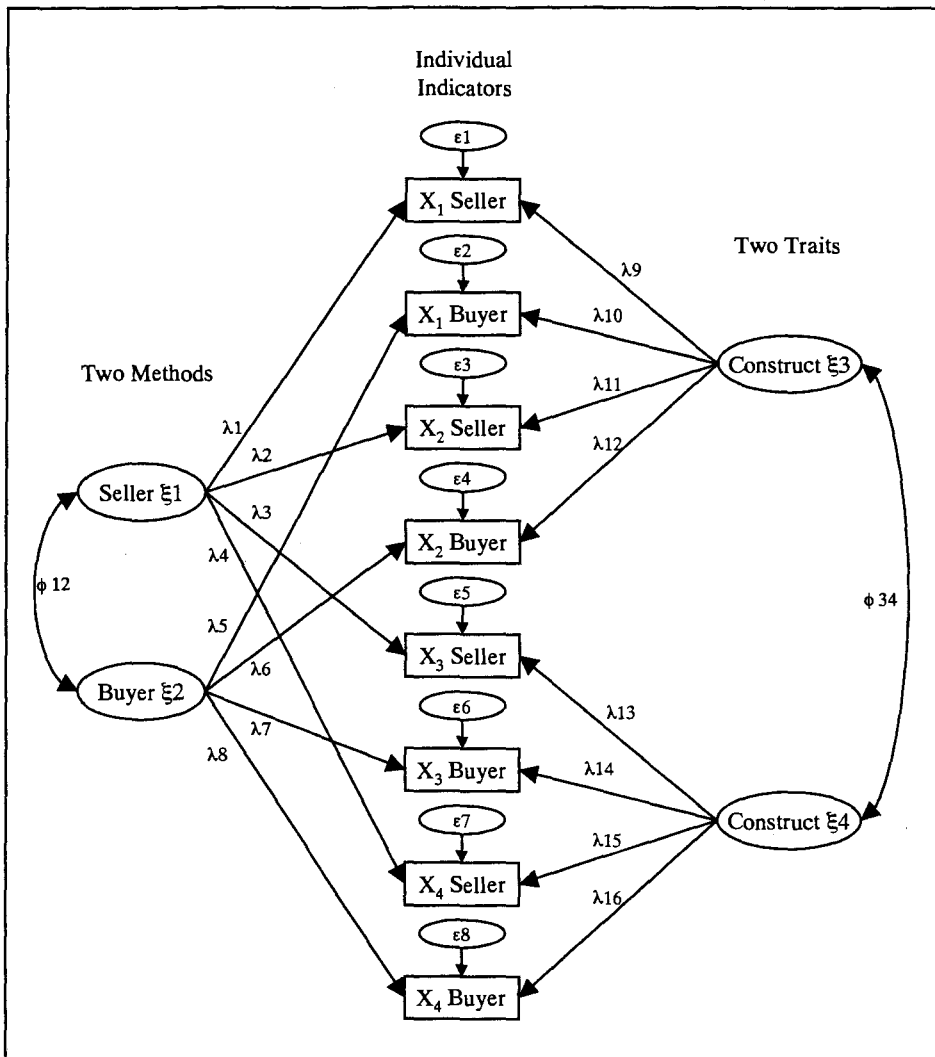


Figure 5.2, MTMM Matrix

The ksi (ξ) factors represent latent independent variables. The methods (ξ_1 and ξ_2), which in this case represent the buyer and the seller sides of the data, are allowed to correlate, as represented by the curved line labeled phi 12 (ϕ_{12}). The indicators (Xs) represent individual items reported by the individual key-informants from their respective sides of the dyad. They are set to load onto the methods with respect to which side of the dyad they represent, and onto the traits with respect to which construct they represent. The traits (ξ_3 and ξ_4) represent two distinct constructs, for example, external uncertainty and internal complexity. In the example, each construct has four indicators, two from the seller side and two

from the buyer side of the dyad. The constructs are allowed to correlate, as represented by the curved line labeled ϕ_{34} . This model allows for the partitioning of variance at the indicator level between traits, methods, and error. Trait variance is equal to θ^2 for each construct loading, method variance is equal to δ^2 for each method loading, and error variance is equal to $\theta\delta$. Good model fit indicates convergent validity when controlling for methods factors. This model can be broken down into a trait-only model for a stricter test of convergent validity.

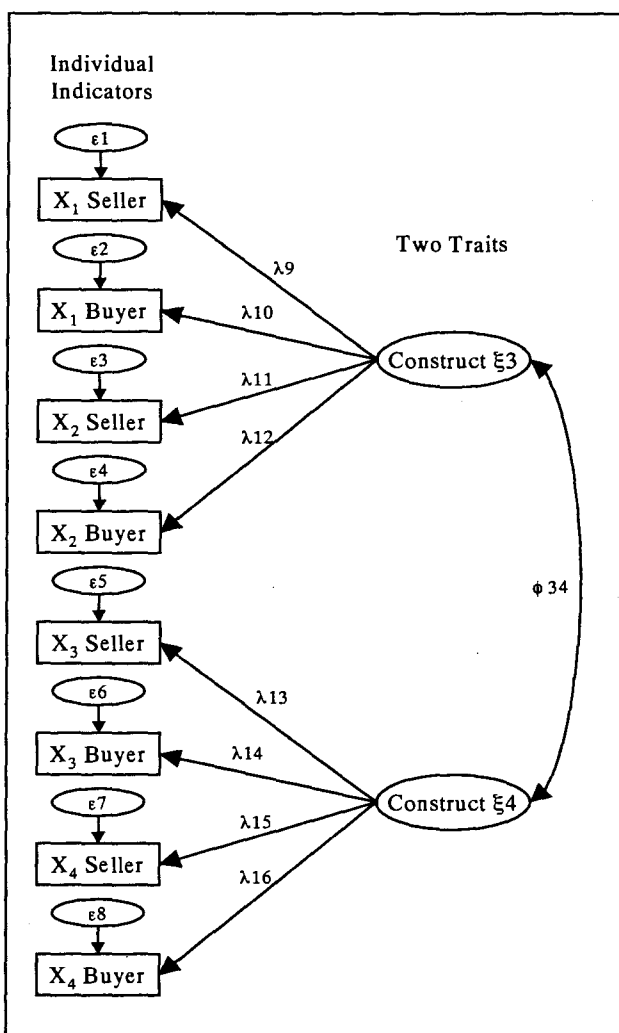


Figure 5.3, Trait-Only Model

A trait-only model (figure 5.3) allows for a test of convergent validity without methods factors. Again, good model fit indicates convergent validity. The model suggests that informant reports are a function of the reality of what is being measured and error. If model fit is not satisfactory, then partitioning the variance between traits, methods, and error is necessary to determine if the traits explain a sufficient portion of total variance, or if much of the variance is due to the systematic bias of key-informants because of their perspective from one side of the dyad.

5.3 SCREENING THE DATA

This section describes basic data screening procedures carried out prior to running the measurement models. This includes response rates, missing data, normality, reliability, and unidimensionality.

5.3.1 RESPONSE RATES

Of 780 supplier companies contacted by telephone, 665 agreed to recruit a buyer respondent and participate in the study. Both respondents were faxed or mailed the questionnaire. One follow-up call was made to non-respondents within a week of sending the questionnaire. In total, 317 questionnaires from dyads were returned. The response rates were virtually identical, presumably because buyers were recruited directly through the suppliers. Most likely buyers felt some degree of pressure to participate on behalf of the seller referent. Two sets of responses had excessive outliers, and given no reason to suspect they represented a characteristic of the population they were removed from the analysis. The 315 dyadic responses used in the analysis represent a 41% response rate based on the 780 suppliers initially contacted. This response rate is consistent with other recent marketing channel studies lying roughly in the middle (e.g. Dahlstrom and Nygaard 1999; Doney and Cannon 1997; Grayson and Ambler 1999; Jap 1999). Because the vast majority of respondents opted for the fax, responses were quite immediate, thus we did not compare early and late responses to assess non-response bias.

5.3.2 MISSING DATA

Regarding missing data the most widely used approach is to apply listwise deletion, which removes any observation that has missing information for any of the variables. This can create problems with inconsistent estimates if the missing values are not missing at random, which introduces systematic bias into the sample, or if the number of missing cases is large relative to the sample size. As the effective sample size drops toward the number of observed variables, the seriousness and magnitude of the missing data problem grows (Bollen 1989, p. 370).

Randomness is examined through a graphical display of the missing data with cases on one axis and indicators or variables on the other (Hair et al. 1998). No consistent patterns were found at the indicator level, thus the missing values are assumed to be random.

Preliis (Jöreskog and Sörbom 1996b) generates a table of percentages of missing values. The most extreme cases were under 10% with no aggregation, 16% with partial aggregation, and 16% with full aggregation. Given that the absolute worst effective sample size (n=264) far exceeds the number of observed variables (the maximum is 68 with no aggregation), missing data do not constitute any problem.

5.3.3 NORMALITY

Univariate normality was checked at the individual item level and aggregated levels because heavily skewed, flat, or peaked distributions may influence correlations and factor solutions (Hair et al. 1998). Kurtosis and skewness statistics calculated in SPSS for individual indicators as well as the two levels of aggregation were all less than one. What is most important is that the kurtosis statistics (see table 5.1 for partial and full aggregation) are all substantially higher than the skewness statistics, indicating that deviations from normality are most likely caused by kurtosis, not skewness. Olsson et al. (2000) found that maximum likelihood estimation in structural equation modeling is robust against abnormality

Variable	Seller		Buyer	
	Skewness	Kurtosis	Skewness	Kurtosis
Collaboration	0.033	-0.965	-0.105	-0.710
Trust	-0.365	-0.684	-0.246	-0.676
Complexity	0.228	-0.601	0.191	-0.704
Uncertainty	-0.155	-0.910	-0.169	-0.930
Asset Specificity	-0.214	-0.739	-0.189	-0.503
Infshare	-0.323	-0.849	-0.101	-0.816
Interpretation	-0.129	-0.656	-0.150	-0.687
Memory	-0.275	-0.640	-0.149	-0.524
Relearn	-0.261	-0.605	-0.137	-0.822
Absolute Average	-0.162	-0.739	-0.117	-0.708

Table 5.1, Univariate Normality (SPSS)

related to excessive kurtosis, thus it is acceptable to use maximum likelihood estimation on the relationship learning data.

Prelis 2 (Jöreskog and Sörbom 1996b), a companion program to Lisrel 8, provides D'Agostino's (1986) tests of univariate normality. Table 5.2 shows partial and full aggregation values generated after refining the scales in the reliability and unidimensionality analyses. Although we are concerned about multivariate normality, the univariate tests have merit because they pinpoint variables that sharply deviate from a normal distribution (Bollen 1989, p. 422). P-values greater than 0.05 (assuming $\alpha = 0.05$) would indicate univariate normality, insofar as they show that the skewness and kurtosis are not significantly statistically different from that of normal distributions. Again, from the table we see that deviations from normality are more related to kurtosis than skewness, therefore, given the Olsson et al. (2000) conclusions regarding normality and kurtosis, deviations from normality in the relationship learning data are not a problem.

Variable	Skewness		Kurtosis		Skewness and Kurtosis	
	Z-Score	P-Value	Z-Score	P-Value	Chi-Square	P-Value
scollab	0.307	0.759	-4.460	0.000*	19.990	0.000*
bcollab	0.085	0.933	-3.483	0.000*	12.141	0.002*
strust	-2.626	0.009*	-3.076	0.002*	16.358	0.000*
btrust	-1.363	0.173	-3.561	0.000*	14.539	0.001*
sTRxCB	2.421	0.015*	-4.238	0.000*	23.819	0.000*
bTRxCB	3.034	0.002*	-3.006	0.003*	18.241	0.000*
scomplex	1.275	0.202	-3.630	0.000*	14.804	0.001*
bcomplex	1.902	0.057	-2.366	0.018*	9.215	0.010*
suncert	-0.769	0.442	-4.876	0.000*	24.362	0.000*
buncert	-1.173	0.241	-4.694	0.000*	23.409	0.000*
sasset	-2.202	0.028*	-3.892	0.000*	19.996	0.000*
basset	-2.081	0.037*	-3.045	0.002*	13.604	0.001*
sinfshare	-1.117	0.264	-6.255	0.000*	40.370	0.000*
binfshare	-1.199	0.230	-2.412	0.016*	7.256	0.027*
sinterpr	-0.448	0.654	-3.645	0.000*	13.487	0.001*
binterpr	-0.565	0.572	-3.696	0.000*	13.980	0.001*
smemory	-1.020	0.308	-3.329	0.001*	12.121	0.002*
bmemory	-1.060	0.289	-2.258	0.024*	6.224	0.045*
srelearn	-0.515	0.460	-3.216	0.001*	10.609	0.005*
brelearn	-0.739	0.009*	-3.683	0.000*	14.104	0.001*

* indicates abnormal at $\alpha = 0.01$

Table 5.2, Test of Univariate Normality for Continuous Variables (Prelis)

5.3.4 RELIABILITY ANALYSIS (COEFFICIENT ALPHA)

As a test of reliability, Churchill (1979, p. 68) recommends that coefficient alpha should be calculated prior to any factor analysis. All scales except complexity were above the recommended 0.7 cutoff (Nunnally 1978). By dropping items 1 and 3 the complexity scale passed the reliability test (see Table 5.3). The three remaining items should still sufficiently represent the construct because they deal with both product and relationship complexity.

<u>Variable</u>	<u>Items</u>	<u>Seller</u>	<u>Buyer</u>
Collaboration	1-5	0.9361	0.9120
Trust	4-8	0.9248	0.8874
Complexity	2,4,5	0.7260	0.7297
Uncertainty	1-5	0.8538	0.8367
Asset Specificity	1-2	0.7535	0.7296
Information Sharing	1-7	0.8795	0.8387
Interpretation	1-4	0.8177	0.8052
Memory	1-6	0.8735	0.8185
Relationship Learning	1-17	0.9431	0.9215

Table 5.3, Reliability Analysis (Coefficient Alpha)

5.3.5 UNIDIMENSIONALITY

A necessary condition when constructs are measured with multiple indicators is that they are acceptably unidimensional, that is, each set of indicators has only one construct in common. A relatively straightforward test of unidimensionality is to run an exploratory factor analysis. Items should have loadings greater than 0.4 on the first factor with the theoretically correct sign (Anderson and Weitz 1992, p. 23), and they should load properly (Dahlstrom and Nygaard 1999, p. 164). That is, they should not significantly cross-load on multiple factors.

I ran the analysis on all possible pairs of constructs using eigen values to determine the number of factors. The recommended cutoff eigen value is 1 for a factor to be considered significant, although if the number of variables is below 20 there is a tendency to extract a conservative number of factors (Hair et al. 1998, p.

103). Therefore, in some cases I reduced the cutoff to below 1 to force a two-factor solution. All loadings were significant, however, there were some problems with cross-loading. As a result I dropped items 1, 2, and 5 from the information sharing scale, item 4 from the interpretation scale, item 3 from the memory scale, and item 2 from the uncertainty scale. Given that all of the constructs were still measured with multiple indicators and none of the dimensions within constructs disappeared, there should be no problem in removing these items.

Cross-loading between information sharing, interpretation, and memory integration was so serious that I chose not to remove any indicators based on this criteria. It would have adversely affected measurement of the constructs. Instead, I take the cross-loadings as an indication of the close relationship between the constructs and as support for a single relationship learning construct.

As a check on the exploratory factor analysis I examined item-to-total correlations for individual items (Nunnally 1978). Items for each construct should be highly correlated with the composite scale score (Churchill 1979, p. 68). The rule of thumb is that correlations should exceed 0.5 (Hair et al. 1998). The correlations ranged from 0.629-0.900 and all were significant at the $\alpha=0.01$ level (two-tailed), thus mirroring the exploratory factor analysis.

The final check of unidimensionality is to run a confirmatory factor analysis to assess convergent and discriminant validity at the item level between pairs of constructs (Anderson and Gerbing 1988). These assessments are developed and shown in the next section.

5.4 THE MEASUREMENT MODEL

A two-step approach to structural equation modeling is often recommended (Anderson and Gerbing 1988), whereby the measurement model is initially specified and validated prior to the structural model. The measurement model specifies relationships between observed measures and their corresponding latent

variable, and latent variables are allowed to correlate. No structural relationships are specified. That is to say, causal relationships are not inferred (Bollen 1989, p. 182). The rationale is that this alleviates the interaction of the measurement and structural models allowing for a more accurate assessment of validity and reliability (Hair et al. 1998, p. 600).

Based on robustness against abnormality and ease of interpretation, Pearson correlation matrices were generated in Prelis for input into Lisrel. The interaction effect, represented as the product of collaboration and trust, was calculated in Prelis prior to input into Lisrel.

5.4.1 SCALE INVARIANT ESTIMATES

To attain scale invariant estimates you can either fix one indicator loading on each latent construct to 1, or fix the diagonal of the phi matrix to 1 (recommended by Anderson and Gerbing 1988, p. 415). All final solutions for the measurement model were attained by manually fixing the diagonal of the phi matrix to one. For the discriminant validity tests I resorted to fixing one indicator for each latent construct in order to attain model convergence.

5.4.2 STARTING VALUES

In many of the initial models I did not attain convergence, and the program asked for better starting values. Default starting values for parameter estimation in Lisrel 8.30 are 0. Starting values are simply initial estimates, and in some cases the program needs help in starting iterations by manually setting them (Jöreskog and Sörbom 1996a, p. 18). The program may suggest starting values or you can systematically try different ones. This should have no substantive effect on the solution. To attain solutions for all final models I had to suggest starting values in the range of 0.3-1.

5.4.3 OFFENDING ESTIMATES

Offending estimates are estimated coefficients that exceed acceptable limits, for example, negative error variances or standardized coefficients greater than 1.

When offending estimates are encountered, they must be resolved before interpreting the results because a change in one part of the model may significantly affect other parts of the model (Hair et al. 1998, p. 610).

All loadings between indicators and their related constructs should be significant and in the proper direction (Schumacker and Lomax 1996, p. 106), thus verifying the relationships. Problematic loadings should be resolved before model

Parameter	Scale	Variable	Estimate (std. error)	t-value
$\lambda_{1,1}$	Collab	Seller	0.76 (0.08)	9.00
$\lambda_{2,1}$		Buyer	0.70 (0.07)	9.69
$\lambda_{3,2}$	Trust	Seller	0.49 (0.16)	3.06
$\lambda_{4,2}$		Buyer	0.47 (0.15)	3.15
$\lambda_{5,3}$	TRxCB	Seller	0.72 (0.10)	7.26
$\lambda_{6,3}$		Buyer	0.64 (0.09)	7.04
$\lambda_{7,4}$	Complex	Seller	0.71 (0.06)	11.37
$\lambda_{8,4}$		Buyer	0.75 (0.05)	14.75
$\lambda_{9,5}$	Uncert	Seller	0.68 (0.07)	9.08
$\lambda_{10,5}$		Buyer	0.66 (0.07)	9.41
$\lambda_{11,6}$	Asset	Seller	0.69 (0.10)	7.00
$\lambda_{12,6}$		Buyer	0.47 (0.08)	5.99
$\lambda_{13,7}$	Relearn	Seller	0.64 (0.13)	4.87
$\lambda_{14,7}$		Buyer	0.63 (0.12)	5.40
$\lambda_{1,8}$	Seller	Collab	0.46 (0.11)	4.29
$\lambda_{3,8}$		Trust	0.71 (0.11)	6.23
$\lambda_{5,8}$		TRxCB	0.56 (0.12)	4.81
$\lambda_{7,8}$		Complex	0.37 (0.08)	4.51
$\lambda_{9,8}$		Uncert	0.35 (0.10)	3.56
$\lambda_{11,8}$		Asset	0.50 (0.11)	4.39
$\lambda_{13,8}$		Relearn	0.68 (0.12)	5.56
$\lambda_{2,9}$		Buyer	Collab	0.46 (0.09)
$\lambda_{4,9}$	Trust		0.60 (0.12)	4.97
$\lambda_{6,9}$	TRxCB		0.57 (0.09)	6.44
$\lambda_{8,9}$	Complex		0.34 (0.08)	4.06
$\lambda_{10,9}$	Uncert		0.32 (0.10)	3.27
$\lambda_{12,9}$	Asset		0.49 (0.07)	6.54
$\lambda_{14,9}$	Relearn		0.59 (0.12)	5.01

Table 5.4, Final Factor Loadings Fullagg

aggregation. Aggregated indicators that include insignificant individual indicators may hide unresolved problems and adversely affect interpretation (Bagozzi and Edwards 1998). At the partagg level I had identification problems with the phi parameters related to asset specificity. By fixing the asset specificity loadings to the values suggested at the fullagg level I attained a good model. My primary goal at the partagg level was to examine the relationships between information sharing, interpretation, and memory integration prior to aggregating the

relationship learning construct. Therefore, I was not concerned with the asset specificity problems.

