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Essays on Retail Store Delivery System Design Strategies

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ESSAYS ON RETAIL STORE DELIVERY SYSTEM DESIGN STRATEGIES

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ABSTRACT

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Thesis directed by Professors Lawrence D. Fredendall and Aleda V. Roth

This research develops and empirically tests multiple theory-based models of retail store design strategies. Specifically, we examine the impact that different 'bricks and mortar' (store channel) service delivery system design strategies have on merchandise retailer effectiveness; which we measure in terms of satisfaction, operating, and financial performance. We draw our theory from a multidisciplinary literature base in the areas of organizational design, service marketing and operations strategy, retail management, and analyses of capital markets. The aim is to provide insights for advancing service operations research and to offer retail store managers and designers a method to weigh the tradeoffs associated with specific store design choices. In particular, retailers can test the effectiveness of their store design strategies using these performance models.

Towards this end, three essays are developed to address gaps in the extant service operations and marketing literatures with respect to the evaluation of retail store design strategies that focus on customer service encounters and environmental changes. We use a combination of empirical methods, including survey and dynamic panel data analysis techniques, to address the several important issues. First, we conduct a field survey of 175 store managers in the Southeast U.S. to develop and empirically validate multi-item measures of important retail store design factors that can be used by retail store managers to monitor the alignment of the service concept intent to actual store operating design strategies. In the second essay, we construct a retail store design strategy model to show the structural links among store operating complexity factors, customer information requirements, store encounter design choices, and customer satisfaction. We find that the store's perception of customer service encounter information requirements is the primary motivator of customer encounter store design choice - particularly how much stores will use design for customer self-selection or will give task empowerment to front-line store employees. We establish an important link between high customer information requirements and the need to use more front-line employee empowerment to enhance both employee and customer satisfaction. Finally, the third essay applies panel data collected from retail company 10-K reports and the Compustat financial database, to examine retailer store system design responses to product line margin shifts over time. We operationalize measures of store system 'design responsiveness' to evaluate retail firm design performance. Using econometric modeling and dynamic panel analysis techniques, we find that aligning store capital with product margin shifts over time is critical to grow firm profits. Moreover, we find that not aligning store labor requirements with product margins tends to quickly diminish retail firm performance. While the financial benefits of being design responsive are seen only in the short-term, there may also be positive carryover effects of being responsive on forward customer satisfaction scores. Collectively, these essays argue for the importance of aligning store design strategy decisions with retail-specific operational complexity factors to promote the long-term sustainability and survival of retail service firms.

DEDICATION

To Megan and Scott.

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There are literally dozens of people who have made major contributions to both the development of my academic scholarship and as a person. In thinking about the road just travelled, I cannot help but think that earning a Ph.D. is as much (if not more) about strength of will and character as it is strength in scholarship. In both important areas, I have been blessed to receive the support of a number or individuals and organizations. A lot of what is good about this dissertation can be attributed to these individuals, while its shortcomings are entirely my own.

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CHAPTER 1

Introduction

"No business can succeed in any great degree without being properly organized"
-James Cash Penney

1.1 Practical and Theoretical Background

This dissertation research focuses on how 'brick and mortar' store retailers can strategically organize and deploy store service delivery systems to manage the information and customer contact requirements of service encounters, while still maintaining or expanding profits. Retailing is "the business of providing goods and services to customers for their personal or household use" (Ghosh, p.51). Retail service delivery system design strategy is the specification of the roles of people (e.g., service workers), technology, physical facilities, equipment, and the specific process by which a retail service is created and delivered (Chase and Bowen, 1991; Goldstein et al., 2002; Roth and Jackson 1995; Huete and Roth, 1988). From the production operations management perspective, retail service design strategy transforms incomplete customer raw material (i.e., incomplete information, products, skills) into useful value propositions for customers (Sampson and Froehle, 2006) whether that be in stores or through web-based channels.

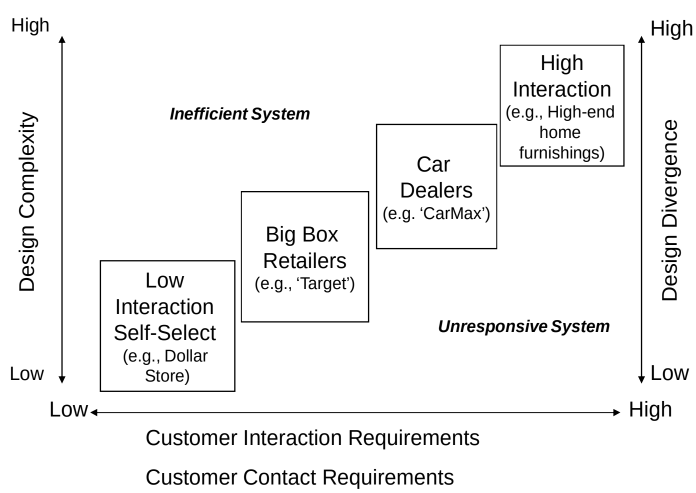
Product-selling retail store services are value-added when they perform a useful activity for customers making a product-selection decision. Services are generally defined as "time-perishable, intangible experience(s) performed for the customer acting in the role of co-producer" (Fitzsimmons and Fitzsimmons, 2003, p.5). Value-added services, on the other hand, are those "services that make the customer's life easier…(involving) information, problem-solving, sales and/or field support" (Chase, Jacobs, and Aquilano, 2004, pp.10-11). Retail store design strategies will be useful to customers to the degree that they satisfy either informational (problem-solving) and/or experiential needs regarding product-selection decisions. While information and problem-solving needs for both retailers and customers are the primary focus of this dissertation research, we acknowledge that service delivery system design choices may have significant positive or negative effects on consumer's emotions (Voss, Roth, and Chase, 2008). Nevertheless, as more customers migrate to web-based channels for product-selection, it is clear that service designs in our modern society are often judged by their customer problem-solving capabilities (Siehl, Bowen, and Pearson, 1992).