In the partagg with only traits model, the correlations in the phi matrix between the relationship learning constructs (information sharing, interpretation, and memory) exceeded 1, which is theoretically impossible given that a correlation matrix was used as input. The parameters should be between -1 to 1 , although Jöreskog (1999) demonstrated that in models with high multicollinearity it is quite possible to get standardized coefficients greater than 1. When this happens, the options are to consider dropping a construct or to ensure true discriminant validity between the constructs. Dropping a construct is not an option. Discriminant validity tests indicate that there are problems between the constructs, supporting the argument to aggregate the three elements into a single construct of relationship learning. The problem disappeared with aggregation. Final factor loadings at the fullagg level are shown in table 5.4.

5.4.4 INTER-ITEM CORRELATIONS

To improve model fit, the program will often suggest allowing error terms for indicators to correlate. In most situations this would be theoretically unfounded, and thus a violation of the assumption with maximum likelihood estimation that error terms should not be correlated. In a case like relationship learning where identical measures are taken across a dyad, it is conceivable that the error of the responses could be highly correlated. As an experiment to improve model fit I allowed the errors across the dyad to correlate, however, there was no particular improvement in model fit, therefore, in the final models none of the error terms between respondents were allowed to correlate.

Because the interaction variable is a direct function of the variables that formed it (collaboration and trust), it is feasible that error terms should correlate. Indeed, model fit improved substantially when these error terms were allowed to correlate.

5.4.5 MULTITRAIT-MULTIMETHOD CORRELATIONS

Consistent with the criteria set out by Campbell and Fiske (1959, p. 82) for assessing convergent and discriminant validity by the multitrait-multimethod matrix, the next step is to examine correlations. The rule of thumb is that we want high correlations between methods (informants) to establish convergent validity, and low correlations between traits (scales representing constructs) to establish discriminant validity (Churchill 1979, p. 70). However, Bollen and Lennox (1991, p. 309) demonstrate how correlations alone can lead to erroneous conclusions, therefore, they recommended cross validation with confirmatory factor analysis.

For the sake of space, only full aggregation is shown for all constructs in table 5.5. Partial aggregation is shown in table 5.6 for the components of relationship learning to allow for assessment as to whether the construct should be aggregated. The shaded inter-method (buyer and seller respondent) correlations should exceed other relevant cross-construct correlations. Correlations in bold in both tables show possible problems with discriminant validity for all constructs except complexity. The high correlation between constructs may be problematic within the model, however, it supports aggregating information sharing, interpretation, and memory integration into a single relationship learning construct.

	scb	bcb	str	btr	scx	bcx	suc	buc	sas	bas	srl
scb	1										
bcb	0.64	1									
str	0.57	0.37	1								
btr	0.34	0.45	0.47	1							
scx	0.25	0.23	0.12	0.01	1						
bcx	0.10	0.26	-0.01	0.05	0.60	1					
suc	0.52	0.44	0.49	0.38	0.16	0.04	1				
buc	0.47	0.47	0.37	0.44	0.10	0.07	0.52	1			
sas	0.55	0.47	0.40	0.29	0.23	0.05	0.60	0.44	1		
bas	0.34	0.41	0.29	0.39	0.07	0.07	0.39	0.45	0.49	1	
srl	0.70	0.52	0.69	0.42	0.28	0.11	0.60	0.49	0.60	0.39	1
brl	0.53	0.62	0.45	0.56	0.13	0.21	0.53	0.61	0.48	0.53	0.66

Table 5.5, Fullagg Correlations

	sinf	binf	sint	bint	smem	bmem
sinf	1.00					
binf	0.51	1.00				
sint	0.64	0.49	1.00			
bint	0.47	0.59	0.56	1.00		
smem	0.72	0.53	0.67	0.49	1.00	
bmem	0.44	0.69	0.48	0.61	0.54	1.00

Table 5.6, Partagg Correlations for only Relationship Learning

5.4.6 FIT INDICES

In confirmatory factor analysis, overall model fit determines the degree to which the model fits the sample data (Schumacker and Lomax 1996, p. 124). Fit measures evaluate the entire model and can indicate inadequacies not apparent with individual components (e.g. t-values) (Bollen 1989, p. 256). In that no single fit measure is universally agreed upon as being superior, and each has inherent strengths and weaknesses, Lisrel 8.30 provides several. It is wise to assess several fit measures.

5.4.6.1 CHI-SQUARE

The chi-square statistic tests whether the observed and the estimated matrices significantly differ. A non-significant chi-square relative to the degrees of freedom indicates that the matrices are not statistically different, and thus the data fit the model (Schumacker and Lomax 1996, p. 125). This is bolstered by the P value which should be greater than 0.05 (assuming $\alpha = 0.05$) to consider the model as acceptable (Bagozzi and Yi 1988, p. 77). An alternative is to use the normed chi-square, which is the ratio of the chi-square statistic divided by the degrees of freedom (Hair et al. 1998; Jöreskog and Sörbom 1993). As a general rule the chi-square statistic should be divided by the number of degrees of freedom, and the result should be between 1 and 2. Values below 1 indicate the possibility of overfitting, while values greater than 2 indicate that the model needs improvement (Hair et al. 1998).

When using chi-square in structural equation modeling, sample size needs to be considered. As the sample size increases, the chances of rejecting the model increases (Bagozzi and Yi 1988, p. 77). As a rule of thumb, the sample size becomes critical above 200 (Schumacker and Lomax 1996, p. 125). In this case, the smallest effective sample size is $n=255$, which casts doubt on relying too heavily on chi-square.

5.4.6.2 ROOT MEAN SQUARE ERROR OF APPROXIMATION (RMSEA)

The root mean square error of approximation (RMSEA) is a measure of the discrepancy between the generated and the true covariance matrices, and is less sensitive to sample size than chi-square. Browne and Cudeck (1992) suggest that values below 0.05 indicate good fit, with zero indicating perfect fit. Olsson, Troye, and Howell (1997) cast doubt on this when comparing across estimation methods, therefore, it is important to compare it with other fit indices.

5.4.6.3 GOODNESS OF FIT INDEX (GFI)

The goodness of fit index (GFI) is a non-statistical measure within a range of 0 –1. It indicates the relative amount of variances and covariances jointly accounted for by the hypothesized model (Schumacker and Lomax 1996, p. 125). Zero indicates a poor fit of the data to the model, while one indicates a perfect fit. Though debatable, the generally accepted threshold indicating an acceptable model is 0.9 (Hair et al. 1998).

5.4.6.4 ADJUSTED GOODNESS OF FIT INDEX (AGFI)

The adjusted goodness of fit index (AGFI) also indicates the relative amount of variances and covariances jointly accounted for by the hypothesized model. It is basically the same as GFI, except that it is adjusted for the number of degrees of freedom relative to the number of variables (Schumacker and Lomax 1996, p. 126). The range will usually be between 0 –1, with values greater than or equal to 0.9 indicating an acceptable fit (Bagozzi and Yi 1988, p. 79).

The advantage of GFI and AGFI over other methods (especially chi-square) is that they are, according to Jöreskog and Sörbom (1984), not affected by sample size and are relatively independent of normality. However, this is buffered by Marsh and Hau (1996) who postulate that AGFI incorporates a penalty for parsimony because of its dependence on degrees of freedom. In other words using AGFI could encourage adding constructs to attain better fit.

5.4.6.5 CRITICAL N

Critical N is a goodness of fit measure indicating the sample size that would make the obtained Chi-square just significant at a chosen significance level. Bollen (1989) recommends that CN should be at least 200.

5.4.7 MODEL FIT

When models without methods factors achieve poor fit, the next step is to include methods factors to assess if lack of fit is attributable to biases associated with the informants from either side of the dyad (Phillips 1981, p. 400). The methods represent a systematic source of distortion, meaning the difference in perceptions between sellers and buyers on the same phenomenon.

	<u>Noagg</u>		<u>Partagg</u>		<u>Fullagg</u>	
	<u>No</u>	<u>Methods</u>	<u>No</u>	<u>Methods</u>	<u>No</u>	<u>Methods</u>
df	1567	1508	95	79	54	39
Chi ²	4287.72	2746.87	478.57	117.84	333.49	71.30
p-value	0.00	0.00	0.00	0.003	0.00	0.001
RMSEA	0.11	0.051	0.14	0.039	0.15	0.046
GFI	0.56	0.77	0.81	0.96	0.83	0.97
AGFI	0.52	0.74	0.65	0.91	0.68	0.92
NFI	0.67	0.79	0.91	0.98	0.92	0.98
NNFI	0.75	0.88	0.88	0.99	0.89	0.98
CFI	0.76	0.89	0.92	0.99	0.93	0.99
CN	126	188	86	297	77	276

Table 5.7, Fit Indices

Table 5.7 shows fit statistics for the final measurement models after resolving estimation difficulties and dropping troublesome items. Models were estimated with and without methods factors for all levels of aggregation. For all levels of

aggregation methods factors were important to achieve good fit. Model fit also improves with aggregation, which may be a function of inflated error from including all indicators in each construct at the noagg level (Bagozzi and Edwards 1998, p. 53). In addition to the discussed fit indices I also show the normed fit index (NFI), the non-normed fit index (NNFI), and the comparative fit index (CFI). In all cases the suggested cutoff is that values should exceed 0.9.

Clearly, methods factors were necessary to achieve good model fit, and fit improved considerably with aggregation.

5.4.8 VARIANCE EXTRACTED

Although measures of a construct may satisfy the composite reliability criterion, this says nothing about the amount of variance captured by the construct compared to the amount of variance due to measurement error (Fornell and Larcker 1981, p. 45). To attain this information, Fornell and Larker (1981) suggest a measure of variance extracted that should exceed 0.5; otherwise, variance due to measurement error is larger than variance due to the construct.

	Noagg	Partagg	Fullagg
Collaboration	0.62	0.68	0.68
Trust	0.54	0.40	0.41
TRxCB	-----	0.55	0.69
Complexity	0.45	0.62	0.61
Uncertainty	0.40	0.51	0.51
Asset Specificity	0.46	0.47	0.47
Information Sharing	0.38	0.45	-----
Interpretation	0.46	0.53	-----
Memory	0.37	0.57	-----
Relationship Learning	-----	-----	0.66

Table 5.8, Variance Extracted

Table 5.8 shows mixed results. Some constructs improved with aggregation, while some did not. Asset Specificity is the only measure that is not satisfactory at

any level of aggregation. Interestingly, it again highlights the importance of examining scales at each level of aggregation.

5.4.9 COMPOSITE RELIABILITY

Fornell and Larker (1981, p. 45) suggest a measure of composite reliability to assess the internal consistency of the indicators of the latent constructs. They recommend that composite reliability should exceed 0.7. Reliabilities for models with methods factors are listed in table 5.9. At noagg the measures are all highly reliable, however, at higher levels of aggregation uncertainty, asset specificity, and trust drop below the cutoff. This contradicts the previous Cronbach Alpha reliability calculations.

	Noagg	Partagg	Fullagg
Collaboration	0.94	0.81	0.81
Trust	0.92	0.57	0.58
CBxTR	0.93	0.82	0.81
Complexity	0.82	0.76	0.76
Uncertainty	0.80	0.67	0.67
Asset Specificity	0.77	0.63	0.63
Infshare	0.78	0.62	-----
Interpretation	0.84	0.70	-----
Memory	0.85	0.73	-----
Relationship Learning	-----	-----	0.80

Table 5.9, Composite Reliability

5.4.10 PARTITIONING THE VARIANCE

According to Phillips (1981, p. 405), partitioning the variance between trait, method, and error provides an indication for the reliability between informants as well as an indication of the validity of the reports. In addition, comparisons can be made of the distribution of variance between components at the different levels of aggregation. High trait variance and low error variance means that the measures of traits explain the majority of what is going on in the data. High method variance means that the variance is due to systematic differences between respondents across the dyad. In this case we are looking for high trait variance with low method and error variance. Trait variance and method variance are calculated by squaring theta (λ^2) for each construct's respective factor loading, and error variance is equal to theta-delta (θ_δ).

At the noagg level (table 5.10) the average trait variances between seller (39%) and buyer (40%) are about equal, however, the systematic error is considerably higher for the seller (21%) than for the buyer (12%). This means the validity of either side to report on the constructs is about equal. Trust and information sharing are the lowest at about 30%.

	Seller				Buyer		
	Trait	Method	Error		Trait	Method	Error
Collab1	0.58	0.16	0.26	Collab1	0.35	0.38	0.27
Collab2	0.61	0.15	0.24	Collab2	0.36	0.28	0.36
Collab3	0.64	0.13	0.23	Collab3	0.32	0.38	0.29
Collab4	0.56	0.18	0.26	Collab4	0.31	0.48	0.21
Collab5	0.61	0.12	0.27	Collab5	0.40	0.30	0.30
Trust1	0.27	0.40	0.33	Trust1	0.49	0.03	0.48
Trust2	0.31	0.46	0.22	Trust2	0.56	0.04	0.40
Trust3	0.30	0.48	0.22	Trust3	0.67	0.04	0.29
Trust4	0.28	0.55	0.17	Trust4	0.55	0.04	0.41
Trust5	0.23	0.55	0.22	Trust5	0.50	0.07	0.43
Complex1	0.22	0.04	0.74	Complex1	0.23	0.09	0.68
Complex2	0.49	0.08	0.43	Complex2	0.55	0.04	0.42
Complex3	0.56	0.05	0.39	Complex3	0.50	0.05	0.45
Uncert1	0.35	0.12	0.54	Uncert1	0.37	0.02	0.61
Uncert2	0.29	0.14	0.57	Uncert2	0.41	0.03	0.56
Uncert3	0.44	0.04	0.52	Uncert3	0.37	0.05	0.58
Asset1	0.46	0.12	0.42	Asset1	0.40	0.05	0.55
Asset2	0.44	0.08	0.48	Asset2	0.40	0.01	0.59
Infshare1	0.27	0.26	0.47	Infshare1	0.31	0.08	0.60
Infshare2	0.26	0.25	0.49	Infshare2	0.34	0.10	0.56
Infshare3	0.35	0.14	0.52	Infshare3	0.41	0.12	0.47
Interp1	0.49	0.10	0.41	Interp1	0.36	0.04	0.60
Interp2	0.52	0.10	0.38	Interp2	0.41	0.10	0.49
Interp3	0.31	0.18	0.51	Interp3	0.37	0.14	0.49
Memory1	0.29	0.25	0.46	Memory1	0.38	0.05	0.56
Memory2	0.35	0.25	0.40	Memory2	0.34	0.08	0.58
Memory3	0.34	0.20	0.46	Memory3	0.31	0.04	0.65
Memory4	0.19	0.28	0.53	Memory4	0.28	0.08	0.64
Memory5	0.31	0.18	0.51	Memory5	0.35	0.12	0.53
Average	0.39	0.21	0.40		0.40	0.12	0.48

Table 5.10, Partitioning the Variance-Noagg

At the partagg (table 5.11) and fullagg (table 5.12) levels, the buyer trait variances are about equal (37% and 38%), as are the systematic errors (26% and 24%).

While the systematic error is considerably higher than at the noagg level, the reports are equally valid for all levels when considering only buyers. At the partagg level the seller trait variance average is 42% and systematic error average is 26%, which is not markedly different from any of the other partitionings.

	Seller				Buyer		
	Trait	Method	Error		Trait	Method	Error
Collab	0.59	0.20	0.20	Collab	0.49	0.19	0.32
Trust	0.24	0.50	0.26	Trust	0.23	0.31	0.46
CBxTR	0.50	0.34	0.16	CBxTR	0.41	0.31	0.28
Complex	0.58	0.14	0.29	Complex	0.52	0.12	0.37
Uncert	0.41	0.13	0.46	Uncert	0.50	0.06	0.43
Asset	0.48	0.25	0.27	Asset	0.22	0.27	0.51
Infshare	0.23	0.45	0.32	Infshare	0.29	0.37	0.34
Interp	0.40	0.29	0.31	Interp	0.35	0.30	0.35
Memory	0.32	0.48	0.20	Memory	0.34	0.36	0.30
Average	0.42	0.31	0.27	Average	0.37	0.26	0.37

Table 5.11, Partitioning the Variance, Partagg

Seller reports present a very interesting picture at the fullagg level. Average trait variance is 47% with systematic error at 29% and random error at 25%. The seller reports are thus clearly more valid on average at reporting on the relationship learning model at the fullagg level. It is also interesting to note that the relationship learning construct is more validly measured as an aggregated construct than when measured as individual elements. Again this supports

	Seller				Buyer		
	Trait	Method	Error		Trait	Method	Error
Collab	0.58	0.21	0.21	Collab	0.49	0.21	0.30
Trust	0.24	0.50	0.26	Trust	0.22	0.36	0.42
CBxTR	0.52	0.31	0.17	CBxTR	0.41	0.32	0.27
Complex	0.58	0.14	0.29	Complex	0.50	0.12	0.38
Uncert	0.46	0.12	0.42	Uncert	0.44	0.10	0.46
Asset	0.48	0.25	0.27	Asset	0.22	0.24	0.54
Relearn	0.41	0.46	0.13	Relearn	0.40	0.35	0.26
Average	0.47	0.29	0.25	Average	0.38	0.24	0.37

Table 5.12, Partitioning the Variance, Fullagg

aggregation of the construct.

Particularly problematic constructs at the fullagg or partagg levels are trust for either sellers or buyers and asset specificity on the buyer side. This does not show up at the noagg level for asset specificity. The noagg level gives indications of possible problematic items, however, dropping more items may begin to adversely affect measurement of the constructs.

5.4.11 CONSTRUCT VALIDITY

Testing for convergence and divergence between different measures, often referred to as convergent and discriminant validity, establishes construct validity. Cook and Campbell refer to, "Testing for a *convergence* across different measures or manipulations of the same thing and, second, testing for a *divergence* between measures and manipulations of related but conceptually distinct things (1979, p. 61)."

5.4.12 CONVERGENT VALIDITY

Convergent validity refers to the degree to which multiple attempts to measure the same concept by maximally different methods are in agreement (Campbell and Fiske 1959). A test of convergent validity is to examine the goodness of fit indices and t-values associated with the individual items (Anderson and Gerbing 1988, p. 416), at each level of aggregation without method (respondent) factors (Phillips 1981, p. 400). Good fit and significant t-values indicate convergent validity. All t-values for factor loadings in all final models were significant, however, as shown previously in table 5.7, none of the models without methods factors achieved good fit, thus convergent validity is only attained for models with methods factors. Substantively this means that there are systematic differences between sellers and buyers when reporting on this model.

5.4.13 DISCRIMINANT VALIDITY

“Discriminant validity refers to the extent to which a given construct is different from other constructs (John and Reve 1982, p. 520).” The easy test of discriminant validity is to estimate a confidence interval (\pm two standard errors) around the standardized correlations between latent constructs (off diagonal of the phi matrix). The phi matrix for fullagg with methods and traits is shown in table 5.13. Standardized correlations are shown with standard errors in brackets. At the fullagg level all constructs pass the easy test, although trust has some very high standard errors.

	Collab	Trust	Complx	Uncert	Asset	Relearn	Seller
Collab	1						
Trust	0.58 (0.12)	1					
Complx	0.15 (0.12)	-0.37 (0.35)	1				
Uncert	0.72 (0.07)	0.76 (0.11)	0.01 (0.12)	1			
Asset	0.60 (0.09)	0.22 (0.27)	-0.02 (0.16)	0.83 (0.07)	1		
Relearn	0.77 (0.06)	0.63 (0.18)	0.02 (0.18)	0.88 (0.06)	0.60 (0.12)	1	
Seller							1
Buyer							0.56 (0.15)

Table 5.13, Fullagg Phi Matrix

A stronger test of discriminant validity is to perform a chi-square difference test between pairs of constructs in two models. I do not test the interaction effect because it is the product of collaboration and trust so it will be so highly correlated with its parent constructs that it will certainly fail the test. In the first model the constructs are allowed to freely correlate. In the second model the correlation between constructs is fixed to 1. A significant difference indicates discriminant validity (Bagozzi and Phillips 1982). The test is conducted for pairs of constructs

to eliminate interaction between multiple constructs that may distort results (Anderson and Gerbing 1988, p. 416). All constructs easily pass this test (see table 5.14).

Cutoff for $\chi^2 = 3.84$ (1 degree of freedom)	Restricted	Unrestricted
	χ^2	χ^2
Collab and Complex	187.84	18.85
Collab and Uncert	47.38	3.33
Collab and Asset	65.19	8.13
Collab and Relearn	71.74	47.29
Collab and Trust	86.67	35.74
Complex and Uncert	160.55	1.32
Complex and Asset	159.59	1.26
Complex and Relearn	191.74	15.33
Complex and Trust	155.23	8.71
Uncert and Asset	53.14	13.34
Uncert and Relearn	38.08	16.21
Uncert and Trust	48.20	9.60
Asset and Relearn	64.38	29.55
Asset and Trust	67.27	13.54
Relearn and Trust	94.36	57.32

Table 5.14, Discriminant Validity by χ^2 Difference Test

A final strong test of discriminant validity is to check if the squared correlations in the phi matrix are greater than variance extracted (Fornell and Larcker 1981, p. 46). Apparently there may be some problems with the uncertainty construct (table 5.15). In light of the chi squared difference tests they are not deemed particularly serious.

	Collab	Trust	Complx	Uncert	Asset	Relearn	Variance Extracted
Collab	1						0.68
Trust	0.34	1					0.41
Complx	0.02	0.00	1				0.61
Uncert	0.52	0.61	0.00	1			0.51
Asset	0.36	0.05	0.00	0.69	1		0.47
Relearn	0.59	0.40	0.14	0.77	0.36	1	0.66

Table 5.15, Phi Correlations² and Variance Extracted

5.5 SUMMARY OF MEASURE VALIDATION

By conventional measures the scales seem to be reasonably reliably and valid. Clearly the measures perform best at the fullagg level. Discriminant and convergent validity are reasonable although uncertainty and trust give reason for concern. As for explained variance, the seller key informants provide more valid data. There is clear support for aggregating information sharing, interpretation, and memory integration into one construct of relationship learning.

In the next chapter the hypotheses are tested.

6. HYPOTHESIS TESTS

This chapter presents a detailed description of the hypothesis tests as well as a discussion of the results. Given the results of measure validation, I limit myself to only testing the fully aggregated data with methods factors. Following Anderson and Gerbing's (1988) two-step approach, after measure validation the next step is to specify the structural relationships, in this case using structural equation modeling in Lisrel. It is through the structural relationships that causality is inferred (Bollen 1989, p. 182). As with the measurement model, methods factors representing the seller and buyer informants can be included, thus allowing the variance to be partitioned into trait (construct of interest), method (systematic informant bias), and random error (Phillips 1981).

6.1 TESTING INTERACTION EFFECTS

Kenny and Judd (1984) introduced the first structural equation model using product variables to represent interaction effects (Jöreskog 1998, p. 239). A product variable is formed when two direct effect variables are multiplied together and the product is introduced into the model as a new variable. Formulated as a nonlinear regression equation it looks like this:

$$y = \alpha + \gamma_1 \xi_1 + \gamma_2 \xi_2 + \gamma_3 \xi_1 \xi_2 + \zeta$$

where there is a direct effect from each of the latent variables ξ_1 and ξ_2 as well as an interactive effect of the product of $\xi_1 \xi_2$ on the dependent variable y . α is the intercept term, the γ s are the coefficients, and ζ represents error.

Although the procedure has been developed and refined it remains technically demanding and model complexity often leads to convergence problems during

estimation (Rigdon, Schumacker, and Wothke 1998, p. 7). There are also implications for sample size, estimation techniques, test statistics, and fit statistics (Jöreskog and Yang 1996, p. 85). With the relationship learning model this is exacerbated by the addition of methods factors.

6.2 STRUCTURAL MODEL IN LISREL

I followed an example by Jonsson (1998) for specifying interaction effects. I divided the analysis into two distinct strategies, one where I kept all hypothesized relationships, and the other where I eliminated insignificant relationships such that I arrived at a nested model. In both approaches I followed a plan of eliminating offending estimates (like insignificant parameters), and adding theoretically justifiable paths suggested by the modification indices. In both cases it was difficult to attain a good structural model. I had convergence problems, starting value problems, and severe problems with offending estimates.

df	51
Chi ²	41.01
p-value	0.84
RMSEA	0.00
GFI	1.00
AGFI	0.99
NFI	0.99
NNFI	1.00
CFI	1.00
CN	593

Table 6.1, Fit Indices:
Full Model

Results of the full-model strategy are as follows. The fit indices indicate a very good fit of the model to the data (Table 6.1), although the Chi² suggests that there is a risk of over-fitting, thereby capitalizing on chance (Hair et al. 1998, p. 658). Considering the estimated loadings for the traits and methods factors it becomes quickly apparent that there are other problems as well. Trait variance and method variance are calculated by squaring theta (λ^2) for each construct's respective factor loading, and error

variance is equal to theta-delta (θ_δ). Although the random error (θ_δ) is not shown, it is easy to conclude that relative to methods or random error variance, trait variance is very low with only complexity getting above 16% (top half of table 6.2). This means that systematic and random error explain the vast majority of what is happening in the data.

Parameter	Scale	Variable	Estimate (std. error)	Explained Variance	t-value
$\lambda_{1,1}$	Collab	Seller	0.30 (0.10)	0.09	3.06
$\lambda_{2,1}$		Buyer	0.23 (0.08)	0.05	2.71
$\lambda_{3,2}$	Trust	Seller	0.40 (0.07)	0.16	5.37
$\lambda_{4,2}$		Buyer	0.39 (0.07)	0.15	5.59
$\lambda_{5,3}$	TRxCB	Seller	0.44 (0.09)	0.19	4.77
$\lambda_{6,3}$		Buyer	0.35 (0.09)	0.12	3.85
$\lambda_{7,4}$	Comple	Seller	-0.57 (0.09)	0.32	-6.50
$\lambda_{8,4}$		Buyer	-0.61 (0.09)	0.37	-6.92
$\lambda_{9,5}$	Uncert	Seller	0.39 (0.08)	0.15	4.61
$\lambda_{10,5}$		Buyer	0.38 (0.08)	0.14	4.65
$\lambda_{11,6}$	Asset	Seller	0.29 (0.08)	0.08	3.43
$\lambda_{12,6}$		Buyer	0.30 (0.07)	0.09	4.21
$\lambda_{13,7}$	Relearn	Seller	0.09 (0.03)	0.01	3.32
$\lambda_{14,7}$		Buyer	0.10 (0.03)	0.01	3.19
$\lambda_{1,8}$		Seller	0.71 (0.05)	0.50	13.24
$\lambda_{3,8}$		Trust	0.57 (0.06)	0.32	9.91
$\lambda_{5,8}$		TRxCB	0.70 (0.06)	0.49	11.03
$\lambda_{7,8}$		Complex	0.61 (0.08)	0.37	7.78
$\lambda_{9,8}$		Uncert	0.63 (0.06)	0.40	11.08
$\lambda_{11,8}$		Asset	0.63 (0.05)	0.40	13.12
$\lambda_{13,8}$		Relearn	0.82 (0.06)	0.67	14.85
$\lambda_{2,9}$	Buyer	Collab	0.74 (0.05)	0.55	16.42
$\lambda_{4,9}$		Trust	0.50 (0.06)	0.25	8.75
$\lambda_{6,9}$		TRxCB	0.74 (0.06)	0.55	12.92
$\lambda_{8,9}$		Complex	0.54 (0.10)	0.29	5.30
$\lambda_{10,9}$		Uncert	0.59 (0.06)	0.35	10.21
$\lambda_{12,9}$		Asset	0.49 (0.05)	0.24	10.00
$\lambda_{14,9}$		Relearn	0.78 (0.06)	0.61	13.70

Table 6.2, Factor Loadings and Explained Variance: Full Model

The structural relationships representing the hypothesized causal relationships are also troubling (Table 6.3). By including methods factors it was necessary to represent all latent constructs as Ksi (ξ) variables, whereas independent variables would normally be Eta (η) variables and dependent variables Ksi variables.

Consequently the structural relationships are specified in the Beta (β) matrix.

Assuming valid and reliable results, this would mean that H_1 concerning the positive effect of collaborative objectives on relationship learning is not confirmed

Parameter		Estimate (std. error)	t-value
$\beta_{1,2}$	Collab → Relearn	-0.29 (0.61)	-0.47
$\beta_{1,3}$	Trust → Relearn	0.92 (0.29)	3.15
$\beta_{1,4}$	TRxCB → Relearn	-0.34 (0.91)	-0.37
$\beta_{1,5}$	Complex → Relearn	0.90 (0.31)	2.91
$\beta_{1,6}$	Uncert → Relearn	0.90 (0.31)	2.91
$\beta_{1,7}$	Asset → Relearn	0.90 (0.31)	2.91

Table 6.3, Structural Path Coefficients: Full Model

because the loading is neither significant nor the correct sign. The interaction effect (H_3) is also not significant, although it is the correct sign. The standard errors are also very high, especially for the interaction effect (0.91).

df	13
Chi ²	16.74
p-value	0.84
RMSEA	0.03
GFI	0.99
AGFI	0.96
NFI	1.00
NNFI	1.00
CFI	1.00
CN	520

Table 6.4, Fit Indices:
Nested Model

The results for the nested model are just as problematic. The fit indices indicate a very good fit of the model to the data (Table 6.4), and over-fitting is apparently not a problem. Trait variance is definitely better (Table 6.5) than for the full model (Table 6.2), however, it is still not great. The relationship learning construct is very poor at 9% for the seller and 16% for the buyer.

Considering the structural relationships (Table 6.6), the model includes some insignificant relationships despite the strategy of eliminating insignificant relationships. All possible combinations were tried yet no model was acceptable. I settled on this model because it is the theoretically most rational choice given the findings from the two-stage least squares analysis that will be discussed next. It also fit the data better than any other model.

Parameter	Scale	Variable	Estimate (std. error)	Explained Variance	t-value
$\lambda_{1,1}$	Collab	Seller	0.73 (0.09)	0.53	8.39
$\lambda_{2,1}$		Buyer	0.46 (0.06)	0.21	7.85
$\lambda_{3,2}$	Trust	Seller	0.53 (0.06)	0.28	8.29
$\lambda_{4,2}$		Buyer	0.67 (0.09)	0.45	7.81
$\lambda_{5,3}$	TRxCB	Seller	0.75 (0.07)	0.56	10.99
$\lambda_{6,3}$		Buyer	0.33 (0.07)	0.11	4.69
$\lambda_{7,4}$	Uncert	Seller	0.52 (0.06)	0.27	8.58
$\lambda_{8,4}$		Buyer	0.70 (0.07)	0.49	10.52
$\lambda_{9,5}$	Relearn	Seller	0.30 (0.03)	0.09	8.91
$\lambda_{10,5}$		Buyer	0.40 (0.05)	0.16	8.67
$\lambda_{1,8}$	Seller	Collab	0.60 (0.07)	0.36	8.98
$\lambda_{3,8}$		Trust	0.65 (0.06)	0.42	10.65
$\lambda_{5,8}$		TRxCB	0.65 (0.06)	0.42	10.17
$\lambda_{7,8}$		Uncert	0.49 (0.06)	0.24	7.85
$\lambda_{9,8}$		Relearn	0.69 (0.07)	0.48	10.52
$\lambda_{2,9}$	Buyer	Collab	0.82 (0.14)	0.67	5.79
$\lambda_{4,9}$		Trust	0.40 (0.11)	0.16	3.58
$\lambda_{6,9}$		TRxCB	1.07 (0.20)	1.14	5.43
$\lambda_{8,9}$		Uncert	0.32 (0.09)	0.10	3.50
$\lambda_{10,9}$		Relearn	0.46 (0.12)	0.21	3.96

Table 6.5, Factor Loadings and Explained Variance: Nested Model

All direct effects are the correct hypothesized sign and are significant at the $\alpha = 0.10$ level. The interaction effect ($\beta_{1,4}$) is the correct sign, however, it is not significant.

Parameter		Estimate (std. error)	t-value
$\beta_{1,2}$	Collab \rightarrow Relearn	-0.62 (0.32)	1.93
$\beta_{1,3}$	Trust \rightarrow Relearn	0.77 (0.21)	3.70
$\beta_{1,4}$	TRxCB \rightarrow Relearn	-0.30 (0.27)	-1.12
$\beta_{1,5}$	Uncert \rightarrow Relearn	0.94 (0.26)	3.65

Table 6.6, Structural Path Coefficients: Nested Model

6.2.1 INTERPRETING THE RESULTS OF THE STRUCTURAL MODEL

None of the structural models are within acceptable bounds. Due to the presence of offending estimates, like insignificant relationships, the parameter estimates cannot be trusted (Hair et al. 1998, p. 610). Either the effects indeed are not significant, or something is interfering with attaining a reasonable solution. Two distinct possibilities are that the complexity of the model may be confounding the results (Jöreskog and Yang 1996, p. 85; Rigdon, Schumacker, and Wothke 1998, p. 7), or there are severe problems with multicollinearity.

Examining the correlations between variables for the combined data (Table 6.7) tends to suggest that the structural relationships should be significant because all correlations except one (trust and complexity) are significant at the $\alpha = 0.01$ level. The trust-complexity correlation is extremely close to significant at $\alpha = 0.01$, and easily significant at $\alpha = 0.05$. Because offending estimates can substantially affect the results and interpretation of the structural relationships, and there are several of them, the complexity of the structural model is very likely causing at least part of the problem.

	Relearn	Collab	Trust	CB*TR	Uncert	Complex	Asset
Relearn	1						
Collab	0.684 (0.000)	1					
Trust	0.675 (0.000)	0.530 (0.000)	1				
CB*TR	0.750 (0.000)	0.903 (0.000)	0.815 (0.000)	1			
Uncert	0.633 (0.000)	0.520 (0.000)	0.474 (0.000)	0.559 (0.000)	1		
Complex	0.243 (0.000)	0.253 (0.000)	0.102 (0.011)	0.182 (0.000)	0.119 (0.003)	1	
Asset	0.579 (0.000)	0.480 (0.000)	0.413 (0.000)	0.495 (0.000)	0.544 (0.000)	0.141 (0.001)	1

Table 6.7, Correlations for Combined Data

However, multicollinearity is very likely the most serious issue. It can greatly inflate standard errors (Newbold 1994, p. 560), which clearly evident. This will

also cause t-values to be conservative, which may be the reason for the insignificant relationships. It can also result in standard parameter estimates exceeding 1, which is the case in table 6.5 ($\lambda_{6,9}$, TRxCB) where the standardized parameter estimate is 1.07. According to Jöreskog, "... if the factors are *correlated (oblique)*, the factor loadings are *regression coefficients and not correlations* and as such they can be larger than one in magnitude. This can indeed happen also for any factor loading or structural coefficient in any LISREL model. ... a standardized coefficient of 1.04, 1.40, or even 2.80 does not necessarily imply that something is wrong, although, as will be seen, it might suggest that there is a high degree of multicollinearity in the data (1999, p. 1)."

The introduction of the interaction effect introduces a potentially high level of multicollinearity into the data. Looking at the correlation matrix in table 6.1, the correlation between the interaction effect (CB*TR) and collaboration is above 0.9, indicating a strong possibility for multicollinearity (Hair et al. 1998). Therefore, an alternative method that can account for the multicollinearity would hopefully give a valid and reliable result.

6.3 ALTERNATIVE ESTIMATION METHODS

While many researchers turn to moderated multiple regression models estimated with ordinary least squares (e.g. Heide and John 1992), the technique can lead to erroneous interpretations of models (Irwin and McClelland 2001). Given that the interaction is formed as the product of two direct effect variables it introduces correlated error terms between the interaction variable and its parents, and multicollinearity between the variables is highly likely. From table 6.1, the correlation between the interaction effect (CB*TR) and collaboration is above 0.9, indicating a strong possibility for multicollinearity (Hair et al. 1998). Thus, for ordinary least squares regression two of the classical assumptions are violated (Studenmund 1997, p. 94).

An alternative would be to use a multi-sample approach by creating a categorical dichotomous variable to represent high and low levels of trust. This is not recommended, however, because of the immediate loss of information in dropping from an interval to an ordinal level of measurement (Rigdon, Schumacker, and Wothke 1998), and it can lead to erroneous interpretations of the results (Irwin and McClelland 2001).

The best solution is to find an estimation method that allows for the indicant product approach, like with Kenny and Judd (1984). Two-stage least squares regression allows the indicant product approach yet avoids many of the problems associated with ordinary least squares (Bollen and Paxton 1998; Li and Harmer 1998). It removes correlated error terms and reduces the potential for multicollinearity. The relative simplicity of the technique also makes it easier to attain solutions. The down-side compared to structural equation modeling is that it does not allow for partitioning of the variance between the informants and random error. At best a dummy variable can be introduced to determine if the difference between informant reports is significant, however, this says nothing about the proportion of error it introduces into the equation.

6.4 TWO-STAGE LEAST SQUARES REGRESSION

Figure 6.1 shows an example of an interaction model with the direct effects of collaborative objectives (CB) and trust (TR), and the interaction effect of the product of collaborative objectives and trust (CB x TR) on relationship learning (RL).

Ovals enclose latent variables, boxes enclose observed variables, single-head straight lines represent main effects, and single-head jagged lines represent interaction effects. Curved double-headed lines represent bivariate correlation. ξ_1 (Ksi) and ξ_2 represent the latent construct main effects and $\xi_1\xi_2$ the latent construct interaction effect. The observed reflective indicators are the xs with their

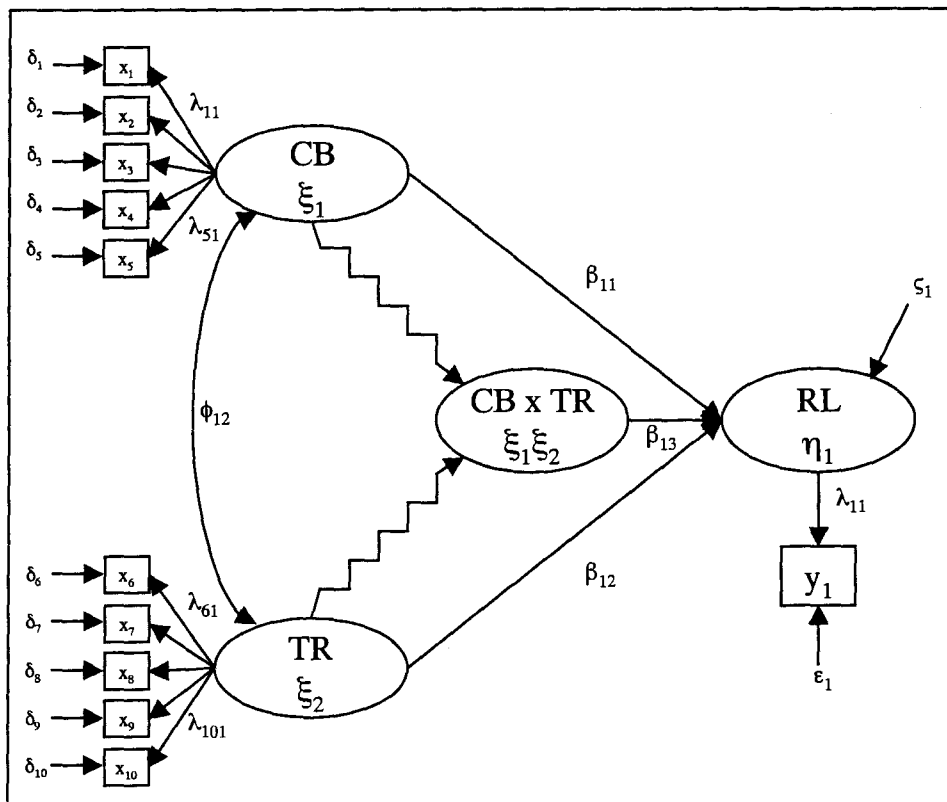


Figure 6.1, Two-Stage Least Squares Interaction Model

respective δ (Delta) error terms. The interaction variable ($\xi_1 \xi_2$) has no error because it is an exact nonlinear function of the direct effects ($\xi_1 \times \xi_2$). η_1 (Eta) represents the latent dependent variable with a single y observed reflective indicator with its ϵ (Epsilon) respective error term. ζ (Sigma) represents error for the structural equation. β_{11} (Beta) and β_{12} represent the main effects coefficients, and β_{13} represents the interaction effect coefficient. λ (Lambda) represents loadings between latent and observed variables. ϕ (Phi) is the covariance of the latent independent variables.