Academics, retail investment analysts and practitioners have had particular difficulty linking specific store operating design strategies with the market and operating performance of product-selling retail service firms (Gage, *Forbes*, 2007). The service operations academic literature also suggests that service organizations, retailers included, generally do a poor job connecting their service delivery concept (what they intend the system to do) to their production system design choices that create value for customers (Goldstein et al., 2002; Roth and Menor, 2003). As such, service operations literature suggests that services should build and deploy organizational resources to meet the customer-driven requirements of the operating system. Voss et al. (2008), for example, argue that a service firm's deliberate design choices communicate the design and role of the physical settings the management and organization of people (service workers) to deliver upon the service concept and experience. Furthermore, service architecture - made up of infrastructural (e.g. job task design), structural (physical capital elements), and integrative (coordinative) resources - must be continuously aligned with customer contact requirements for effective service co-production to occur (Roth and Jackson 1995; Roth and Menor, 2003). However, to date there has been little empirical testing of the effectiveness or motivations for different design architectures, particularly for product-selling store retailers in dynamic environments.

1.2 Contributions of Service Marketing and Operations Design Research

Service marketing and operations strategy research both support a retail store design positioning framework like the one depicted in Figure 1.1, in which retail stores must manage design strategy tradeoffs, at least to some degree. Service marketing research has argued that design strategy positioning has two main content elements (vertical axis): 1) factors or decisions that create design complexity, or the predefined products, steps, and sequences that constitute a service production process (Shostack, 1984, 1987), and 2) factors or decisions that create divergence, defined as the degree of freedom allowed to servers or inherent in a process step (Shostack, 1984, 1987). The marketing literature has examined service production systems design through this lens by constructing service blueprints (e.g., Patricio, Fisk, and Falcao e Cunha, 2008) or describing the appropriate servicescape environments for service encounter interactions to occur (e.g., Bitner, 1992). Nevertheless, the degree to which retailers effectively align these different production elements into a comprehensive operating system strategy for managing service encounters poorly understood (Menor, Roth, and Mason, 2001). Presumably, if retailers have more design complexity and divergence in their store systems than is necessary, then those systems will be inefficient and the cost of providing the service will be too high. On the other hand, if retailers operate with less design complexity when more interaction (or customer contact) is required (Chase, 1978), then they risk having a delivery system that is unresponsive to heterogeneous customer demands. Despite the fact that store retailing is such a highly competitive and dynamic landscape (Fisher and Raman, 2001; Ghosh, 1990), surprisingly little empirically validated measurement or research examines how design complexity or design divergence should be managed in actual retail store systems.

Figure 1.1: Retail Store Design Strategy Tradeoff Framework



Service management research guided by organizational information processing theory (OIPT: Galbraith, 1973, 1974) provides some insight into the interaction and customer contact links between design complexity (Figure 1.1, horizontal axis) and the divergence allowed for servers in store operating systems. Service design complexity and variation determine the service encounter information requirements of customer co-producers (Siehl et al., 1992). In service organizations, customers provide the raw material for service co-production to occur (Xue and Field, 2008; Sampson and Froehle, 2006; Buzacott, 2000; Siehl et al., 1992). Store designs must also anticipate the customer's information requirements and create a systems of servers to respond to unanticipated events (e.g., provide for task divergence). The retail store design serves as a mechanism to integrate incomplete information needs required by customers and store employees to transform information-seeking into purchasing service activities (Seihl et al., 1992); and this process may either enhance or diminish the service encounter experience (Cho and Menor, 2007; Bitner et al., 1997).

Service operations literature provides some empirical evidence that improving coordination and flexibility helps reduce service operational failures in complex task environments (Tucker, 2004), and that managing customer knowledge and information needs about the store's product and service offering mix is critical for effective retail store execution (Fisher, Krishnan, and Netessine, 2006). Store manager incentives can have a direct and significant effect on store profits, particularly if store managers are aware of what the right profit drivers are for the system (DeHoratius and Raman, 2007). While retail store designers might wish for customers to conform to a prescribed set of process tasks, customers shop stores primarily to gather their own unique product information, and to experience products first hand (Browne, Durrett, and Wetherbe, 2004). Service research examining design strategy choices is also relatively scant when compared to manufacturing production design strategies (Menor et al., 2001). Moreover, the important links between customer encounter interaction (contact) needs, specific organizational design solutions and tradeoffs, and the delivery system architecture responses of retail firms has not been the subject of much empirical work.

1.3 Gaps in the Service Design Strategy Literature

In an effort to build towards a comprehensive service design and positioning theory, the service operations strategy literature has presented a wide variety of general taxonomies, theoretical frameworks, and classifications to explain design structure tradeoffs. These have been based on customer requirements for human contact (e.g. Chase, 1981; Kellogg and Chase, 1995; Kellogg and Nie, 1995), labor-service customization profiles (e.g., Silvestro, Fitzgerald, Johnston, and Voss, C. 1992; Wemmerlov, 1990; Schmenner, 1986) or along a continuum similar to the Hayes-Wheelwright (1979) matrix for product goods manufacturing (e.g. Hayes, Pisano, Upton, and Wheelwright, 2005; Huete and Roth, 1988; Boyer, Hallowell, and Roth, 2002; Heim and Sinha, 2001, Buzacott, 2000). Still, advocates for a "service science," an interdisciplinary research focus that recognizes and promotes the inherent differences between services and forms of production using methods and approaches from many academic fields (Chesbrough and Spohrer, 2006; ifM and IBM, 2007), argue that more definitional rigor and academic understanding around services design and positioning is needed. This research hopes to initiate a new effort to help fill that gap.

Store operating complexity, the nature of customer interactions, and customer encounter design choices have been considered indirectly in service management theory (e.g., Sampson and Froehle (2006) discuss the importance of design strategy to manage variation from customer “raw material” or “incomplete” inputs). However, these strategic design-related constructs come from disparate service operations and marketing strategy research streams. Moreover, there is much inconsistency about the content and definitions surrounding service design strategy relationships and descriptions of service production systems. For example, service marketing research offers a “service logic model” which argues that service encounter enhancement comes from the simultaneous internal customer integration of the marketing, operations, and human resource functions of the firm (Kingman-Brundage, George, and Bowen, 1995). However, these service systems only become manageable to the firm (deployable) when the key strategic elements are specifically defined and designed. On the other hand, service operations management research has used the customer contact framework to empirically examine and define information richness, speed, and intimacy as key indicators of customer contact and interaction requirements (Kellogg and Chase, 1995). This research stream also suggests that technology capital can substitute and mediate for direct physical contact in many cases (Froehle and Roth, 2004). Service marketing literature is also highly focused on the importance of managing service encounters, which it defines as the simultaneous interaction of the customer, contact personnel, product/service offering, and the service system structure (Lovelock and Gummesson, 2004). The marketing-driven design strategy discussion has been fuelled by a transition in service strategy thinking from a ‘goods-dominant logic’ to a ‘service-dominant logic’ (S-DL) as suggested by Vargo and Lusch (2004). According to S-DL, customers do not buy goods or services. Rather, they buy because of the value propositions that are of service to them. S-DL proposes that customers co-create value in any economic system, and that the ‘value-added’ in any specific activity or task is actualized in the customer usage process rather than in supplier value chain activities (Vargo and Lusch, 2004).

Service design strategy research from both marketing and operations management traditions offers few empirical models that deal directly with store operating design strategy decisions. Even under the umbrella of “services,” more tangible service offerings that have both a physical product and a service offering component will have different operating characteristics, customer service encounter requirements, value propositions, and transactional risk versus more “pure” services (Murray and Schlacter, 1990), where the service delivery itself is the sole product (e.g., a haircut at a barber shop). In store retailing, for example, goods and services always (or almost always) appear together. Therefore, a more complete view of the retail service co-production that incorporates both product offering and customer interaction elements of retail store design strategy is warranted.

While the nature of retail store design strategy relationships are not fully developed or defined in extant literature, service research has examined the role of customer encounter choices in improving overall firm financial performance. Customer encounter choices and channels, whether they are automated or delivered by face-to-face contact, directly affect firm profits and customer retention (Xue, Hitt, and Harker, 2007). However, getting retail customers to switch to more cost-efficient (self-service) channels is a key challenge, as doing so may affect perceptions of overall service quality if the customer perceives a gap between service delivery expectations and performance (Parasuraman, Zeithaml, and Berry, 1985), or does not feel that they have any personal "control" over the self-service encounter outcomes (Bateson, 1985). Similarly, store channel design problems hinder managerial execution if they are inconsistent with the store's inventory display and product selling strategy (Raman, DeHoratius, and Zeynep, 2001).

1.4 Dissertation Contributions

This research fills an important gap in service design strategy literature by focusing in on how store delivery system design choices are linked to the operating complexity and market conditions present in retail store operating environments. As such, it examines specifically WHAT salient factors and retail store delivery system architecture tradeoffs are needed to achieve strategic consistency across store operating complexity and dynamism, customer interaction needs, customer encounter choices, and operational performance (as measured by customer satisfaction and financial operating returns).

Furthermore, this research addresses two broad questions of interest to store retailers. First, Chapters 2 and 3 examine the operational links between the retail store operating complexity factors, customer information processing, and the delivery system design strategy decisions of U.S. retailers by asking: Do retail stores link customer service encounter information processing requirements to specific customer encounter strategies to manage information (such as design for self-selection and employee task empowerment strategies), and do these strategies improve or hinder overall delivery satisfaction? Chapter 4 examines the design responses of retailers to product line margin changes in dynamic retailing environments by asking: Should product-selling retailers manage the design of their store operating systems to be responsive to product line margin changes? By answering these important questions, this research provides insight, definitional rigor, empirical evidence and tools for academics, retail investors, and practitioners on how to align retail store design strategy decisions with the desired operational conditions, firm profits, and customer satisfaction.