The equation expressing the structural relationships between the two interacting variables is:

$$\eta_1 = \alpha + \beta_{11}L_1 + \beta_{12}L_2 + \beta_{13}L_1L_2 + \varepsilon \quad (1)$$

where η is the dependent variable, α is the intercept. The β s are the coefficients, and the L s are the latent variables. This equation decomposes into the equation (for proof see Bollen and Paxton 1998; Li and Harmer 1998):

$$y_1 = \alpha + \beta_{11}x_1 + \beta_{12}x_6 + \beta_{13}x_1x_6 + u_1 \quad (2)$$

where y is the predicted value of the dependent variable, α is the intercept for the regression line, β_{11} and β_{12} represent the main effects regression coefficients and β_{13} represents the interaction effect regression coefficient, x_1 and x_6 represent the respective scaling indicators for the latent variables, and u_1 is a composite error term and. As described earlier, the problem with estimating this type of interaction with ordinary least squares regression is that the error term is correlated with the independent variables. This is where two-stage least squares comes in, which requires the creation and selection of instrumental variables.

Stage 1: Form product variables by taking each indicator of the first latent variable and multiply it by each indicator of the second latent variable forming all possible product pairs between variables. Combinations of the independent variables x_1 and x_6 are ineligible as instrumental variables because they correlate with the error term. Instrumental variables are the remaining product variables plus linear indicators, that is, $x_2 - x_5$ and $x_7 - x_{10}$. The instrumental variables are regressed on the variables x_1 , x_6 , and x_1x_6 to form predicted values, and the coefficient of

determination (R^2) is checked. R^2 below 0.1 indicates that the selection of instrumental variables is poor (Bollen and Paxton 1998, p. 135).

Stage 2: In the second stage, the predicted values are regressed on y_1 to estimate the coefficients in the original system by OLS regression, shown in equation 3 (Bollen and Paxton 1998, p. 129):

$$y_1 = \alpha + \beta_{11} \hat{x}_1 + \beta_{12} \hat{x}_6 + \beta_{13} x_1 x_6 + u_1 \quad (3)$$

The coefficients from stage 2 are consistent with equation 1, however, the error term does not correlate with the independent variables. Additional exogenous variables that are independent of the error term can be added to the equation and can even be used as additional instrumental variables, and the estimates are robust against abnormal distributions (Bollen and Paxton 1998, p. 130).

6.5 ANALYSIS

I ran the analysis in three ways: the seller and buyer data separately as well as the combined data set. With the combined data I used a dichotomous dummy variable to control for significant differences between seller and buyer. Because the variable was never significant I removed it from the analysis so that it would not interfere with the model. Therefore, I do not report the dummy variable in the results.

6.5.1 DESCRIPTIVE STATISTICS

Looking at the descriptive statistics in table 6.8, skewness and kurtosis indicate that the distributions are relatively normal. The standard deviation of the interaction effects is high relative to the other variables for all data sets. This is because they are product variables.

		N	Range	Min	Max	Mean	Std. Dev.	Variance	Skewness	Kurtosis
SELLER	Relearn	280	5.83	1.00	6.83	4.56	1.18	1.39	-0.18	-0.68
	Collab	286	5.78	1.09	6.87	4.46	1.31	1.71	-0.08	-0.83
	Trust	286	5.35	1.35	6.70	4.76	1.20	1.43	-0.48	-0.52
	CBxTR	286	45.09	0.44	45.53	22.44	10.30	106.2	0.19	-0.83
	Uncert	308	6.00	1.00	7.00	4.65	1.34	1.80	-0.09	-0.93
	Complex	314	6.00	1.00	7.00	3.75	1.38	1.90	0.23	-0.62
	Asset	303	6.00	1.00	7.00	4.51	1.47	2.16	-0.20	-0.76
	Valid N listwise	261								
BUYER	Relearn	283	5.17	1.75	6.92	4.57	1.06	1.13	-0.11	-0.83
	Collab	293	5.06	1.71	6.77	4.48	1.14	1.30	0.03	-0.88
	Trust	293	5.27	1.59	6.86	4.75	1.17	1.36	-0.31	-0.71
	CBxTR	293	39.82	3.84	43.66	22.03	9.45	89.32	0.26	-0.77
	Uncert	305	5.00	2.00	7.00	4.74	1.22	1.49	-0.14	-0.95
	Complex	307	6.00	1.00	7.00	3.72	1.36	1.84	0.23	-0.64
	Asset	308	6.00	1.00	7.00	4.73	1.35	1.82	-0.17	-0.54
	Valid N listwise	271								
COMBINED	Relearn	563	6.00	1.00	7.00	4.57	1.12	1.26	-0.16	-0.72
	Collab	484	5.72	1.14	6.86	4.69	1.20	1.43	-0.37	-0.52
	Trust	484	5.61	1.19	6.79	4.98	1.13	1.28	-0.73	0.18
	CBxTR	484	44.53	0.74	45.28	24.33	9.32	86.83	-0.01	-0.61
	Uncert	613	6.00	1.00	7.00	4.70	1.28	1.65	-0.12	-0.92
	Complex	621	6.00	1.00	7.00	3.74	1.37	1.87	0.23	-0.63
	Asset	611	6.00	1.00	7.00	4.62	1.41	2.00	-0.20	-0.63
	Valid N listwise	442								

Table 6.8, Descriptive Statistics

6.5.2 CORRELATIONS

I present the seller, then buyer, then combined correlation matrices. The input variables for collaborative objectives and for trust are the predicted values for the first indicator for each variable derived from the instrumental variables. The interaction effect is the predicted value for the product of the first indicators for collaborative objectives and trust.

	Relearn	Collab	Trust	CB*TR	Uncert	Complx	Asset
Relearn	1						
Collab	0.764 (0.000)	1					
Trust	0.745 (0.000)	0.692 (0.000)	1				
CB*TR	0.793 (0.000)	0.936 (0.000)	0.873 (0.000)	1			
Uncert	0.623 (0.000)	0.596 (0.000)	0.594 (0.000)	0.642 (0.000)	1		
Complx	0.293 (0.000)	0.245 (0.000)	0.134 (0.024)	0.170 (0.004)	0.165 (0.004)	1	
Asset	0.613 (0.000)	0.570 (0.000)	0.501 (0.000)	0.554 (0.000)	0.598 (0.000)	0.221 (0.000)	1

Table 6.9, Seller Correlation Matrix

	Relearn	Collab	Trust	CB*TR	Uncert	Complx	Asset
Relearn	1						
Collab	0.704 (0.000)	1					
Trust	0.604 (0.000)	0.555 (0.000)	1				
CB*TR	0.727 (0.000)	0.899 (0.000)	0.847 (0.000)	1			
Uncert	0.647 (0.000)	0.535 (0.000)	0.462 (0.000)	0.542 (0.000)	1		
Complx	0.186 (0.002)	0.323 (0.000)	0.099 (0.090)	0.240 (0.000)	0.067 (0.245)	1	
Asset	0.539 (0.000)	0.479 (0.000)	0.461 (0.000)	0.505 (0.000)	0.476 (0.000)	0.052 (0.367)	1

Table 6.10, Buyer Correlation Matrix

	Relearn	Collab	Trust	CB*TR	Uncert	Complx	Asset
Relearn	1						
Collab	0.703 (0.000)	1					
Trust	0.623 (0.000)	0.551 (0.000)	1				
CB*TR	0.725 (0.000)	0.904 (0.000)	0.824 (0.000)	1			
Uncert	0.633 (0.000)	0.525 (0.000)	0.457 (0.000)	0.542 (0.000)	1		
Complx	0.243 (0.000)	0.276 (0.000)	0.080 (0.077)	0.191 (0.000)	0.119 (0.003)	1	
Asset	0.579 (0.000)	0.499 (0.000)	0.402 (0.000)	0.476 (0.000)	0.544 (0.000)	0.141 (0.001)	1

Table 6.11, Correlations Combined

Almost all correlations are significant in all three matrices indicating that the variables are good candidates for 2SLS regression. Unfortunately the correlations between collaborative objectives and the interaction effect are above 0.9 indicating there may be problems with multicollinearity.

6.5.3 2SLS REGRESSION RESULTS

I analyzed all possible combinations of independent variables onto relationship learning (Relearn). Predicted values from the instrumental variables for collaborative objectives (Collab), trust (Trust), and the interaction effect (CB*TR) were used as input. Environmental uncertainty (Uncert), relationship complexity (Complex), and asset specificity (Asset) were input in their original form. An example of the full regression equation is as follows:

$$Relearn = \alpha + \beta_1 Collab + \beta_2 Trust - \beta_3 CB*TR + \beta_4 Uncert + \beta_5 Complex + \beta_6 Asset + error$$

Table 6.12 shows standardized beta coefficients and associated t-values in brackets. Significant coefficients are flagged with a superscript to indicate significant at $\alpha = 0.01^A$, significant at $\alpha = 0.05^B$, and significant at $\alpha = 0.10^C$. The F-statistic is shown, as is adjusted R-squared (R^{2adj}). The individual regression estimates are on the horizontal. The three combinations of seller, buyer, and combined are run in the eight possible ways (follow the shading).

The explained variance (R^{2adj}) is in the range of 49.4% to 69.8%, which I consider quite good. In all cases the F-statistic is clearly significant, indicating that the overall equation is significant. In one-sided t-tests the individual coefficients are

consistently significant with the correct sign. The buyer data has the only problems with inconsistent signs.

Though not shown, the variance inflation factors (VIF), which measure multicollinearity, were stable for all combinations: around 15 for collaborative objectives, 9 for trust, and 35 for the interaction effect. All other variables were between 1-2. Preferably the VIF factors should be below 10 (Hair, Anderson, Tatham, and Black 1998). The most serious implication is that the effects of these three variables are difficult to separate (Studenmund 1997, p. 265). T-values will also fall, meaning that they are conservative relative to their true value.

In general, uncertainty has a greater influence on relationship learning than either complexity or asset specificity. The explained variance improves only marginally by adding complexity or asset specificity, therefore, for the sake of parsimony they could be dropped. While the t-statistics and F-statistic is better for the combined data with only uncertainty, the seller side has a 10% higher explained variance (R^{2adj} is 0.680), the F-statistic at 143.0 is clearly significant, and all the coefficients are significant at the $\alpha=0.05$ level. This means that for the sake of simplicity we could measure only the seller. Nevertheless, I will concentrate on the combined data with the parsimonious equation. It is as follows:

$$Relearn = \alpha + \beta_1 Collab + \beta_2 Trust - \beta_3 CB*TR + \beta_4 Uncert + error$$

With standardized coefficients the estimated equation for the combined data is:

$$\hat{y} (Relearn) = 0.625Collab + 0.447Trust - 0.364CB*TR + 0.245Uncert + e$$

t-values	(5.517)	(4.886)	(-2.063)	(6.541)
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t-values significant at $\alpha=0.01$ (cutoff 1.960 one-sided)

		Beta Coefficients							
		^A =significant at $\alpha=0.01$ (t-statistic cutoff 1.960 one-sided) ^B =significant at $\alpha=0.05$ (t-statistic cutoff 1.645 one-sided) ^C =significant at $\alpha=0.10$ (t-statistic cutoff 1.282 one-sided)							
		Collab	Trust	CB*TR	Uncert	Cmplx	Asset	R ² _{adj}	F-stat
1	S	0.633 ^A (4.618)	0.523 ^A (4.872)	-0.302 ^C (-1.414)				0.632	155.3
	B	0.619 ^A (2.979)	0.407 ^A (2.320)	-0.213 (-0.646)				0.492	90.4
	C	0.768 ^A (6.201)	0.525 ^A (5.596)	-0.440 ^A (-2.396)				0.527	169.8
2	S	0.518 ^A (3.300)	0.460 ^A (4,317)	-0.268 (-1.201)	0.127 ^A (2.579)	0.085 ^A (2.354)	0.134 ^A (2.818)	0.708	106.0
	B	0.234 (1.187)	0.094 (0.577)	0.187 (0.628)	0.298 ^A (6.145)	0.051 ^C (1.289)	0.142 ^A (3.305)	0.632	78.3
	C	0.544 ^A (4.340)	0.394 ^A (4.281)	-0.269 ^C (-1.526)	0.211 ^A (5.472)	0.078 ^A (2.505)	0.085 ^A (2.215)	0.617	119.4
3	S	0.628^A (4.233)	0.542^A (5,081)	-0.399^B (-1.823)	0.181^A (3.843)			0.680	143.0
	B	0.278 ^C (1.414)	0.139 (0.843)	0.139 (0.457)	0.361 ^A (7.493)			0.601	104.9
	C	0.625^A (5.157)	0.447^A (4.886)	-0.364^A (-2.063)	0.245^A (6.541)			0.592	164.5
4	S	0.632 ^A (4.130)	0.542 ^A (5,047)	-0.305 ^C (-1.369)		0.096 ^A (2.532)		0.663	133.0
	B	0.620 ^A (2.939)	0.407 ^A (2.298)	-0.215 (-0.645)		0.010 (0.209)		0.494	68.0
	C	0.728 ^A (5.785)	0.505 ^A (5.381)	-0.395 ^A (-2.142)		0.067 ^A (1.982)		0.539	132.5
5	S	0.620 ^A (3.975)	0.509 ^A (4,690)	-0.348 ^C (-1.568)			0.190 ^A (4.213)	0.684	141.9
	B	0.547 ^A (2.706)	0.320 ^B (1.889)	-0.157 (-0.498)			0.197 ^A (4.002)	0.554	86.1
	C	0.699 ^A (5.636)	0.474 ^A (4.439)	-0.393 ^A (-2.782)			0.147 ^A (5.940)	0.562	144.0
6	S	0.554 ^A (3.660)	0.506 ^A (4,753)	-0.304 ^C (-1.379)	0.171 ^A (3.713)	0.093 ^A (2.537)		0.694	121.5
	B	0.250 (1.258)	0.125 (0.760)	0.176 (0.577)	0.359 ^A (7.445)	0.041 (1.019)		0.608	85.8
	C	0.577 ^A (4.715)	0.425 ^A (4.674)	-0.308 ^B (-1.747)	0.240 ^A (6.512)	0.078 ^A (2.489)		0.605	138.1
7	S	0.547 ^A (5.190)	0.474 ^A (4,222)	-0.257 ^A (-2.518)		0.088 ^B (1.813)	0.185 ^A (4.983)	0.694	119.0
	B	0.538 ^A (2.614)	0.316 ^B (1.848)	-0.148 (-0.466)		0.027 (0.626)	0.198 ^A (3.999)	0.559	69.7
	C	0.655 ^A (5.190)	0.453 ^A (4.222)	-0.345 ^A (-2.518)		0.069 ^B (1.813)	0.148 ^A (4.983)	0.572	119.3
8	S	0.587 ^A (3.842)	0.492 ^A (4,641)	-0.356 ^C (-1.626)	0.136 ^A (2.707)		0.136 ^A (2.814)	0.698	121.9
	B	0.274 ^C (1.407)	0.113 (0.697)	0.139 (0.466)	0.301 ^A (6.165)		0.137 ^A (2.919)	0.624	91.5
	C	0.595 ^A (5.217)	0.417 ^A (4.154)	-0.329 ^A (-2.714)	0.216 ^A (4.537)		0.082 ^A (3.221)	0.605	137.4

Table 6.12, 2SLS Regression Results

6.5.4 2SLS REGRESSION RESULTS WITH DEMOGRAPHICS

I tested the demographic variables (table 6.13) with the combined data (buyer and seller) and found that across all combinations there are some significant relationships.

Equation #	1	2	3	4	5	6	7	8
F-statistic	68.5	68.7	77.1	63.1	71.7	71.8	0.544	73.6
R ^{2adj}	0.530	0.623	0.593	0.544	0.578	0.606	66.4	0.613
	Beta Coefficients							
	^A =significant at $\alpha=0.01$ (t-statistic cutoff 1.960 one-sided)							
	^B =significant at $\alpha=0.05$ (t-statistic cutoff 1.645 one-sided)							
	^C =significant at $\alpha=0.10$ (t-statistic cutoff 1.282 one-sided)							
Collab	0.754 ^A (5.750)	0.483 ^A (3.643)	0.591 ^A (4.585)	0.698 ^A (5.248)	0.634 ^A (4.702)	0.542 ^A (4.163)	0.586 ^A (4.281)	0.529 ^A (4.046)
Trust	0.539 ^A (5.369)	0.373 ^A (3.798)	0.444 ^A (4.514)	0.515 ^A (5.140)	0.454 ^A (4.446)	0.424 ^A (4.345)	0.434 ^A (4.271)	0.390 ^A (3.955)
CB*TR	-0.442 ^A (-2.254)	-0.220 (-1.165)	-0.344 ^B (-1.815)	-0.382 ^B (-1.941)	-0.341 ^B (-1.747)	-0.286 ^C (-1.510)	-0.289 ^C (-1.475)	-0.275 ^C (-1.459)
Uncert		0.212 ^A (5.319)	0.261 ^A (6.682)			0.251 ^A (6.505)		0.220 ^A (5.473)
Complex		0.078 ^A (2.353)		0.086 ^A (2.395)		0.082 ^A (2.423)	0.081 ^A (2.354)	
Asset		0.124 ^A (3.146)			0.196 ^A (4.975)		0.191 ^A (4.902)	0.126 ^A (3.161)
% sales/supply	-0.028 (-0.822)	-0.034 (-1.083)	-0.008 (-0.259)	-0.053^C (-1.549)	-0.029 (-0.885)	-0.032 (-1.006)	-0.050^C (-1.524)	-0.014 (-0.443)
Respondent years with company	-0.058^C (-1.430)	-0.023 (-0.620)	-0.025 (-0.652)	-0.074^B (-1.813)	-0.030 (-0.756)	-0.039 (-1.034)	-0.044 (-1.135)	-0.010 (-0.264)
Firm years in relationship	0.028 (0.722)	0.045^C (1.259)	0.057^C (1.568)	0.013 (0.336)	0.039 (1.054)	0.042 (1.147)	0.025 (0.69)	0.059^B (1.648)
Respondent years in relationship	0.037 (0.811)	0.031 (0.753)	0.023 (0.550)	0.047 (1.053)	0.032 (0.741)	0.033 (0.782)	0.042 (0.978)	0.022 (0.528)

Table 6.13, 2SLS Regression with Demographic Variables

6.5.5 SUMMARY OF DEMOGRAPHIC VARIABLES

(% sales/supply) This customer/supplier represents approximately _____ % of our total sales.

This variable is significant and negative once at the $\alpha=0.10$ level in equation 4. This means that the higher the percentage, the lower will be relationship learning.

(Respondent years with company) How long have you personally been with your company? _____ years.

This variable is significant and negative once at the $\alpha=0.10$ level in equation 1, and significant and negative once at the $\alpha=0.05$ level in equation four. This means that the longer a person has been working at his or her respective company, the lower will be relationship learning.

(Firm years in relationship) How long have the two companies been involved in the relationship? _____ years.

This variable is significant and positive twice at the $\alpha=0.10$ level in equations 2 and 3. This means that the longer the relationship, the higher will be relationship learning.

(Respondent years in relationship) How long have you personally been involved in the relationship with the other company? _____ years.

This variable is never significant.

(Type of business) What is the primary focus of your business?

Producer – Wholesaler – Retailer – Service Provider – Other

This variable is not shown in the table because to properly test it within a regression equation would require creating four dummy variables (one less than the number of categories: Studenmund 1997, p. 233). Instead, I ran a one-way

ANOVA with relationship learning as the dependent variable and type of business as the factor. The F-statistic was 2.137, which is below the critical value of 2.37 at $\alpha=0.05$ (df = 4 numerator, 556 denominator). This means there are no significant differences between type of business with regards to relationship learning.

6.5.6 CONCLUSIONS REGARDING DEMOGRAPHIC VARIABLES

The pattern of the significant demographic variables is sporadic and the relative level of significance is fairly low with only one variable significant at the $\alpha=0.05$ level. Given this, adding the demographic variables to the analysis does not provide any important information. This does not, however, negate their importance for evaluating the suitability of respondents.

6.6 SUMMARY OF HYPOTHESES:

For ease of interpretation I present the hypotheses and discussion in order. I use table 6.12 as my reference point, that is, the results without demographic variables.

Hypotheses	Effect	Result
H ₁ : Collaborative objectives are positively related to relationship learning.	+	Strongly supported
H ₂ : Trust is positively related to relationship learning.	+	Strongly supported
H ₃ : As collaborative objectives and trust increase they will interact to have a negative effect on relationship learning.	-	Generally supported
H ₄ : Environmental uncertainty is positively related to relationship learning.	+	Strongly supported
H ₅ : Structural complexity is positively related to relationship learning.	+	Strongly supported
H ₆ : Asset Specificity is positively related to relationship learning.	+	Strongly supported

Table 6.14, Summary of Hypotheses

H₁: Collaborative objectives are positively related to relationship learning.

There are only two instances where this hypothesis is not supported, however in both cases it is close to significant at the $\alpha=0.10$ level. Given the possibility of conservative t-values because of the presence of collinearity with the interaction term (Studenmund 1997, p. 265), I conclude that this hypothesis is strongly supported.

H₂: Trust is positively related to relationship learning.

There are four instances where this hypothesis is not supported, all on the buyer data, otherwise it is clearly significant. There is the possibility of conservative t-values due to collinearity as well as potential reliability problems on the buyer side data, therefore I conclude that this hypothesis is strongly supported.

H₃: As collaborative objectives and trust increase they will interact to have a negative effect on relationship learning.

In general, the evidence supports this hypothesis. With the buyer data it is never supported, and the coefficient shifts sign in half of the equations. As with the previous variable, this could be due to reliability problems and conservative t-values. With the seller data it always has the correct sign and is significant in every case except one, however it is close at the $\alpha=0.10$ level. It is always significant with the correct sign with the combined data. I conclude that this hypothesis is supported.

The interaction effect can be subjected to a further significance test of the incremental increase to explained variance using the following equation (Jaccard, Turrisi, and Wan 1990, p. 18):

$$F = \frac{(R_2^2 - R_1^2) / (k_2 - k_1)}{(1 - R_2^2) / (N - k_2 - 1)}$$

Where F is the test statistic, R_2^2 is the explained variance for the equation with the interaction, R_1^2 is the explained variance without the interaction, k_2 is the number of parameters in the equation with the interaction, and k_1 is the number of parameters without the interaction, and N is the total sample size. The result is:

$$F = \frac{(0.530^2 - 0.524^2) / (3 - 2)}{(1 - 0.530^2) / (630 - 3 - 1)} = 5.50$$

Critical $F_{1,626}$ at $\alpha=0.05$ is 3.84. $5.50 > 3.84$, therefore, the interaction is statistically significant.

H_4 : Environmental uncertainty is positively related to relationship learning.

For all equations this hypothesis is supported at the $\alpha=0.01$ level, therefore I conclude that it is strongly supported.

H_5 : Structural complexity is positively related to relationship learning.

This hypothesis is supported in the majority of equations, six times at the $\alpha=0.01$ level, therefore I conclude that it is strongly supported, although problems with reliability in the measurement model should be kept in mind.

H_6 : Asset Specificity is positively related to relationship learning.

For all equations this hypothesis is supported at the $\alpha=0.01$ level, therefore I conclude that it is strongly supported.

6.7 DISCUSSION OF THE RESULTS

There are three main points from the hypothesis tests that deserve highlighting:

1. The evidence is strong that all hypothesized direct effects are confirmed.
2. The evidence generally supports the hypothesized interaction effect. This means there is a dark side of trust that can potentially have a negative effect on relationship learning
3. Accounting for parsimony and simplicity, relationship learning can be measured by collecting data from only the seller side on collaborative objectives, trust, uncertainty, and relationship learning. However, data from both sides of the dyad including all control variables presents the broadest picture.

Regarding interpreting the interaction effect, I use the equation with standardized coefficients and combined data for only collaborative objectives, trust, and the interaction effect with relationship learning as the dependent variable:

$$\hat{y} (\text{Relearn}) = 0.625\text{Collab} + 0.447\text{Trust} - 0.364\text{CB*TR} + e$$

otherwise:

$$Y = \beta_1 X_1 + \beta_2 X_2 - \beta_3 X_1 X_2 + e$$

β_3 (-0.364) indicates the number of units that the slope of Y (Relearn) on X_1 (Collab) changes, given a one-unit change in X_2 (Trust) (Jaccard, Turrisi, and Wan 1990, p. 25). This means that for every unit that trust increases, the slope of relationship learning on collaborative intentions will decrease by -0.364.

Using the regression coefficients, I can calculate the effect of collaborative objectives on relationship learning given different values of trust. I illustrate this

using the two most extreme possibilities in our measurement, 1 for low trust and 7 for high trust. Starting with 1 for X_2 yields:

$$Y = 0.625X_1 + 0.447(1) - 0.364X_1(1) + error$$

Which factors to the linear equation of collaborative objectives when trust is low:

$$Y = 0.447 + 0.261X_1 + error$$

Note the positive coefficient on X_1 .

Starting with 7 for X_2 yields:

$$Y = 0.625X_1 + 0.447(7) - 0.364X_1(7) + error$$

Which factors to the linear equation of collaborative objectives when trust is high:

$$Y = 3.129 - 1.923X_1 + error$$

Note the negative coefficient on X_1 .

This means that when trust is very low there is a positive relationship between collaborative objectives and relationship learning, however, as trust rises the effect drops and very quickly becomes negative. With the present sample it is already negative when trust is 2, which is still very low.

The interaction effect may not be so serious in light of the other independent variables. Referring to table 6.6, with the combined data the interaction effect is significant in all cases except when all variables are included. Though not presented, with only environmental uncertainty, structural complexity, and asset specificity as independent variables (leaving out collaborative objectives, trust,

and the interaction) and relationship learning as the dependent variable, all possible combinations are significant. This means that when environmental uncertainty, structural complexity, and asset specificity are all high they may buffer the negative interaction effect of collaborative objectives and trust.

The conclusion to all this is that alone, trust and collaborative objectives have positive effects on relationship learning. However, trust breeds' complacency in collaborative relationships, which has a negative effect on relationship learning. Factors like environmental uncertainty, structural complexity, and asset specificity will counterweight the complacency, thus buffering the negative effects.

7. DISCUSSION AND IMPLICATIONS

In this final chapter I discuss theoretical and managerial implications, followed by the limitations of the study and suggestions for future research.

7.1 OBJECTIVES AND CONTRIBUTION

The objectives of the research were to (1) further develop the construct of relationship learning, (2) relate it to existing inter-organizational theory, (3) operationalize the constructs as perceptual measures, and (4) empirically test the relationship learning model. Through this, the theoretical contribution is to develop the construct and model, and to empirically demonstrate that relationships can indeed learn and that trust carries a hidden cost that is largely unrecognized in the extant literature. This has practical implications for how inter-organizational relationships can be managed to enhance relationship learning. The scale provides the first attempt at developing a measure for firms to assess their relationship learning capabilities.

7.2 IMPLICATIONS FOR THEORY

This dissertation is in response to a limitation in organizational learning theory. While there is a growing literature on inter-organizational learning (e.g. Hamel 1991a; Larsson et al. 1998; Lukas et al. 1996; Lyles 1988; Pine et al. 1995; Powell et al. 1996; Quinn et al. 1996; Wathne et al. 1996), it suffers from an imbalance. Typically the firm is treated as an autonomous unit, the implications of which are to focus on individual firms learning *from* each other. The attempt here is to balance this focus by exploring how firms learn *with* each other. This distinction is important (Child and Faulkner 1998, p. 288), because "*from*" may give rise to a competitive learning race (e.g. Hamel 1991a), whereas "*with*" perpetuates mutual synergies of innovation (e.g. Powell et al. 1996). Each approach entails a different set of ground rules.

7.2.1 THE LEARNING RACE

A learning race implies an underlying assumption of opportunism (e.g. Williamson 1975). Within this train of thought is the metaphor of firms being separated by a pervious membrane through which flow skills and capabilities (Hamel 1991, p. 100). Inter-organizational learning is a function of the degree of permeability and the direction of permeability. Access to people, facilities, documents, and other forms of knowledge determine permeability. While relevant as a conceptualization within the context of opportunism, it biases the way we look at learning between firms. It draws a boundary where in many cases a boundary is not discernable (Håkansson and Johanson 1988, p. 369; Håkansson and Snehota 1995a). This has two consequences. First, it denies that relationships may exist as entities themselves. Relationships are living systems that develop independently of their constituents (Moss Kanter 1994). The membrane keeps the organizations separate no matter how much flows through it. The membrane exists, nothing in between. I have argued, and my results support, that relationships do exist as quasi-organizations. Therefore, while in some cases the membrane metaphor may apply, a new metaphor may be more applicable where the relationship is an amorphous fog blurring the boundaries and joining the two organizations.

Second, the membrane metaphor emphasizes the independence, rather than interdependence of organizations. While the membrane is pervious, it still separates the organization from its environment. This propagates the “me against them” syndrome captured in the opportunistic perspective. I agree that opportunism is alive and well in learning relationships (e.g. Hamel 1991), however, it should not be treated as the norm. Trusting collaboration between firms is a common and growing phenomenon (e.g. Astley 1984; Child and Faulkner 1998; Contractor and Lorange 1988), especially in circumstances where relationship learning is an important facet of the relationship (e.g. Doz 1996; von Krogh and Roos 1996). As firms specialize they become more dependent on their environment for innovation (Cohen and Levinthal 1990; Powel et al. 1996), and use trusting collaboration as a means for creating knowledge or accessing

knowledge that resides outside firm boundaries (Huber 1991). Even from a competitive strategies perspective (e.g. Porter 1985), clusters of complementary firms are recognized as an avenue to competitive advantage. The existence of a cluster is merely an extrapolation on the existence of a relationship as a quasi-organization. Viewed this way, collaborative objectives and trust are fundamental variables for relationship learning. Thus, rather than “me against them”, “us against them” may be a more appropriate perspective (Moss Kanter 1994, p. 100).

7.2.2 THE RELATIONSHIP LEARNING DEFINITION

When developing the case for the relationship learning construct, I divided the argument between two dichotomies that I see in the literature. The behavioral-cognitive dichotomy is widely recognized and debated (e.g. Fiol and Lyles 1985), whereas the values-process dichotomy is not. My goal is to contribute to the way researchers think about relationship learning, or even organizational learning. The idea comes from the market orientation literature (see Kohli and Jaworski (1990) for a process definition, and Deshpandé, Farley, and Webster (1993) for a values definition). My meaning is not to splinter the field more than it already is, rather, processes and values are reconcilable and intertwined. For example, Hamel’s (1991) values of openness, receptiveness, and intent are an integral part of the relationship learning process. Nevertheless, the distinction is important.

Values are enduring beliefs that some mode of conduct or end-state is preferable to its opposite, and form the basis for attitudes (Rokeach 1973). Attitudes are held by an entity and directed at something (Fishbein 1980). A values orientation to relationship learning may presuppose focusing on the entities that constitute the relationship, whereas a process orientation accentuates the interplay between firms. To be consistent with the focus on mutuality within the dyad, the relationship learning definition is oriented to the process.

Relationship learning is the process of understanding and gaining new insights at the intersection between firms (Lukas et al. 1996). Information processing is a

critical aspect of this (e.g. Day 1994a; Lukas et al. 1996; Shrivastava 1983; Sinkula 1994; Slater and Narver 1995). Specifically, information processing that encompasses information sharing, mutual interpretation, and integration into relationship memory (Selnes and Sallis 1999), leading to a potential behavior change (Huber 1991, p. 89). Information sharing is recognized as facilitating coordination of inter-firm activities (c.f. Anderson and Weitz 1992; Buvik and John 2000; Cannon and Perreault 1999; Jap 1999). Mutual interpretation is related to group sense-making (c.f. Ring and Van De Ven 1994, p. 194) leading to shared understandings that form a collective sense of identity and purpose (c.f. Nonaka 1991, p. 97). Relationship memories are captured in the shared beliefs, values, assumptions, norms, and behaviors that transcend the organizational boundaries and are captured in the relationship (c.f. Lukas et al. 1996; Moorman and Miner 1997; Walsh and Ungson 1991).

The definition illuminates actionable alternatives to enhance relationship learning, like improving mechanisms for information sharing, interpretation, or memory integration. The values-process logic aids to refine the issues surrounding relationship learning.

7.2.3 THE MODEL

To arrive at a model, data from field interviews was combined with the literature on transaction cost economics, network theory, resource-based theory, and agency theory. All of these theoretical approaches are, or can be applied to the inter-organizational setting. None of them, however, specifically concerns relationship learning. Transaction cost economics is concerned with how to most efficiently organize transactions along a market-hierarchy dichotomy (Williamson 1975). Network theory is concerned with the embeddedness of transactions within a network of relationships, offering a socialized view of economic behavior (Johanson and Mattsson 1987). Resource based theory traditionally focuses on the individual firm and how unique resources can be combined in unique ways to achieve competitive advantage (Barney 1991), although it has recently been

extended to encompass inter-organizational relationships (Dyer and Singh 1998). Agency theory takes up the question of control mechanisms across the principal-agent relationship (Ouchi 1979), and is amenable to the inter-organizational setting. Lack of a specific guiding theory exposes the research to criticism surrounding model specification.

I hypothesized that collaborative objectives, trust, environmental uncertainty, structural complexity, and asset specificity all positively influence relationship learning. I also hypothesized that trust interacts with collaborative objectives to have a negative impact on relationship learning. The two-stage least squares results strongly support accepting the hypotheses. However, the structural equation modeling results are ambiguous, which could be taken as evidence of model misspecification. There are standardized estimates that exceed 1, difficulties with insignificant factor loadings, and relationships that change sign from one model to the next. Conceivably these problems could be a result of misspecification, alternatively, the problems could result from high multicollinearity (Jöreskog 1999, p. 1; Newbold 1994, p. 560; Studenmund 1997, p. 265).

As an experiment I ran an ordinary least squares regression with relationship learning as the dependent variable, and collaborative objectives, trust, and CB*TR as the independent variables. I did not do anything to reduce multicollinearity. The correlation between collaborative objectives and CB*TR was 0.906, indicating the presence of multicollinearity (Studenmund 1997). The variance inflation factor for the CB*TR parameter was 36.580, indicating a very high level of multicollinearity (Hair et al. 1998). The evidence is strong, then, that multicollinearity is a problem.

Another perplexing result is the relationship between CB*TR and relationship learning. In a correlation matrix, CB*TR is significantly positively correlated with relationship learning (0.725 significant at $\alpha = 0.01$), whereas in either structural equation modeling or two-stage least squares it comes out as a negative relationship. This also may indicate model misspecification. However, Irwin and

McClelland (2001, p. 105) demonstrate how the correlation between a dependent variable and a product interaction term can, with their data, range from -0.81 to $+0.97$. This is because the correlation is a function of the component independent variables that make up the interaction term. In a simple correlation matrix between the dependent variable and the interaction term, the component variables are not accounted for. Thus, when they are accounted for, which is the case in the structural equation modeling and the two-stage least squares regression, it is quite conceivable that the effect changes sign.

Still, there may be problems with misspecification. Wilson (1995, p. 337) proposed a list of relationship variables for inclusion in empirical models of buyer-seller relationships. It is legitimate to argue that any one, or even all of these variables should have been included.

• Commitment	• Adaptation
• Trust	• Non-retrievable investments
• Cooperation	• Shared technology
• Mutual Goals	• Summative constructs
• Interdependence/power imbalance	• Structural bonds
• Performance satisfaction	• Social bonds
• Comparison level of alternative	

Table 7.1, Buyer-Seller Relationship Variables (Wilson 1995, p. 337)

The dilemma in developing the model comes down to paradoxical choices. On the one hand, according to grounded theory, phenomena should be allowed to emerge from the data (Glaser and Strauss 1967, p. 1; Strauss and Corbin 1990, p. 23). Alternatively, previous research provides confidence in proposed models (Churchill 1979; Eisenhardt 1989). Mitigating this is the desire for parsimony (Frankfort-Nachmias and Nachmias 1996, p. 42). Given that transaction cost economics, network theory, resource-based theory, and agency theory do not specifically address relationship learning, and given the lack of a theory that does,

the data did play a large role in arriving at the model. This is why I term the approach as quasi-grounded theory. Nevertheless, the explained variance in the two-stage least squares regression is consistently high ranging from 50-70%, and in the best model (without complexity and asset specificity) with combined data it is 68%. Even in the full model with the combined data it is 63%. The low t-value on the interaction effect in the full model (-1.201) is not too troubling because it is quite likely conservative because of a substantial degree of multicollinearity (VIF = 35.919) despite the two-stage least squares estimation.

A final theoretical issue is the potential buffering effect of environmental uncertainty, structural complexity, and asset specificity. With the combined data (Table 6.6), the interaction effect is significant in all cases except when all variables are included. Though not presented, with only environmental uncertainty, structural complexity, and asset specificity as independent variables (leaving out collaborative objectives, trust, and the interaction) and relationship learning as the dependent variable, all possible combinations are significant and positive. This means that when environmental uncertainty, structural complexity, and asset specificity are all high they may buffer the negative interaction effect of collaborative objectives and trust.

7.2.4 SUMMARY OF THEORETICAL IMPLICATIONS

All hypothesized relationships were supported. For the direct effects, this is no great surprise. The interaction effect, however, is somewhat perplexing. Dwyer, Schurr, and Oh (1987) developed a framework for how inter-organizational relationships start, evolve, and dissolve. Central to the development and maintenance of relationships are establishing norms of conduct that allow for future exchange and increased risk-taking in the relationship. The most fundamental norm is trust, which provides the foundation for understanding expectations and for cooperation in the relationship. As commitment increases, value systems converge creating a fruitful interdependence. Dodgson (1993) and Doz (1996) extend the framework, recognizing the pivotal role of learning in the

relationship. Common to all three studies is the central role of trust. Dodgson goes so far as to say that, “Effective learning between partners depends on the construction of a “climate” of trust engrained in organizational modes of behavior, and supported by the belief in the mutual benefits of collaboration throughout the organization (Dodgson 1993, p. 78).”

The negative interaction effect, then, seems counterintuitive. Trust is recognized as a positive force in inter-organizational relationships (e.g. Child and Faulkner 1998; Dodgson 1993b; Jap and Weitz 1996), with few exceptions (e.g. Eisenhardt et al. 1997; Hamel 1991a). Our findings expose a potential hidden cost. A likely explanation is that as trust develops the parties relinquish explicit control in favor of implicit faith. Besides the risk for opportunism, the parties may become complacent or even reticent to ask sensitive questions (Eisenhardt, Kahwajy, and Bourgeois 1997). Their value systems may converge to the extent where they fail to recognize alternative perspectives. They develop a common psychological identity (Gaertner et al. 1996, p. 273) and lose the ability for higher level learning because there is no impetus to question norms, policies, and objectives. Isomorphism negates the relationship learning process. Factors like environmental uncertainty, structural complexity, and asset specificity counterweight this complacency, thus buffering the negative interaction effect.