To fill gaps in the extant retail design strategy literature, this study offers three essays to build toward a more comprehensive theory of retail store design strategies. To formulate a retail store design theory, it is first useful to relate a retail store's product and service offering strategy to its service production strategy by developing appropriate constructs and operational measures from an integration of organizational design and service strategy theory (Essay#1 – Chapter 2). Next, it is important to develop a better understanding how store design strategy works, by analyzing the ability of retailers to effectively link customer encounter strategies with service encounter informational uncertainty (Essay#2 – Chapter 3). Finally, it is important to view store system design strategies within the context of the larger retail landscape over a recent 13 year period

(1994-2006) by examining retail design responses to product line margin changes, and the impact that being design responsive has on firm financial operating performance and satisfaction (Essay#3 – Chapter 4). Each of the three essays in this dissertation is developed from literature reviews and practitioner interviews, and each gathers empirical evidence to address theoretical gaps in extant work.

In the first essay (Chapter 2), "*Information Processing Factors that form Retail Store Design Strategy: Construct Development and a Confirmatory Model*," we develop the key constructs of a retail store design theory. This essay presents a conceptual model – grounded in service strategy and organizational design theory - to examine the key elements of retail store design strategy, including the store operating complexity factors, customer service encounter information requirements, and the customer encounter choices of retailers. We applied a rigorous two-stage approach in developing the relevant constructs, defining them, and develop a survey instrument. We then conducted a field survey of 175 retail store managers in the Southeast U.S. and constructed a cross-sectional store design strategy database. From this database, using the measurement model of structural equation modeling (SEM), we empirically confirm the key operational measures pertaining to our organizational information processing framework of retail store design strategy.

In the second essay (Chapter 3), "*Linking Customer Information Requirements, Retail Store Design Strategies, and Satisfaction: A Structural Model Analysis,*" we tested a proposed retail store design strategy structural model. In this research, we accomplish two things. First, we find that customer service encounter information requirements are strongly associated with the customer encounter choices of retailers to manage customer information processing needs. Second, we find evidence that retail store managers perceive more satisfied customers and store employees when customer encounter strategies are in sync with customer service encounter information requirements. Research has examined the impact of channel design strategies and customer information processing using single case studies and web-based channels (e.g., Boyer, Hallowell, and Roth, 2002), but we examine design-strategy links across a wide spectrum of 'bricks and mortar' retail store service offerings. In doing so, we utilize SEM methods, as well as multiple regression techniques to better understand the motivations and nomological network of relationships that link a retail store's operating design strategies and customer service encounter information requirements to store employee and customer satisfaction.

The third essay (Chapter 4) "*Evaluating Store Design Responsiveness to Product Line Margin Changes: An Empirical Study of U.S. Public Retailers"* we build on the methodological work of Rumyantsev and Netessine (2005, 2007b) and utilize econometric modeling techniques to longitudinally examine store system design management and the operating performance of publicly-traded store retailers within a variety retail industry segments (see Gaur, Fisher, and Raman, 2005 as an example of industry sample selection). Controlling for segment, timing, macroeconomic, and other firm-specific variables in our model, we examine the operating "design responsiveness" of store systems to product line margin changes over a 13 year period. We derive relevant performance ratios based on publicly reported store square footage and employee headcount data, and control for the persistent effects of the profit-derived dependent variables. Retail strategy literature provides some limited evidence that retail firms have better managed inventories to become more cost-efficient since the mid 1990s (Gaur et al., 2005, Chen, Frank, and Wu, 2007). Some retail strategy research has further argued that there has been a "Wal-Martization" of the retail landscape which has manifested itself in retail store design strategy shifts (Boyd and Bresser, 2008) towards improving economies of scale through technology and supply chain investments (Fisher and Raman, 2001). What has been missing to complement this literature stream is an analysis of retailer operating strategy that considers how a retailer's ability to respond to dynamic product line margins with shifts to their store system design strategy affects profits. This research examines different econometric variables as proxies for different retail design strategy shifts, including the management of store system labor and capital intensity to discover how retailers should respond to product line margin changes. Finally, we examine the strategic drivers of retail performance, role of store system design strategy, and the effect retail product margin changes on operational performance by measuring accounting returns over time.

In Chapter 5, *Conclusions*, we discuss the collective findings and contributions of the three essays and offer insights to the role of service delivery design strategy as part of a larger retail operations systems thinking. In addition, we offer some ideas for future research.