7.3 IMPLICATIONS FOR METHODOLOGY

Measuring phenomena across organizational level dyads is a dubious process (Heide and John 1994; John and Reve 1982; Phillips 1981), exacerbated by the fact that data is frequently collected from key informants who report on higher order constructs. The constructs are often latent, meaning that they are not directly observable or measurable. Higher order means that the respondent is not representing their individual perspective, but rather, the perspective of an abstract entity, usually an organization. Using key informants, especially when only one is used per organization, compromises the level of measurement, giving heed to the

argument that it is the individual's perceptions being measured, not the organizational phenomena.

Phillips (1981) and John and Reve (1982) tested the reliability and validity of key informant reports with dyadic data, with mixed results. With few exceptions (e.g. Anderson and Weitz 1992; Bagozzi and Phillips 1982), pooling dyadic data in channels research is problematic (e.g. Anderson and Narus 1990; John and Reve 1982; Kumar et al. 1993; Phillips 1981). Informant bias leads to poor model fit, thus many researchers resort to analyzing each side of the data separately (e.g. Jap and Weitz 1996). What Heide and John (1994, p. 540) recognized, and what this dissertation capitalizes on, is that the issue is not the key informant reports per se, but the theoretical nature of the construct in question. Heide and John (1994, p. 534) suggest that perceptual differences between key informants can in fact be used to measure particular inter-organizational constructs that are a collective property of a higher order construct. Relationship learning is such a construct and is thus amicable to dyadic measurement.

The issue becomes how to assure the validity and reliability of the results. Arbitrarily aggregating measures to form constructs risks masking incongruous relationships between indicators or sub-dimensions, and hiding measurement problems. To address this I combined the multitrait-multimethod (MTMM) matrix approach (Campbell and Fiske 1959), modeled as a covariance structure (Jöreskog 1974), with Bagozzi and Edwards' (1998) general approach for representing constructs in organizational research through applying structural equation modeling at varying levels of aggregation. Stepwise aggregation provides justification for either aggregating, or not aggregating. With relationship learning it provided guidance for refining the constructs and aggregating the sub-dimensions of information sharing, interpretation, and memory integration into one construct. This, in turn, improved model fit. It also mitigated difficulties with treating ordinal variables as continuous by helping to normalize the distributions (Bollen 1989, p. 438). In conjunction with the MTMM approach, the aggregation

approach builds confidence in the validity and reliability of the measurement model, and thus the results. The reasonably high trait variance, despite different organizations, backgrounds, countries, and cultures, supports what Heide and John (1994) contend, that key informants can in fact be used to measure particular inter-organizational constructs that are a collective property of a higher order construct.

7.4 IMPLICATIONS FOR PRACTICE

The paradox of trust is that it is at once enabling and crippling. In isolation it is a positive force for relationship learning, yet, combined with collaborative objectives it has a dark side. That the interaction comes out as a negative effect relative to relationship learning is, I believe, a surrogate-warning signal for isomorphism. Institutional theory holds that organizational adaptation is a function of isomorphic pressure (Martinez 1999). In lieu of a better plan, institutions conform to the status quo in their environments. They gain legitimacy through playing the game as others do. Conformity supplants thinking!

This begs the question, how does isomorphism relate to relationship learning?

Innovation is strongly influenced by external links to the firm (Cohen and Levinthal 1990). The underlying logic is that novel ideas are difficult to cultivate within the firm because they are not prioritized. Resources usually get funneled to core capabilities and skilled people avoid non-core projects (Leonard-Barton 1992). Firms get trapped exploiting and extending existing capabilities at the expense of exploring new alternatives that challenge the status quo (March 1991). Yet, many managers recognize that as environmental uncertainty and the rapidity of technological change increases so does the importance of exploring novel ideas (Stata 1989). Therefore, they cultivate inter-organizational relationships.

Broadly, an inter-organizational relationship is a mutual orientation of at least two organizations toward each other wherein interaction norms are established (Johanson and Mattsson 1987). As the norm of reciprocity develops (Oliver 1990,

p. 244), a collective consciousness is born and the relationship attains a unique identity (Van de Ven 1976, p. 25). Psychological contracts supplant formal agreements and the parties build mutual interpretations (Ring and Van De Ven 1994). In other words, they isomorphize. In their effort to understand each other and make the relationship work, they inadvertently undermine one of the reasons for being in the relationship.

In line with the normative literature on organizational learning (e.g. Argyris and Schön 1996; Garvin 1993; Quinn, Anderson, and Finkelstein 1996; Senge 1990), relationships need to develop the ability to question the status quo. Concentrating too much on developing trust may prove dysfunctional because more trust may mean less learning. Just like within organizations, rotating people in and out of the relationship may help neutralize some of the isomorphism.

Innovative firms are often involved with more new products, technologies, and markets than less successful innovators (McKee 1992). Having a diversity of relationships may also be fruitful because innovation is not simply a function of external links, it is also a function of a broad scope of external links.

7.5 LIMITATIONS

The research process constitutes a series of interlocking choices that inevitably lead to compromise. Consequently, the results must be interpreted within the context of certain limitations.

In choosing to define relationship learning as a process I measure the magnitude of information sharing, interpretation, and memory integration, however, this says nothing directly about quality. Knowing a lot is not comparable to knowing the right things, thus a small amount of high quality learning may prove superior to a large amount of inferior learning.

So far as using dyadic data, two opposing problems arise. I attempted to address the problem of validity and reliability issues through my methodology. However, while extending research that focuses on only one side of the dyad, this still ignores the complexity of the network of inter-firm ties (Anderson et al. 1994; Wathne, Biong, and Heide 2001). The learning in one relationship is quite certainly a function of the learning in other relationships, thus the level of abstraction may not be high enough.

Finally, in the multimethod-multitrait matrix approach (Campbell and Fiske 1959), in structural equation modeling (Jöreskog 1974), the optimal result would have been to achieve good model fit with no methods factors and low error. This would indicate no significant perceptual differences across the dyad. The next best scenario is to improve fit by including methods factors, which is indeed what happened. Nevertheless, by partitioning the variance I was able to show that the greatest portion of variance was accounted for by the traits, close to 50%. The judgment as to whether this is sufficiently high lies with the reader.

7.6 FUTURE RESEARCH

Difficulty in attaining a good structural model gives clear evidence that there is more work to be done specifying the structural relationships, although given the combinations I ran I believe this goes beyond mere re-specification. There are other variables that may be important, like reciprocity (e.g. Granovetter 1985; Joshi and Stump 1999; Oliver 1990). It may be that the values dimensions (e.g. Hamel 1991a) of openness and receptivity should play an explicit role in the model.

Regarding trust, my original plan was to measure it at the interpersonal level, the inter-organizational level, and across levels between a person and an organization. The measures failed to discriminate. Despite this, I believe it could be very useful to pursue developing a better measure of these three dimensions and look at how

they interact in inter-organizational relationships (e.g. Doney and Cannon 1997; Zaheer et al. 1998).

When partitioning the variance, particularly for sellers, the systematic error for trust was high at 50% (36% for buyers). This indicates that perceptions varied in a systematic fashion across respondents. It may be fruitful to determine if there is a connection between, for example, type of business and trust. It may be that because of systematic differences between industries relative to trust levels, some industries are more conducive to relationship learning than others. Determining what the key systematic differences are and whether they are transferable may provide valuable practical implications for how to enhance relationship learning.

Finally, the quantitative study is based on perceptual measures. A study that incorporated more concrete measures would provide a more robust test of the theory.

APPENDIX 1: INTERVIEW GUIDE

The following interview guide was used as a general framework for conducting the interviews of both the suppliers and customers who took part in the research project. It underwent some revisions as the interviewing process progressed, reflected in the following version.

Question 1 (general learning)

1. Can you describe how you learn from your customer/supplier?
Please give examples.

2. Do you consider the relationship with your customer/supplier complex?
 - a) Is this related to the complexity of the product?
 - b) Does this complexity motivate information sharing?

3. What changes has your company made based on what you have learned from your customer/supplier?
For example: new products or systems.

Question 2 (memory and processing)

1. How is learning memorized in your organization?
 - a) Individuals?
 - b) Systems?
 - c) Databases?
 - d) Products?
 - e) Other?

2. What factors influence how information (from the customer/supplier) is stored in your organization?
 - a) Systems for storage?

- b) Incentives?
 - c) Organization of people?
 - d) Other?
3. What factors influence how information (from the customer/supplier) is processed in your organization?
- a) Organization of people?
 - b) Authority (centralized or decentralized)?
 - c) Competence?
 - d) Trust in the customer's/supplier's expertise in the area?
 - e) Other?

Question 3 (driving forces and benefits)

1. What is motivating learning in the relationship?
- a) Curiosity?
 - b) Expertise?
 - c) Desire to influence?
 - d) Other?
2. What factors are influencing your motivation to share information with the supplier?
- a) Trust?
 - b) Real need for improvements? In what way?
 - c) Market turbulence?
 - d) Other?
3. What benefits has your company achieved through a learning relationship with the customer/supplier?
- a) Better products?
 - b) Better service?
 - c) Reduced costs?

- d) Increased commitment to the relationship?
- e) Other?

Question 4 (learning by the other party)

1. How do you think your customer/supplier is learning from you?
 - a) What do they learn?
 - b) What are the consequences?
2. Do you perceive that your customer/supplier has changed based on learning from your company?
For example: new products or systems.

Question 5 (organizational questions)

1. Is decision making centralized in your organization, or do people have a great deal of autonomy?
2. Is information about the customer/supplier shared openly in your organization?
 - a) Is there much opportunity for informal “hall talk”, or are people expected to use formal channels of communication?
 - b) Do people from different departments mix easily?
 - c) Do junior members of your organization mix easily with senior members?
3. Are there many contact points between your organization and the customer/supplier?
 - a) Do these contact points facilitate the transfer of information?

Question 6 (suggestions)

How can the relationship be changed so that both parties learn more and faster?

APPENDIX 2: QUESTIONNAIRE

* indicates items removed in the analysis.

GOALS: Measured on a seven point scale from Low (1) to High (7) with a category for Not Relevant (?).

1. To what degree do you discuss company goals with the other party in this relationship (Borys and Jemison 1989; Hamel 1991; Sheth and Parvatiyar 1992)?
2. To what degree are these goals developed through joint analysis of potentials (Borys and Jemison 1989; Hamel 1991; Sheth and Parvatiyar 1992)?
3. To what degree are these goals formalized in a joint agreement or contract (Borys and Jemison 1989; Hamel 1991; Sheth and Parvatiyar 1992)?
4. To what degree are these goals implemented in day-to-day work (Borys and Jemison 1989; Hamel 1991; Sheth and Parvatiyar 1992)?
5. To what degree have you developed measures that capture performance related to these goals (Borys and Jemison 1989; Hamel 1991; Sheth and Parvatiyar 1992)?

COMPLEXITY: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

6. * There are several different products exchanged in our relationship!
7. These products are generally very complex!
8. * These products are highly customized for this relationship!
9. There are many operating units involved from both organizations!
10. There are many contact points between different departments or professions between the two organizations (Cohen and Levinthal 1990)!

TRUST: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

11. * I trust the contact people from the other organization (Doney and Cannon 1997)!

12. * I trust that the contact people from the other organization are concerned about my well being (Doney and Cannon 1997)!
13. * I believe that the other organization will consider my company's well being when making important decisions (Doney and Cannon 1997)!
14. I believe the other organization will respond with understanding in the event of problems (Doney and Cannon 1997)!
15. I trust that the other organization is able to fulfill contractual agreements (Doney and Cannon 1997)!
16. We trust that the other organization is competent at what they are doing (Doney and Cannon 1997)!
17. There is general agreement in my organization that the other organization is trustworthy (Doney and Cannon 1997)!
18. There is general agreement in my organization that the contact people in the other organization are trustworthy (Doney and Cannon 1997)!

INFORMATION SHARING: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

19. * Our companies exchange information on successful and unsuccessful experiences with products exchanged in the relationship (Slater and Narver 1996)!
20. * Our companies exchange information related to changes in end-user needs, preferences, and behavior (Jaworski and Kohli 1993)!
21. Our companies exchange information related to changes in market structure, such as mergers, acquisitions, or partnering (Jaworski and Kohli 1993)!
22. Our companies exchange information related to changes in the technology of the focal products (Jaworski and Kohli 1993)!
23. * Our companies exchange information as soon as possible of any unexpected problems (Anderson and Narus 1990)!
24. Our companies exchange information on changes related to our two organization's strategies and policies!
25. Our companies exchange information that is sensitive for both parties, such as financial performance and company know-how (Heide and John 1992)!
26. It is my company's policy to openly share information in this relationship!

27. The interaction between our two organizations is mediated through an extensive network of people from both sides (Cohen and Levinthal 1990)!
28. It is common to establish joint teams to solve operational problems in the relationship (Hedberg 1981)!
29. It is common to establish joint teams to analyze and discuss strategic issues (Hedberg 1981)!
30. The atmosphere in the relationship stimulates productive discussion encompassing a variety of opinions (Moorman 1995)!
31. * We have a lot of face-to-face communication in this relationship!
32. It is my company's policy to encourage interpersonal contact between companies in this relationship (Moorman 1995)!
33. In the relationship we frequently adjust our common understanding of end-user needs, preferences, and behavior!
34. In the relationship we frequently adjust our common understanding of trends in technology related to our business!
35. * In the relationship we frequently evaluate, and if needed adjust our routines in order-delivery processes!
36. We frequently evaluate and if needed update the formal contracts in our relationship!
37. We frequently meet face-to-face in order to refresh the personal network in this relationship!
38. We frequently evaluate, and if needed update information about the relationship stored in our electronic databases!

UNCERTAINTY: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

39. End-user needs and preferences change rapidly in our industry (Heide and John 1990; Jaworski and Kohli 1993)!
40. The competitors in our industry frequently make several aggressive moves to capture market share (Heide and John 1990; Jaworski and Kohli 1993)!
41. Crises have caused some of our competitors to shut down or radically change the way they operate (Meyer et al. 1990)!

42. It is very difficult to forecast where the technology will be in the next 2-3 years in our industry (Heide and John 1990; Huber 1996; Jaworski and Kohli 1993)!
43. In recent years, a large number of new product ideas have been made possible through technological breakthroughs in our industry (Heide and John 1990; Jaworski and Kohli 1993)!

CONSEQUENCES: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

44. The relationship with the other company has resulted in lower logistics costs!
45. Flexibility to handle unforeseen fluctuations in demand has been improved because of the relationship!
46. The relationship with the other company has resulted in better product quality!
47. Synergies in joint sales and marketing efforts have been achieved because of the relationship!
48. The relationship has a positive effect on our ability to develop successful new products!
49. Investments of resources in the relationship, such as time and money, have paid off very well!
50. The relationship helps us to detect changes in end-user needs and preferences before our competitors!

DESCRIPTIVE STATISTICS: Measured on a seven point scale from Strongly Disagree (1) to Strongly Agree (7) with a category for Not Relevant (?).

51. Our company has made significant investments dedicated to this relationship (Heide and John 1990)!
52. Our company has made several adaptations to accommodate the other party's technological norms and standards (Heide and John 1990)!
53. The other company can easily be replaced if the relationship was terminated (Heide and John 1990)!
54. Our company's systems and processes can easily be adapted to a new partner (Heide and John 1990)!
55. In our company we are very satisfied with this relationship!

56. In our company we find this relationship more attractive than other relevant alternatives!

57. In our company we are highly motivated to continue this relationship!

58. In our company we are highly motivated to collaborate in this relationship!

59. In our company we talk favorably about this relationship!

DEMOGRAPHIC QUESTIONS: Completed by the recruiter during the recruitment process.

60. Choose the appropriate question:

a) This customer represents approximately _____% of our total sales.

b) This supplier represents approximately _____% of our total supply.

61. What is the primary focus of your business?

Circle one

f) Producer g) Wholesaler h) Retailer i) Service Provider j) Other

62. How long have you personally been with your company? _____years.

63. How long have the two companies been involved in the relationship?
_____years.

64. How long have you personally been involved in the relationship with the other company?

_____years.

APPENDIX 3: SPSS SYNTAX

* This first syntax shows an example of how some of the seller data is summed into aggregated variables.

```
compute scollab=(s1+s2+s3+s4+s5)/5.
compute scomplex=(s7+s9+s10)/3.
compute suncert=(s39+s41+s42+s43)/4.
compute sasset=(s51+s52)/2.
compute srelearn=(s21+s22+s24+s25+s28+s29+s30+s33+s34+s36+s37+s38)/12.
compute strust=(s14+s15+s16+s17+s18)/5.
compute sperf=(s44+s45+s46+s47+s48+s49+s50)/7.

missing values all (99).
recode all (9=99) (sysmis=99).
execute.
```

* This syntax shows how to export the aggregated data and create a file that Preliis can read. It includes the buyer data as well.

```
Write outfile = "c:\lisrel83\relearn\fullagg.dat"
/ scollab bcollab scomplex bcomplex suncert buncert sasset basset srelearn brelearn
sperf bperf strust btrust (14F6.0).
execute.
```

* This syntax shows how to create product variables that are used as instrumental variables for two-stage least squares regression.

```
compute sc1xst1=s1*s14.
compute sc2xst2=s2*s15.
compute sc2xst3=s2*s16.
compute sc2xst4=s2*s17.
compute sc2xst5=s2*s18.
compute sc3xst2=s3*s15.
compute sc3xst3=s3*s16.
compute sc3xst4=s3*s17.
compute sc3xst5=s3*s18.
compute sc4xst2=s4*s15.
compute sc4xst3=s4*s16.
compute sc4xst4=s4*s17.
compute sc4xst5=s4*s18.
compute sc5xst2=s5*s15.
compute sc5xst3=s5*s16.
compute sc5xst4=s5*s17.
```

```
compute sc5xst5=s5*s18.
```

```
missing values all (99).  
recode all (9=99) (sysmis=99).  
execute.
```

* This syntax shows how the instrumental variables (original variables, product variables, and exogenous variables) are regressed on the first indicator of the collaborative objectives construct, the trust construct, and the product of the first two indicators (the interaction) to form predicted values.

```
REGRESSION  
/MISSING LISTWISE  
/STATISTICS COEFF OUTS R ANOVA  
/CRITERIA=PIN(.05) POUT(.10)  
/NOORIGIN  
/DEPENDENT s1  
/METHOD=ENTER s2 s3 s4 s5 s15 s16 s17 s18 sc2xst2 sc2xst3 sc2xst4 sc2xst5  
sc3xst2 sc3xst3 sc3xst4 sc3xst5 sc4xst2 sc4xst3 sc4xst4 sc4xst5 sc5xst2  
sc5xst3 sc5xst4 sc5xst5 scomplex suncert sasset  
/SAVE PRED .
```

```
REGRESSION  
/MISSING LISTWISE  
/STATISTICS COEFF OUTS R ANOVA  
/CRITERIA=PIN(.05) POUT(.10)  
/NOORIGIN  
/DEPENDENT s14  
/METHOD=ENTER s2 s3 s4 s5 s15 s16 s17 s18 sc2xst2 sc2xst3 sc2xst4 sc2xst5  
sc3xst2 sc3xst3 sc3xst4 sc3xst5 sc4xst2 sc4xst3 sc4xst4 sc4xst5 sc5xst2  
sc5xst3 sc5xst4 sc5xst5 scomplex suncert sasset  
/SAVE PRED .
```

```
REGRESSION  
/MISSING LISTWISE  
/STATISTICS COEFF OUTS R ANOVA  
/CRITERIA=PIN(.05) POUT(.10)  
/NOORIGIN  
/DEPENDENT sc1xst1  
/METHOD=ENTER s2 s3 s4 s5 s15 s16 s17 s18 sc2xst2 sc2xst3 sc2xst4 sc2xst5  
sc3xst2 sc3xst3 sc3xst4 sc3xst5 sc4xst2 sc4xst3 sc4xst4 sc4xst5 sc5xst2  
sc5xst3 sc5xst4 sc5xst5 scomplex suncert sasset  
/SAVE PRED .
```

```
missing values all (99).  
recode all (9=99) (sysmis=99).  
execute.
```