CHAPTER 2

Information Processing Factors that form Retail Store Design Strategy:
Construct Development and a Confirmatory Model

2.1 Purpose of Chapter 2

This chapter develops, defines, and validates constructs and multi-item measures that can be used to evaluate 'bricks and mortar" retail store design strategy. In general, operations strategy literature has argued that the degree to which a company's operating functions are aligned with the market environment will significantly improve production system effectiveness and profit growth (Hill, 2000; Hill and Duke-Wooley, 1983; Hayes, Pisano, Upton, and Wheelwright, 2005; Hayes and Wheelwright, 1979). In the short-term, most retail organizations are successful at linking their corporate strategy to their service production design strategy. As time passes, any service production system tends to fall out of alignment (Hill, 2000) due to changes in product/service markets, mismanagement, or leadership turnover; e.g. what Hill and Duke-Wooley (1983) call 'focus regression' (p.116). Like other service organizations, store retailers can also suffer from mismatches between the service strategy and the service delivery system management, such that the service concept (or service intent) is not effectively linked to the actual store delivery system design strategy (Goldstein, Johnston, Duffy, and Rao, 2002; Roth and Menor, 2003). Retail store customers increasingly have multiple channel options for purchasing products (e.g. the web); however, due to their sales opportunities and costs, developing a better understanding of both the service and store design environment of brick-and-mortar retailers is critical to their continued survival and success.

Moreover, the underlying measurement, definitions, and theory of service design strategy is not well developed, and there is a need to leverage multidisciplinary theory, methods, and tools to construct new models and measurements of key design strategy content to help managers monitor the store delivery system and manage customer-behaviors (Patricio, Fisk, and Falcao e Cuna, 2008; ifM and IBM, 2007; DeHoratius and Raman, 2007; Fisher, Krishnan and Netessine, 2006; Menor and Roth, 2007). Therefore, one important contribution of this study is the development of salient retail design constructs using organizational information processing theory (Galbraith, 1973) as a theoretical lens. Organizational information processing theory (OIPT) would posit this: The appropriateness of a retail store organization's design structure is determined by the level of task uncertainty in its environment. This uncertainty may be due to internal tasks such as scheduling or may result from more complex interactions with customer co-producers due to product offering changes, etc. It is also important for researchers to understand how customer uncertainty affects service delivery process design strategy decision-making (Field, Ritzman, Safizadeh, and Downing, 2006). The implicit assumption of OIPT is that a firm would produce a decision hierarchy based on rules and controlled procedures if there were no task uncertainty. If uncertainty did occur within the organizational system, the decision to resolve it would be made at the appropriate level of authority. As task uncertainty increases, more decisions are required of members so that alternative structures with greater information processing capacity must be used, or the firm must create slack in terms of idle resources or extended lead times to execute the service plan (Galbraith, 1973; 1974).

Besides further developing the theory and content of service design strategy using a customer information processing perspective, a second major contribution of this study is the confirmation of new measures to evaluate these retail store design strategy constructs. Having reliable and valid measures of salient constructs is the primary foundation for theory-building and testing (Churchill 1979). We have adapted Menor and Roth's (2009; 2007) two-stage approach to ensure rigor in our multi-item measurement scale development process. The first stage employs an item-sorting method with independent samples to develop constructs and items tapping into them; and a pilot survey is then developed, tested and revised to provide additional content validity for the scales. We then constructed a field questionnaire to demonstrate that these content elements are related, but conceptually distinct, store design strategy factors. The resulting Stage 2 instrument and hypotheses was confirmed using the measurement model of structural equation modeling (Bollen 1989) in a field sample of 175 retail stores. The third contribution was the development of distinct measurement scales with sufficient reliability and validity to warrant their use in future research and in practice by retail store managers, who have to evaluate if specific store design choices are successful based on their customer's information processing requirements.

Retail managers would benefit from a comprehensive understanding about both the role of the customer in the in-store retail service process (Hefley and Murphy, 2008; ifM and IBM, 2007), and how to create and measure service design content that delivers customer-satisfying service encounters[1]. Retailers make strategic store encounter design choices that determine the level of interaction between customers and servers and the amount of information exchange required during this interaction. For example, a dollar store provides limited customer interactions, while a specialty electronics store (e.g., Best Buy), has sales staff who may initiate contact with the customer to obtain information about customer needs and may offer to help customers to select products, accessories, and related store services (Lal, Knoop, and Tarsis, 2006).

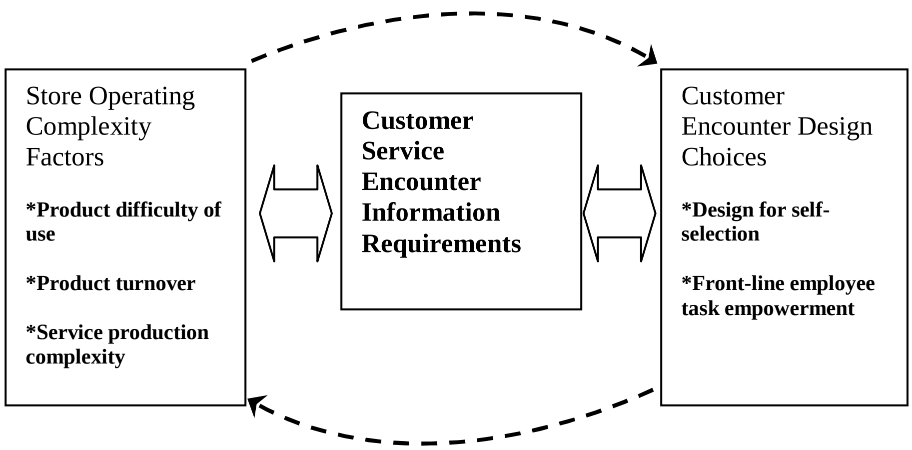
Retail customers co-produce the service by browsing and selecting items from store shelves as well as seeking information from store servers during the service encounter. This incomplete customer information is gathered and processed by servers in order to accomplish tasks just as in other organizational systems (Arrow, 1974; Siehl, Bowen, and Pearson, 1992, p.537). Since information gathering and processing is an essential component of the retail service and store design decisions regarding the roles of the servers, the amount of required customer contact, and the in-store service delivery process, influence the customer's perceptions of the service delivery experience (Chase and Bowen, 1991; Goldstein et al., 2002). For instance, the importance of providing adequate customer contact to service delivery strategy is well-established in the extant operations management literature. There are also many service taxonomies that classify service designs based on customer heterogeneity and contact requirements (Chase, 1978, 1981; Huete and Roth, 1988; Kellogg and Nie, 1995; Wemmerlov, 1990; Silvestro,

[1] A service encounter is generally defined as the moment of interaction (contact point) between server and customer in a service task setting (Roth and Menor, 2003, p. 148), these can occur as one-time events or over extended time periods with multiple servers.

Fitzgerald, Johnston, and Voss, 1992), and frameworks linking customization and production system capabilities (Schmenner, 1986; Hayes et. al, 2005; Boyer, Hallowell, and Roth, 2002; Heim and Sinha, 2001; Menor, Roth and Mason, 2001). While there are many such service framework, few are empirically tested in actual service settings. In addition these frameworks tend to ignore retail store service encounters – where there is simultaneous product offering mix and service process related task uncertainty. Exceptions are Buzacott (2000) and Huete and Roth (1988) who developed continuums similar to Hayes and Wheelwright's (1979) product-process matrix to classify service operating strategy tradeoffs according to their ability to manage different levels of customer variability and heterogeneity. Neither of the exceptions, however, directly specifies an association between operating complexity factors and customer information requirements in a retail store environment, nor consider how customers' may process the required information in the service encounter.

In the next section, we present a conceptual model (Figure 2.1) for examining retail store design strategies and discuss how to unify the related literature from both service marketing and operations management discussing the need for retailers to understand customer service encounter information processing. In section 2.3, we develop multi-item scales to measure each of the retail service design strategy model constructs, and we discuss the methodology and survey instrument development procedures used to develop a hypothesized measurement model. Finally, we examine the validity of the proposed retail design strategy measurement model, and offer opportunities for additional research.. The resulting instrument is a helpful tool for store design managers to evaluate and monitor the current alignment of their customer encounter design choices with the information requirements of the retail store operating system.

Figure 2.1: Retail Store Design Strategy Factors – A Conceptual Model



2.2 The Conceptual Model

In Figure 2.1, three salient constructs pertaining to retail store operating complexity factors - product difficulty of use, product turnover, and service production complexity - are given. These three constructs are shown to be associated with two strategic customer-encounter design choices for retail stores – design for customer self-selection and employee task empowerment. This association is posited to be mediated by the customer's service encounter information requirements. The dotted lines in Figure 2.1 represent the periodic adjustments to store operating complexity factors and customer encounter choices that need to occur over time (Hill, 2000). For example, product/service bundles may become less complex over time as product life cycles change, causing a misfit between the store operating complexity factors and the customer encounter design choices (Hill, 2000; Hayes and Wheelwright, 1979).

Both the services marketing and operations literature has generally examined the amount of complexity and divergence required to complete service tasks as two important levers to manage the operating system design strategy (Shostack, 1984; 1987, p.35; Skaggs and Huffman, 2003; Patricio et al., 2008). Recall from Chapter 1 that a service's design complexity is determined by the number of steps and interdependencies embedded in its process design strategy (Shostack, 1984; 1987; Skaggs and Huffman, 2003), while its design divergence is defined as the degree of freedom allowed (to servers) or inherent in a process step (Shostack 1984; 1987; Patricio et al., 2008). From a similar production perspective, Wemmerlov (1990) defines divergence along a continuum of standardized and customized process tasks, and creates a matrix to show conceptually how divergence and customer contact are linked. He argues that when physical goods, customers, and information are handled simultaneously in a service system, careful attention "must be paid to process design, investment in processing equipment, special labour skills, and (there is) often an added amount of risk" (p.33) to be managed. Furthermore, complex store designs must anticipate the relative need for these resources to manage customer task uncertainty and maintain the right alignment.

Customer prior knowledge of store products and processes is the key source of task uncertainty because store operating complexity factors (both product offering and store process factors) create the ripe conditions for customer-server uncertainty (which OIPT defines as a lack of mutual information). Store operating complexity factors form the raw material inputs that create uncertain tasks in typical service encounter transactions. OIPT logic (adapted to the retail context) can be used to map the appropriate customer encounter choices to resolve the service encounter uncertainty resulting from high degrees of product complexity (difficulty of use), product turnover, or the service production process itself. This uncertainty means that the store has incomplete information about what needs to be done, and how customer information should be processed during the service encounter, and what outcomes are expected (Larsson and Bowen, 1989, p. 216; Siehl et al., 1992, p. 537).