This final syntax is an example of two-stage least squares for the predicted values and exogenous constructs. SPSS offers a 2SLS option where this is all done automatically, however, there is some loss of control over the process so I chose to do it the long way.

```
REGRESSION  
/MISSING LISTWISE  
/STATISTICS COEFF OUTS R ANOVA COLLIN TOL  
/CRITERIA=PIN(.05) POUT(.10)  
/NOORIGIN  
/DEPENDENT srelearn  
/METHOD=ENTER pre_4 pre_5 pre_6 suncert scomplex sasset .
```

APPENDIX 4: PRELIS SYNTAX

This shows the syntax for importing the data from the fullagg file created in SPSS. 14 variables are imported, then the interaction effects are calculated by the NE command, thus 16 variables are exported as a correlation matrix. The CO command declares the variables to be continuous, otherwise for variables with less than 16 distinct values the program will use the ordinal default. Prelis generates various descriptive statistics before exporting the matrix.

```
DA NI=14 NO=315 MI=99 TR=PA
RA FI=c:\lisrel83\relearn\fullagg.dat
CO ALL
```

```
LA
scollab bcollab scomplex bcomplex suncert buncert sasset basset srelearn brelearn
strust btrust sperf bperf
```

```
NE strxscb=strust*scollab
NE btrxbcb=btrust*bcollab
```

```
CO scollab bcollab scomplex bcomplex suncert buncert sasset basset
CO srelearn brelearn strust btrust sperf bperf strxscb btrxbcb
```

```
OU MA=KM KM=c:\lisrel83\relearn\fullagg.cor
```

APPENDIX 5: LISREL SYNTAX

This is an example of the syntax for the fullagg measurement model with methods factors. In other words it is a MTMM matrix in structural equation modeling. Of the 16 imported variables, performance is dropped so only 14 are used in the analysis. The MO and LK lines show the creation of the buyer and seller latent variables, as well as the other variables. The FR lines specify the paths, the VA lines set variances. ST suggests starting values for iterations, and the final two lines specify how the program should run and what output to give.

```
DA NI=16 NO=315 MA=KM
KM FI=C:\lisrel83\relearn\fullagg.cor
```

```
LA
scollab bcollab scomplex bcomplex suncert buncert sasset basset
srelearn brelearn strust btrust sperf bperf strxscb btrxcb
```

```
SE
scollab bcollab scomplex bcomplex suncert buncert sasset basset srelearn brelearn
strust btrust strxscb btrxcb /
```

```
MO NX=14 NK=9 PH=SY,FI TD=SY,FI
```

```
LK
collab complex uncert asset relearn trust trxcb seller buyer
```

```
FR LX(1,1) LX(2,1) LX(3,2) LX(4,2) LX(5,3) LX(6,3) LX(7,4) LX(8,4) LX(9,5)
FR LX(10,5) LX(11,6) LX(12,6) LX(13,7) LX(14,7)
```

```
FR LX(1,8) LX(3,8) LX(5,8) LX(7,8) LX(9,8) LX(11,8) LX(13,8)
```

```
FR LX(2,9) LX(4,9) LX(6,9) LX(8,9) LX(10,9) LX(12,9) LX(14,9)
```

```
VA 1 PH(1,1) PH(2,2) PH(3,3) PH(4,4) PH(5,5) PH(6,6) PH(7,7) PH(8,8) PH(9,9)
```

```
FR PH(1,2) PH(1,3) PH(1,4) PH(1,5) PH(1,6) PH(1,7) PH(2,3) PH(2,4) PH(2,5)
FR PH(2,6) PH(2,7)
```

FR PH(3,4) PH(3,5) PH(3,6) PH(3,7) PH(4,5) PH(4,6) PH(4,7) PH(5,6) PH(5,7)
FR PH(6,7) PH(8,9)

FR TD(1,1) TD(2,2) TD(4,4) TD(5,5) TD(6,6) TD(7,7) TD(8,8) TD(9,9)
FR TD(11,11) TD(12,12) TD(13,13) TD(14,14)

FR TD(1,13) TD(2,14) TD(11,13) TD(12,14)

VA .3 TD(3,3)

ST .7 ALL .

Path Diagram

OU IT=500 SC MI TV AD=OFF

This is an example of the syntax for the fullagg structural model with methods factors. The main difference from the measurement model is that the latent variables are Eta rather than Ksi, and BE specifies the structural relationships in the Beta matrix.

DA NI=16 NO=315 MA=KM
KM FI=C:\lisrel83\relearn\fullagg.cor

LA

scollab bcollab scomplex bcomplex suncert buncert sasset basset
srelearn brelearn strust btrust sperf bperf strxscb btrxcb

SE

scollab bcollab scomplex bcomplex suncert buncert sasset basset srelearn brelearn
strust btrust strxscb btrxcb /

MO NY=14 NE=9 PS=SY,FI TE=SY,FI BE=FU,FI

LE

collab complex uncert asset relearn trust trxcb seller buyer

FR LY(1,1) LY(2,1) LY(3,2) LY(4,2) LY(5,3) LY(6,3) LY(7,4) LY(8,4) LY(9,5)
FR LY(10,5) LY(11,6) LY(12,6) LY(13,7) LY(14,7)

FR LY(1,8) LY(3,8) LY(5,8) LY(7,8) LY(9,8) LY(11,8) LY(13,8)

FR LY(2,9) LY(4,9) LY(6,9) LY(8,9) LY(10,9) LY(12,9) LY(14,9)

VA 1 PS(1,1) PS(2,2) PS(3,3) PS(4,4) PS(5,5) PS(6,6) PS(7,7) PS(8,8) PS(9,9)

VA 1 PS(1,2) PS(1,3) PS(1,4) PS(1,6) PS(2,3) PS(2,4) PS(2,6) PS(2,7)

VA 1 PS(3,4) PS(3,6) PS(3,7) PS(4,6) PS(4,7) PS(1,5) PS(2,5) PS(3,5) PS(4,5)

VA 1 PS(5,6) PS(5,7)

FR PS(8,9) PS(6,7) PS(1,7)

FR TE(1,1) TE(2,2) TE(4,4) TE(5,5) TE(6,6) TE(7,7) TE(8,8) TE(9,9) TE(10,10)

FR TE(11,11) TE(12,12) TE(13,13) TE(14,14)

FR TE(1,2) TE(7,8) TE(11,13) TE(12,14)

VA .3 TE(3,3)

FR BE(5,1) BE(5,2) BE(5,3) BE(5,4) BE(5,6) BE(5,7)

ST .7 ALL

Path Diagram

OU IT=900 ME=UL SC MI TV AD=OFF

REFERENCES

- Anderson, Erin, and Barton Weitz (1992). "The Use of Pledges to Build and Sustain Commitment in Distribution Channels." *Journal of Marketing Research* 29 (1): 18-34.
- Anderson, James C., and David W. Gerbing (1988). "Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach." *Psychological Bulletin* 103 (3): 411-423.
- Anderson, James C., and James A. Narus (1990). "A Model of Distributor Firm and Manufacturer Firm Working Partnerships." *Journal of Marketing* 54 (1): 42-58.
- Anderson, James C., Håkan Håkansson, and Jan Johanson (1994). "Dyadic Business Relationships Within a Business Network Context." *Journal of Marketing* 58 (4): 1-15.
- Argyris, Chris (1977). "Double Loop Learning in Organizations." *Harvard Business Review* 55: 115-125.
- Argyris, Chris, and Donald A. Schön (1978). *Organizational Learning: A Theory of Action Perspective*. Reading, M.: Addison-Wesley.
- Argyris, Chris, and Donald A. Schön (1996). *Organizational Learning II: Theory, Method, and Practice*. New York, NY: Addison-Wesley.
- Astley, W. Graham (1984). "Toward an Appreciation of Collective Strategy." *Academy of Management Review* 9 (3): 526-535.
- Axelrod, Robert (1984). *The Evolution of Cooperation*. New York, NY: Basic Books.
- Badaracco, Joseph L., Jr. (1991). *The Knowledge Link: How Firms Compete Through Strategic Alliances*. Boston, MA: Harvard Business School Press.
- Bagozzi, Richard P., and Jeffrey R. Edwards (1998). "A General Approach for Representing Constructs in Organizational Research." *Organizational Research Methods* 1 (1): 45-87.
- Bagozzi, Richard P., and Lynn W. Phillips (1982). "Representing and Testing Organizational Theories: A Holistic Construal." *Administrative Science Quarterly* 27 (3): 459-490.

Bagozzi, Richard P., and Youjae Yi (1988). "On the Evaluation of Structural Equation Models." *Journal of the Academy of Marketing Science* 16 (1): 74-94.

Barney, Jay (1991). "Firm Resources and Sustained Competitive Advantage." *Journal of Management* 17 (1): 99-120.

Bollen, Kenneth A., and Pamela Paxton (1998). Two-Stage Least Squares Estimation of Interaction Effects. *Interaction and Nonlinear Effects in Structural Equation Modeling*. R. E. Schumacker and G. A. Marcoulides. Mahwah NJ: Lawrence Erlbaum Associates, Publishers: 125-151.

Bollen, Kenneth, and Richard Lennox (1991). "Conventional Wisdom on Measurement: A Structural Equation Perspective." *Psychological Bulletin* 110 (2): 305-314.

Bollen, Kenneth A. (1989). *Structural Equations With Latent Variables*. New York, NY: Wiley.

Borys, Bryan, and David B. Jemison (1989). "Hybrid Arrangements as Strategic Alliances: Theoretical Issues in Organizational Combinations." *Academy of Management Review* 14 (2): 234-249.

Bradach, Jeffery L., and Robert G. Eccles (1989). "Price, Authority, and Trust: From Ideal Types to Plural Forms." *Annual Review of Sociology* 15: 97-118.

Browne, Michael W., and Robert Cudeck (1992). "Alternative Ways of Assessing Model Fit." *Sociological Methods & Research* 21 (2): 230-258.

Burns, Tom R., and G. M. Stalker (1961). *The Management of Innovations*. London, UK: Tavistock.

Burt, Ronald S. (1997). "The Contingent Value of Social Capital." *Administrative Science Quarterly* 42 (2): 339-365.

Buvik, Arnt, and George John (2000). "When Does Vertical Coordination Improve Industrial Purchasing Relationships?" *Journal of Marketing* 64 (4): 52-64.

Calder, Bobby J., Lynn W. Phillips, and Alice M. Tybout (1981). "Designing Research for Application." *Journal of Consumer Research* 8: 197-207.

Campbell, Donald T. (1955). "The Informant in Quantitative Research." *American Journal of Sociology* 60: 339-342.

Campbell, Donald T., and Donald W. Fiske (1959). "Convergent and Discriminant Validation by the Multitrait-Multimethod Matrix." *Psychological Bulletin* 56 (2): 81-105.

- Cannon, Joseph P., and William D. Jr. Perreault (1999). "Buyer-Seller Relationships in Business Markets." *Journal of Marketing Research* 36 (4): 439-460.
- Child, John, and David Faulkner (1998). *Strategies of Cooperation: Managing Alliances, Networks, and Joint Ventures*. Oxford, NY: Oxford University Press.
- Churchill, Gilbert A. Jr. (1979). "A Paradigm for Developing Better Measures of Marketing Constructs." *Journal of Marketing Research* 16 (1): 64-73.
- Churchill, Gilbert A. Jr. (1999). *Marketing Research: Methodological Foundations*. Chicago, IL: The Dryden Press.
- Cohen, Wesley M., and Daniel A. Levinthal (1990). "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly* 35: 128-152.
- Contractor, Farok J., and Peter Lorange, Eds. (1988). *Cooperative Strategies in International Business*. Lexington, MA: Lexington Books.
- Cook, Thomas D., and Donald T. Campbell (1979). *Quasi-Experimentation: Design and Analysis Issues for Field Settings*. Boston, MA: Houghton Mifflin.
- Cyert, Richard M., and James G. March (1963). *A Behavioral Theory of the Firm*. Englewood Cliffs, NJ: Prentice-Hall.
- Cyert, Richard M., and James G. March (1992). *A Behavioral Theory of the Firm: Second Edition*. Cambridge MA: Blackwell Publishers.
- Daft, Richard L., and George P. Huber (1987). "How Organizations Learn: A Communication Framework." *Research in Sociology of Organizations* 5.
- Daft, Richard L., and Karl E. Weick (1984). "Toward a Model of Organizations as Interpretation Systems." *Academy of Management Review* 9 (2): 284-295.
- D'Agostino, R. B. (1986). Tests for the Normal Distribution. *Goodness of Fit Techniques*. R. B. D'Agostino and M. A. Stephens. New York, NY: Marcel Dekker: 367-419.
- Dahlstrom, Robert, and Arne Nygaard (1999). "An Empirical Investigation of Ex Post Transaction Costs in Franchised Distribution Channels." *Journal of Marketing Research* 36 (2): 160-170.
- Das, T. K., and Bing-Sheng Teng (1998). "Between Trust and Control: Developing Confidence in Partner Cooperation Alliances." *Academy of Management Review* 23 (3): 491-512.

- Day, George S. (1994a). "The Capabilities of Market Driven Organizations." *Journal of Marketing* 58 (4): 37-52.
- Day, George S. (1994b). "Continuous Learning About Markets." *California Management Review* 36 (4): 9-31.
- Deshpandé, Rohit, John U. Farley, and Frederick E. Jr. Webster (1993). "Corporate Culture, Customer Orientation, and Innovativeness in Japanese Firms: A Quadrad Analysis." *Journal of Marketing* 57 (1): 23-35.
- Dodgson, Mark (1993a). "Organizational Learning: A Review of Some Literatures." *Organization Science* 14 (3): 375-394.
- Dodgson, Mark (1993b). "Learning, Trust, and Technological Collaboration." *Human Relations* 46 (1): 77-95.
- Doney, Patricia M., and Joseph P. Cannon (1997). "An Examination of the Nature of Trust in Buyer-Seller Relationships." *Journal of Marketing* 61 (2): 35-51.
- Doz, Yves L. (1996). "The Evolution of Cooperation in Strategic Alliances: Initial Conditions or Learning Processes?" *Strategic Management Journal* 17: 55-83.
- Driver, Michael J., and Siegfried Streufert (1966). *Integrative Complexity: An Approach to Individuals and Group as Information-processing Systems*. Institute of Management Science Meeting, Dallas, Texas.
- Dwyer, F. Robert, Paul H. Schurr, and Sejo Oh (1987). "Developing Buyer-Seller Relationships." *Journal of Marketing* 51 (2): 11-27.
- Dyer, Jeffrey H., and Harbir Singh (1998). "The Relational View: Cooperative Strategy and Sources of Interorganizational Competitive Advantage." *Academy of Management Review* 23 (4): 660-679.
- Einstein, Albert (1923). *Sidelights on Relativity*. New York, NY: E. P. Dutton Company.
- Einstein, Albert, and Leopold Infeld (1938). *The Evolution of Physics*. New York, NY: Simon and Schuster.
- Eisenhardt, Kathleen M. (1989). "Building Theories from Case Study Research." *Academy of Management Review* 14 (4): 532-550.
- Eisenhardt, Kathleen M., Jean L. Kahwajy, and L. J. III Bourgeois (1997). "Conflict and Strategic Choice: How Top Management Teams Disagree." *California Management Review* 39 (2): 42-62.

- Fiol, C. Marlene, and Marjorie A. Lyles (1985). "Organizational Learning." *Academy of Management Review* 10 (4): 803-813.
- Fishbein, Martin (1980). *Understanding Attitudes and Predicting Social Behavior*. Englewood Cliffs, NJ: Prentice-Hall.
- Ford, David (1980). "The Development of Buyer-Seller Relationships in Industrial Markets." *European Journal of Marketing* 14 (5/6): 339-353.
- Fornell, Claes, and David F. Larcker (1981). "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error." *Journal of Marketing Research* 18 (1): 39-50.
- Frankfort-Nachmias, Chava, and David Nachmias (1996). *Research Methods in the Social Sciences*. London, UK: St Martin's Press.
- Gaertner, Samuel L., John F. Dovidio, and B. A. Bachman (1996). "Revisiting the Contact Hypothesis: The Induction of a Common Group Identity." *International Journal of Intercultural Relations* 20 (3-4): 271-290.
- Garud, Raghu, and Praveen R. Nayyar (1994). "Transformative Capacity: Continual Structuring by Intertemporal Technology Transfer." *Strategic Management Journal* 15: 365-385.
- Garvin, David A. (1993). "Building a Learning Organization." *Harvard Business Review* 71 (4): 78-91.
- Glaser, Barney G., and Anselm L. Strauss (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. New York, NY: Aldine De Gruyter.
- Granovetter, Mark (1985). "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91 (3): 481-510.
- Grayson, Kent, and Tim Ambler (1999). "The Dark Side of Long-Term Relationships in Marketing Services." *Journal of Marketing Research* 36 (1): 132-141.
- Grønhaug, Kjell (1996). Expert Knowledge as a Strategic Asset. *Rethinking the Boundaries of Strategy*. J. Falkenberg and S. A. Haugland. Copenhagen, Handelshøyskolens Forlag: 219-242.
- Hair, Joseph F. Jr., Rolph E. Anderson, Ronald L. Tatham, and William C. Black (1998). *Multivariate Data Analysis with Readings*. New York, NY: Macmillan Publishing Company.
- Hallén, Lars, Jan Johansen, and Nazeem Seyed-Mohamed (1991). "Interfirm Adaptation in Business Relationships." *Journal of Marketing* 55 (2): 29-37.

- Hamel, Gary (1991). "Competition for Competence and Interpartner Learning Within International Strategic Alliances." *Strategic Management Journal* 12: 83-103.
- Haugland, Sven A., and Kjell Grønhaug (1996). "Cooperative Relationships in Competitive Markets." *Journal of Socio-Economics* 25 (3): 359-371.
- Hedberg, Bo (1981). How Organizations Learn and Unlearn. *Handbook of Organizational Design*. P. C. Nystrom and W. H. Starbuck. Oxford, UK: Oxford University Press. 1: 3-27.
- Heide, Jan B. (1994). "Interorganizational Governance in Marketing Channels." *Journal of Marketing* 58 (1): 71-85.
- Heide, Jan B., and George John (1990). "Alliances in Industrial Purchasing: The Determinants of Joint Action in Buyer-Supplier Relationships." *Journal of Marketing Research* 27 (1): 24-36.
- Heide, Jan B., and George John (1992). "Do Norms Matter in Marketing Relationships?" *Journal of Marketing* 56 (2): 32-44.
- Heide, Jan B., and George John (1994). Measurement Issues in Research on Inter-Firm Relationships. *Business Marketing: An Interaction and Network Perspective*. D. T. Wilson and K. Möller. Boston MA: PWS-Kent: 531-554.
- Huber, George P. (1991). "Organizational Learning: The Contributing Processes and the Literatures." *Organization Science* 2 (1): 88-115.
- Huber, George P. (1996). "Organizational Learning: A Guide for Executives in Technology-Critical Organizations." *International Journal of Technology Management* 11 (7/8): 821-832.
- Hunt, Shelby D. (1993). "Objectivity in Marketing Theory and Research." *Journal of Marketing* 57: 76-91.
- Håkansson, Håkan, and Jan Johanson (1988). Formal and Informal Cooperation Strategies in International Industrial Networks. *Cooperative Strategies in International Business*. F. J. Contractor and P. Lorange. Lexington, MA: Lexington Books: 369-379.
- Håkansson, Håkan, and Ivan Snehota (1995). Analysing Business Relationships. *Developing Relationships in Business Networks*. London, UK: Routledge: 24-49.
- Ilinitch, Anne Y., Richard A. D'Aveni, and Arie Y. Lewin (1996). "New Organizational Forms and Strategies for Managing in Hypercompetitive Environments." *Organizational Science* 7 (3): 211-220.