Thus, a retail store must be deliberate in developing operating design strategies that 1) link store operating complexity factors with uncertainty in customer purchasing knowledge, 2) reflect the impact that each complexity factor may have on customer information processing requirements in service encounters, and 3) determine what specific customer encounter choices are best used to manage the customer information requirements surrounding product-selection decision or task. If one or more of these elements is fixed, then other strategic design decisions must respond to that element. Table 2.1 links the construct definitions used in our conceptual model with the extant literature found on each subject. Each of these constructs is further developed and defined in the next section.

Table 2.1: Construct definitions and the related literature

Construct	Definition (adapted to retailing)	Related Studies
Store Operating Complexity Factors		
Product difficulty of use (DU)	The *difficulty (ease) of use* of the store's product offering and assortment for customers	Malone et al. 1987 Campbell 1988 Ghosh 1990 Safizadeh et al. 1996 Oppewal and Timmermans 1997 Gottfredson and Aspinall 2005 Ketokivi and Jokinen 2005
Product turnover (PT)	The speed at which the store's product offering depreciates, spoils, or becomes out of date.	Hayes and Wheelwright 1979 Huete and Roth 1988 Ghosh, 1990 Hayes et al. 2005 Chen and Watanabe 2007 Ketzenberg and Fergusen 2008
Service production complexity* (SC)	The level of coordination (number of steps and interdependence) required to produce the retail service	Argote 1982 Shostack 1984; 1987 Jones 1987 Valikangas and Lehtinen 1994 Buzacott 2000 Skaggs and Huffman 2003*
Service Context		
Customer service encounter information requirements (IR)	Degree to which customer requirements are unknown (to servers), requiring information or analysis to complete a service transaction	Mills 1986 Mills and Morris 1986 Mills and Turk 1986 Siehl et al. 1992 Kellogg and Chase 1995 Buzacott 2000 Johansson and Olhager 2002 Xue and Field 2008
Customer Encounter Design Choices		
Design for self-selection (SS)	Degree to which the store structure and layout supports a "do it yourself" service environment for customer product selection	Chase 1978 Bateson 1985 Huete and Roth 1988 Bitner 1992 Roth and Jackson 1995 Bitner et al. 1997 Xue et al. 2007
Front-line employee task empowerment* (TE)	Level of control (discretion) provided to front-line employees in the retail service delivery process	Kanter 1979; 1993 Bowen and Lawler 1992; 1995 Hayes 1994* Quinn and Spreitzer 1997 Honold 1997 Argyris 1998 Miller et al. 2000 Melhem 2004 Field et al. 2006

* Scale items and definition from prior research, adapted for the retail survey based on feedback from store managers in Stage 1 of the study.

2.2.1 Operating Complexity Factors in Retail Store Settings

The salient retail store operating complexity factors included in this study are the *product difficulty of use*, the *product turnover,* and the *service production complexity* (see Figure 1). In general, complex tasks cause organizational members (customers and servers) to feel uncertainty until new information resolves the ambiguity (Wood, 1986; Galbraith 1973; 1974) about a task. Each factor is separately discussed because of its distinct affect on store information processing and role in developing a comprehensive retail store design strategy.

Product Difficulty of Use

Product difficulty of use (DU) is operationally defined here as the difficulty that customers will have using the using the products that make up the store product offering (i.e. after the sale). Customers may perceive the stores' product mix as complex and difficult to use because of self-contained technology, features, or because products in the store are bundled with other complementary products or services (e.g. accessories, home delivery, or financing). Product difficulty of use is a significant source uncertainty for customers in retail store systems (IBM, 2005; Ghosh, 1990, pp.349-353), and the greater the range and number of products, features, and options offered, the less likely that customers will have knowledge of the product mix or be able to assess product quality (Boyer et al., 2002, p.179; Fitzsimmons and Fitzsimmons, 2001, pp.21-22; Oppewal and Timmermans, 1997) when they enter the store.

Take, for example, the plethora of big screen TV's that are currently among the core product offerings in retail consumer electronics stores. Big screen TVs are bundled with multiple complementary products and services such as home delivery and warranties. The consumer has some level of task uncertainty about which TV bundle to choose, and seeks information from store servers to resolve this uncertainty. From the customer's perspective, this bundling leads to purchase complexity since specific choice options cannot be eliminated quickly (Campbell, 1988, p.44). And this product difficulty of use requires more information exchange, description, and communication to complete tasks (Malone, Yates, and Benjamin, 1987; Ketokivi and Jokinen, 2005).

Product Turnover

The second store operating complexity factor is ***product turnover*** (PT). Product turnover is defined as the speed at which the store's product offering mix depreciates, spoils, or becomes out-of-date. Product turnover affects the store operating complexity in two important ways. First, highly perishable products create uncertainty about whether they will be consumed before they spoil or lose their value (e.g., groceries, fashion goods). Second, products with short life cycles may have short retail shelf lives so that customers do not become familiar with the product offering, and their existing product knowledge quickly becomes obsolete (Huete and Roth, 1988; Hayes, Pisano, Upton, and Wheelwright, 2005). Whether high product turnover is due to perishable products or to short product life cycles, it may lead to complexity for the retail store operator. Perishable/fashionable products add to the complexity for retail store processes and short product life cycles reduce customer product knowledge (Ghosh, 1990, p. 340). The need to obtain information to manage this type of complexity has been recognized in other operations contexts. For example, it is recognized that more perishable items require the need for information about customer demand (Chen and Watanabe, 2007) and product variety requires internal systems to manage layout and process changes (Ketzenberg and Fergusen, 2008).