- Inkpen, Andrew C., and Mary M. Crossan (1995). "Believing is Seeing: Joint Ventures and Organizational Learning." *Journal of Management Studies* 32 (5): 595-618.
- Irwin, Julie R., and Gary H. McClelland (2001). "Misleading Heuristics and Moderated Multiple Regression Models." *Journal of Marketing Research* 38 (1): 100-109.
- Jaccard, James, Robert Turrisi, and Choi K. Wan (1990). *Interaction Effects in Multiple Regression*. London, UK: Sage.
- Janis, Irving L. (1989). *Crucial Decisions: Leadership in Policymaking and Crisis Management*. New York NY: The Free Press.
- Jap, Sandy D., and Barton A. Weitz (1996). "Achieving Strategic Advantages in Buyer-Seller Relationships." *Marketing Science Institute Working Paper Series* 96-108: 1-43.
- Jap, Sandy D. (1999). "Pie Expansion Efforts: Collaboration Processes in Buyer-Supplier Relationships." *Journal of Marketing Research* 36 (4): 461-475.
- Jaworski, Bernard J., and Ajay Kohli, K (1993). "Market Orientation: Antecedents and Consequences." *Journal of Marketing* 57 (3): 50-70.
- Johanson, Jan, and Lars-Gunnar Mattsson (1987). "Interorganizational Relations in Industrial Systems: A Network Approach Compared with the Transaction-Cost Approach." *International Studies of Management and Organization* 17 (1): 34-48.
- John, George, and Torger Reve (1982). "The Reliability and Validity of Key Informant Data from Dyadic Relationships in Marketing Channels." *Journal of Marketing Research* 19 (4): 517-524.
- Jones, Gareth R., and Jennifer M. George (1998). "The Experience and Evolution of Trust: Implications for Cooperation and Teamwork." *Academy of Management Review* 23 (3): 531-546.
- Jonsson, Fan Yang (1998). Modeling Interaction and Nonlinear Effects: A Step-by-Step Lisrel Example. *Interaction and Nonlinear Effects in Structural Equation Modeling*. R. E. Schumacker and G. A. Marcoulides. Mahwah, NJ: Lawrence Erlbaum Associates, Publishers.
- Joshi, Ashwin W., and Rodney L. Stump (1999). "The Contingent Effect of Specific Asset Investments on Joint Action in Manufacturer-Supplier Relationships: An Empirical Test of the Moderating Role of Reciprocal Asset Investments, Uncertainty, and Trust." *Journal of the Academy of Marketing Science* 27 (3): 291-305.

Jöreskog, Karl G. (1999). How Large Can a Standardized Coefficient Be? Karl's Corner, <http://www.ssicentral.com/lisrel/corner.htm>.

Jöreskog, Karl G. (1998). Interaction and Nonlinear Modeling: Issues and Approaches. *Interaction and Nonlinear Effects in Structural Equation Modeling*. R. E. Schumacker and G. A. Marcoulides. Mahwah NJ: Lawrence Erlbaum Associates, Publishers.

Jöreskog, Karl (1974). Analyzing Psychological Data by Structural Analysis of Covariance Matrices. *Contemporary Developments in Mathematical Psychology*. R. C. Atkinson and e. al. San Francisco, CA: Freeman. 2: 1-56.

Jöreskog, Karl, and Dag Sörbom (1984). *Lisrel: Analysis of Linear Structure Relationships by the Method of Maximum Likelihood*. Moorsville, IN: Scientific Software.

Jöreskog, Karl, and Dag Sörbom (1993). *Lisrel 8: Structural Equation Modeling with the Simplis Command Language*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Jöreskog, Karl, and Dag Sörbom (1996a). *Lisrel 8: User's Reference Guide*. Chicago, IL: Scientific Software International.

Jöreskog, Karl, and Dag Sörbom (1996b). *Prelis 2: User's Reference Guide*. Chicago, IL: Scientific Software International.

Jöreskog, Karl, and Fan Yang (1996). Nonlinear Structural Equation Models: The Kenny-Judd Model with Interaction Effects. *Advanced Structural Equation Modeling: Issues and Techniques*. G. A. Marcoulides and R. E. Schumacker. Mahwah, NJ: Lawrence Erlbaum Associates, Publishers: 57-88.

Kalwani, Manohar, U., and Narakesari Narayandas (1995). "Long-Term Manufacturer-Supplier Relationships: Do They Pay Off for Supplier Firms?" *Journal of Marketing* 59 (1): 1-16.

Kenny, David A., and Charles M. Judd (1984). "Estimating the Nonlinear and Interactive Effects of Latent Variables." *Psychological Bulletin* 96 (1): 201-210.

Kim, Daniel H. (1993). "The Link Between Individual and Organizational Learning." *Sloan Management Review* 35 (1): 37-50.

Kirk, Jerome, and Marc L. Miller (1986). *Reliability and Validity in Qualitative Research*. London, UK: Sage.

- Klein, Katherine J., Fred Dansereau, and Rosalie J. Hall (1994). "Levels Issues in Theory Development, Data Collection, and Analysis." *Academy of Management Review* 19 (2): 195-229.
- Klein, Saul, Gary L. Frazier, and Victor J. Roth (1990). "A Transaction Cost Analysis Model of Channel Integration in International Markets." *Journal of Marketing Research* 27 (2): 196-208.
- Kogut, Bruce (1988). "Joint Ventures: Theoretical and Empirical Perspectives." *Strategic Management Journal* 9: 25-37.
- Kohli, Ajay K., and Bernard J. Jaworski (1990). "Market Orientation: The Construct, Research Propositions, and Managerial Implications." *Journal of Marketing* 54 (2): 1-18.
- Kumar, Nirmalya, Louis W. Stern, and Ravi S. Achrol (1992). "Assessing Reseller Performance From the Perspective of the Supplier." *Journal of Marketing Research* 29 (2): 238-253.
- Kumar, Nirmalya, Louis W. Stern, and James C. Anderson (1993). "Conducting Interorganizational Research Using Key Informants." *Academy of Management Journal* 36 (6): 1633-1651.
- Larsson, Rikard, Lars Bengtsson, Kristina Henriksson, and Judith Sparks (1998). "The Interorganizational Learning Dilemma: Collective Knowledge Development in Strategic Alliances." *Organizational Science* 9 (3): 285-305.
- Lawrence, Paul R., and Jay W. Lorsch (1967). *Organization and Environment: Managing Differentiation and Integration*. Boston, MA: Graduate School of Business Administration, Harvard University.
- Lee, S., J. F. Jr. Courtney, and R. M. O'Keefe (1992). "A System for Organizational Learning Using Cognitive Maps." *Omega International Journal of Management Science* 20 (1): 23-36.
- Levitt, Barbara, and James G. March (1988). "Organizational Learning." *Annual Review of Sociology* 14: 319-340.
- Levitt, Theodore (1983). "The Globalization of Markets." *Harvard Business Review* 61 (3): 92-102.
- Li, Fuzhong, and Peter Harmer (1998). Modeling Interaction Effects: A Two-Stage Least Squares Example. *Interaction and Nonlinear Effects in Structural Equation Modeling*. R. E. Schumacker and G. A. Marcoulides. Mahwah, NJ: Lawrence Earlbaum Associates, Publishers: 125-151.

Lukas, Bryan A., G. Tomas M. Hult, and O. C. Ferrell (1996). "A Theoretical Perspective of the Antecedents and Consequences of Organizational Learning in Marketing Channels." *Journal of Business Research* 36 (3): 233-244.

Lyles, Marjorie A. (1988). "Learning Among Joint Venture Sophisticated Firms." *MIR Special Issue* (Special Issue): 85-97.

MacNeil, Ian R. (1980). *The New Social Contract: An Inquiry into Modern Contractual Relations*. London, UK: Yale University Press.

Mahoney, Joseph T. (1995). "The Management of Resources and the Resource of Management." *Journal of Business Research* 33: 91-101.

March, James G. (1991). "Exploration and Exploitation in Organizational Learning." *Organizational Science* 2 (1): 71-87.

Marsh, Herbert W., and Kit-Tai Hau (1996). "Assessing Goodness of Fit: Is Parsimony Always Desirable?" *The Journal of Experimental Education* 64 (4): 364-390.

Marsh, Herbert W., and Dennis Hocevar (1988). "A New, More Powerful Approach to Multitrait-Multimethod Analysis: Application of Second-Order Confirmatory Factor Analysis." *Journal of Applied Psychology* 73 (1): 107-117.

Martinez, Richard J. (1999). "Efficiency Motives and Normative Forces: Combining Transaction Cost and Institutional Logic." *Journal of Management* 25 (1): 75-96.

McGrath, Joseph E., Joanne Martin, and Richard A. Kulka (1982). *Judgment Calls in Research*. Beverly Hills, CA: Sage.

McKee, Daryl (1992). "An Organizational Learning Approach to Product Innovation." *Journal of Product Innovation Management* 9 (3): 232-245.

McQuarrie, Edward F. (1993). *Customer Visits: Building a Better Customer Focus*. London, UK: Sage Publications.

Meehl, Paul E. (1990). "Appraising and Amending Theories: The Strategy of Lakatosian Defense and Two Principles That Warrant It." *Psychological Enquiry* 1 (2): 108-141.

Metcalf, Lynn E., Carl R. Frear, and R. Krishnan (1990). "Buyer-Seller Relationships: An Application of the IMP Interaction Model." *European Journal of Marketing* 26 (2): 27-46.

Meyer, Alan D., Geoffrey R. Brooks, and James B. Goes (1990). "Environmental Jolts and Industry Revolutions: Organizational Responses to Discontinuous Change." *Strategic Management Journal* 11: 93-110.

Moorman, Christine (1995). "Organizational Market Information Processes: Cultural Antecedents and New Product Outcomes." *Journal of Marketing Research* 32 (3): 318-335.

Moorman, Christine, Rohit Deshpandé, and Gerald Zaltman (1993). "Factors Affecting Trust in Market Research Relationships." *Journal of Marketing* 57 (1): 81-101.

Moorman, Christine, and Anne S. Miner (1997). "The Impact of Organizational Memory on New Product Performance and Creativity." *Journal of Marketing Research* 34 (1): 91-106.

Morgan, Robert M., and Shelby D. Hunt (1994). "The Commitment-Trust Theory of Relationship Marketing." *Journal of Marketing* 58 (3): 20-38.

Narver, John C., and Stanley F. Slater (1990). "The Effect of Market Orientation on Business Profitability." *Journal of Marketing* 54 (4): 20-35.

Newbold, Paul (1994). *Statistics for Business and Economics*. Englewood Cliffs, NJ: Prentice-Hall.

Nonaka, Ikujiro (1991). "The Knowledge-Creating Company." *Harvard Business Review* 69 (6): 96-104.

Noordewier, Thomas G., George John, and John R. Nevin (1990). "Performance Outcomes of Purchasing Arrangements in Industrial Buyer-Vendor Relationships." *Journal of Marketing* 54 (4): 80-93.

Nooteboom, Bart, Hans Berger, and Niels Noorderhaven, G. (1997). "Effects of Trust and Governance on Relational Risk." *The Academy of Management Journal* 40 (2): 308-338.

Nunnally, Jum C. (1978). *Psychometric Theory: Second Edition*. New York, NY: McGraw-Hill.

Ohmae, Kenichi (1989). "Managing in a Borderless World." *Harvard Business Review* 67 (3): 152-161.

Oliver, Christine (1990). "Determinants of Interorganizational Relationships: Integration and Future Directions." *Academy of Management Review* 15 (2): 241-265.

Olsson, Ulf Henning (1979). "Maximum Likelihood estimation of the Polychoric Correlation Coefficient." *Psychometrika* 44: 443-459.

Olsson, Ulf Henning, Tron Foss, Sigurd V. Troye, and Roy D. Howell (2000). "The Performance of ML, GLS, and WLS Estimation in Structural Equation Modeling Under Conditions of Misspecification and Nonnormality." *Structural Equation Modeling* 7 (4): 557-595.

Olsson, Ulf Henning, Sigurd Troye, Villads, and Roy D. Howell (1997). Theoretical Fit versus Empirical Fit: A Simulation Study of the Performance of Maximum Likelihood and Generalized Least Squares Estimation in Structural Equation Models. Oslo: The Norwegian School of Management - BI.

Ouchi, William G. (1979). "A Conceptual Framework for the Design of Organizational Control Mechanisms." *Management Science* 25 (9): 833-848.

Patchen, Martin (1961). "Alternative Questionnaire Approaches to the Measurement of Influence in Organizations." *American Journal of Sociology* (1): 33-46.

Peter, J. Paul (1981). "Construct Validity: A Review of Basic Issues and Marketing Practices." *Journal of Marketing Research* 18: 133-145.

Phillips, Lynn W. (1981). "Assessing Measurement Error in Key Informant Reports: A Methodological Note on Organizational Analysis in Marketing." *Journal of Marketing Research* 18 (4): 395-415.

Pine, B. Joseph II, Don Peppers, and Martha Rogers (1995). "Do You Want to Keep Your Customers Forever?" *Harvard Business Review* 73 (2): 103-114.

Porter, Michael E. (1985). *Competitive Advantage: Creating and Sustaining Superior Performance*. New York, NY: The Free Press.

Powell, Walter W., Kenneth W. Koput, and Laurel Smith-Doerr (1996). "Interorganizational Collaboration and the Locus of Innovation: Networks of Learning in Biotechnology." *Administrative Science Quarterly* 41 (1): 116-145.

Prahalad, C. K., and Gary Hamel (1990). "The Core Competence of the Corporation." *Harvard Business Review* 68 (3): 79-91.

Quinn, James Brian, Philip Anderson, and Sydney Finkelstein (1996). "Managing Professional Intellect: Making the Most of the Best." *Harvard Business Review* 74 (2): 71-80.

Rigdon, Edward E., Randall E. Schumacker, and Werner Wothke (1998). A Comparative Review of Interaction and Nonlinear Modeling. *Interaction and*

Nonlinear Effects in Structural Equation Modeling. R. E. Schumacker and G. A. Marcoulides. Mahwah, NJ: Lawrence Erlbaum Associates, Publishers: 1-16.

Rindfleisch, Aric, and Jan B. Heide (1997). "Transaction Cost Analysis: Past, Present, and Future Applications." *Journal of Marketing* 61 (4): 30-54.

Ring, Peter Smith, and Andrew H. Van De Ven (1992). "Structuring Cooperative Relationships Between Organizations." *Strategic Management Journal* 13 (7): 483-498.

Ring, Peter Smith, and Andrew H. Van De Ven (1994). "Developmental Processes of Cooperative Interorganizational Relationships." *Academy of Management Review* 19 (1): 90-118.

Rokeach, Milton (1973). *The Nature of Human Values*. New York, NY: Free Press.

Rousseau, Denise M., Sim B. Sitkin, Ronald S. Burt, and Colin Camerer (1998). "Not So Different After All: A Cross-Discipline View of Trust." *Academy of Management Review* 23 (3): 393-404.

Schumacker, Randall E., and Richard G. Lomax (1996). *A Beginner's Guide to Structural Equation Modeling*. Mahwah, NJ: Lawrence Erlbaum Associates.

Seidler, John (1974). "On Using Informants: A Technique for Collecting Quantitative Data and Controlling Measurement Error in Organizational Analysis." *American Sociological Review* 39: 816-831.

Selnes, Fred (1998). "Antecedents and Consequences of Trust and Satisfaction in Buyer-Seller Relationships." *European Journal of Marketing* 32 (3/4): 305-322.

Selnes, Fred, and James Sallis (1999). "Relationship Learning with Key Customers." *Marketing Science Institute Working Paper Series Report #99-103*: 1-28.

Senge, Peter M. (1990). *The Fifth Discipline: The Art and Practice of The Learning Organization*. London, UK: Century Business.

Sharma, Subhash, Richard M. Durand, and Oded Gur-Arie (1981). "Identification and Analysis of Moderator Variables." *Journal of Marketing Research* 18 (3): 291-300.

Sheth, Jagdish N., and Atul Parvatiyar (1992). "Towards a Theory of Business Alliance Formation." *Scandinavian International Business* 1 (3): 71-87.

Sheth, Jagdish N., and Atul Parvatiyar (1995). "The Evolution of Relationship Marketing." *International Business Review* 4 (4): 397-418.

- Sheth, Jagdish N., and Atul Parvatiyar, Eds. (2000). *Handbook of Relationship Marketing*. London, UK: Sage.
- Shrivastava, Paul (1983). "A Typology of Organizational Learning Systems." *Journal of Management Studies* 20 (1): 7-28.
- Singh, Jagdip (1991). "Redundancy in Constructs: Problem, Assessment, and an Illustrative Example." *Journal of Business Research* 22: 255-280.
- Sinkula, James M. (1994). "Market Information Processing and Organizational Learning." *Journal of Marketing* 58 (1): 35-45.
- Slater, Stanley F., and John C. Narver (1994). "Market Orientation Isn't Enough: Build a Learning Organization." *Marketing Science Institute* 94-103: 1-30.
- Slater, Stanley F., and John C. Narver (1995). "Market Orientation and the Learning Organization." *Journal of Marketing* 59 (3): 63-74.
- Slater, Stanley F., and John C. Narver (1996). "Competitive Strategy in the Market-Focused Business." *Journal of Market Focused Management* 1: 159-174.
- Spence, Mark T., and Merrie Brucks (1997). "The Moderating Effects of Problem Characteristics on Experts' and Novices' Judgments." *Journal of Marketing Research* 34 (2): 233-247.
- Starbuck, William H. (1992). "Learning by Knowledge-Intensive Firms." *Journal of Management Studies* 29 (6): 713-740.
- Stata, Ray (1989). "Organizational Learning: The Key to Management Innovation." *Sloan Management Review* (spring): 63-74.
- Strauss, Anselm, and Juliet Corbin (1990). *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*. London, UK: Sage.
- Studenmund, A. H. (1997). *Using Econometrics: A Practical Guide*. New York, NY: Addison-Wesley.
- Sykes, J. B., Ed. (1978). *The Pocket Oxford Dictionary*. Oxford, England: Oxford University Press.
- Thorelli, Hans B. (1986). "Networks: Between Markets and Hierarchies." *Strategic Management Journal* 7: 37-51.
- Van de Ven, Andrew H. (1976). "On the Nature, Formation, and Maintenance of Relations Among Organizations." *Academy of Management Review* 1: 24-36.

- Volberda, Henk W. (1996). "Toward the Flexible Form: How to Remain Vital in Hypercompetitive Environments." *Organization Science* 7 (4): 359-374.
- von Krogh, Georg, and Johan Roos, Eds. (1996). *Managing Knowledge: Perspectives on Cooperation and Competition*. London, UK: Sage.
- Walsh, James P. (1995). "Managerial and Organizational Cognition: Notes from a Trip Down Memory Lane." *Organizational Science* 6 (3): 280-321.
- Walsh, James P., and Gerardo Rivera Ungson (1991). "Organizational Memory." *Academy of Management Review* 16 (1): 57-91.
- Wathne, Kenneth, Harald Biong, and Jan B. Heide (2001). "Choice of Supplier in Imbedded Markets: Relationship and Marketing Program Effects." *Journal of Marketing* 65 (2): 54-66.
- Wathne, Kenneth, Johan Roos, and Georg von Krogh (1996). Towards a Theory of Knowledge Transfer in a Cooperative Context. *Managing Knowledge: Perspectives on Cooperation and Competition*. J. Roos and G. von Krogh. London, UK: Sage: 55-81.
- Weick, Karl E. (1965). Laboratory Experimentation with Organizations. *Handbook of Organizations*. J. G. March. Chicago, IL: Rand McNally: 194-260.
- Williamson, Oliver (1975). *Markets and Hierarchies: Analysis and Antitrust Implications*. New York, NY: The Free Press.
- Williamson, Oliver E. (1981). "The Economics of Organization: The Transaction Cost Approach." *American Journal of Sociology* 87 (3): 548-577.
- Woodward, Joan (1965). *Industrial Organization: Theory and Practice*. London, UK: Oxford University Press.
- Zaheer, Akbar, Bill McEvily, and Vincenzo Perrone (1998). "Does Trust Matter? Exploring the Effects of Interorganizational and Interpersonal Trust on Performance." *Organizational Science* 9 (2): 141-159.
- Zaltman, Gerald, Karen LeMasters, and Michael Heffring (1982). *Theory Construction in Marketing: Some Thoughts on Thinking*. New York, NY: John Wiley and Sons.
- Zaltman, Gerald, Christian R. A. Pinson, and Reinhard Angelmar (1973). *Metatheory and Consumer Research*. Hinsdale, IL: Dryden Press.
- Zander, Udo, and Bruce Kogut (1995). "Knowledge and the Speed of Transfer and Imitation of Organizational Capabilities: An Empirical Test." *Organization Science* 6: 76-92.