Service Production Complexity

Service production complexity (SC) is defined as the "level of coordination .. (i.e. the number and interdependence of steps) .. required to produce the retail service" (Skaggs and Huffman, 2003, pp. 778-779). Our operational definition is grounded in Simon's (1962) conceptualization of complexity and is similar to other definitions widely discussed in the service management literature (Shostack, 1987; Argote, 1982; Jones, 1987). Complexity in retail stores can be understood by comparing a dollar store to a high-end jewelry store design. Dollar stores are intentionally designed so that each step in the service encounter has limited interdependence with other steps and limited interaction with store workers. As a result, the dollar store setting has low service production complexity, because generally the customer understands how the service will be delivered. On the other hand, a high-end jewelry store has multiple-steps embedded in the service offering, which are very interdependent; and in turn, create high service production complexity. A jewelry store customer may enter with a vaguely defined goal of selecting something suitable as a gift. During the service encounter, the server must identify an acceptable price range and define what is suitable for the customer. Even then, there is high interdependence between the steps involved in the selection. For example, the selection of an appropriate diamond may depend on the design of the setting, the diamond quality indicators, and the color of the gold. So, the server needs to elicit a high level of information to determine the customer's needs and to resolve the process interdependencies.

The two extreme examples of service production complexity have been referred to as transactional services and interdependent services (Goel, Jain, and Gupta, 2005). Transactional retail services have the lowest service production complexity, while interdependent retail services have the highest service production complexity. In general, the service strategy, operations, and marketing literature would conclude that the greater the number and interdependence of steps required to complete a service transaction, the higher the overall system interdependence and production complexity (Skaggs and Huffman, 2003, p.779; Argote, 1982; Jones, 1987). Operationally, service firms can create sub-tasks and assign them to multiple servers if inquiries are predictable (Buzacott, 2000). This task separation increases coordination costs and creates additional interdependencies within the organizational system (Galbraith, 1974; Larsson and Bowen, 1989; Premkumar, Ramamurthy, and Saunders, 2005).

2.2.2 Customer Service Encounter Information Requirements

Customer service encounter information requirements (IR) refers to the degree to which the customer requirements are unknown (to store servers), requiring information or analysis to complete a service transaction. While little customer information is required from store servers to complete simple transactions-based tasks, more complex tasks may be used to customize the service (Schmenner, 1986; Kellogg and Chase, 1995; Huete and Roth, 1988; Wemmerlov, 1990). In the later case, the server requires more information from the customer to diagnose individual customer needs (Buzacott, 2000, p. 17; Siehl et al., 1992). For example, a high-end clothing store will help the customer create a “look” or “style” that is customized to their desires. Or, as indicated earlier, servers in high-end jewelry stores use more server-customer interaction to obtain information to ascertain what the customer wants, and to provide any anticipated service recovery capability (Johansson and Olhager, 2002, Miller, Craighead, and Karwan, 2000).

The influence of store operating complexity on service strategy design is mediated by the customer service encounter information requirements (Mills, 1986). Thus, increasing operating complexity creates more task uncertainty, which causes a need for more service encounter information processing to occur. Accordingly, retailers can reduce uncertainty by narrowing product offering choices. Or they may choose to offer services (or products) that are new or unfamiliar to the market, highly specialized, or that have high turnover. Such actions may decrease both the potential variance of customer demands and the need for customers to obtain product information (Skaggs and Huffman, 2003; Valikangas and Lehtinen, 1994; Buzacott, 2000). In contrast, when customers need to make more decisions in the service encounter, the result is an increase in the variability of service times and in the amount of customer information required (Buzacott, 2000; Mills and Morris, 1986, p.733).

The greater the uncertainty in any organizational system, the higher the level of information processing required in that system (Galbraith, 1973; 1974). In retail services, we conceptualize the store operating complexity factors discussed above as the main sources of service encounter uncertainty. The appropriate structure for the retail store's design strategies then can be gauged based on customers' service encounter information requirements.

2.2.3 Customer Encounter Design Choices

The retail store customer encounter strategy is captured by two strategic design choices: 1) the level of employee task empowerment, which is a reasonable proxy for the store's information processing capacity of the service encounter and 2) the store's design for customer self-selection, which is a proxy for the level customer information processing. Researchers approach the relationship of customer service encounter information requirements and related design strategies differently. One school of thought assumes that complexity and divergence design specifications are made simultaneously as part of the initial service concept development (e.g. Shostack, 1984; 1987; Heskett, Sasser, and Schlesinger, 1997; Patricio et al., 2008). Accordingly, services can have simultaneous high complexity/low divergence design strategies at least at the point of an individual step or sequence (e.g. Shostack, 1987).

In contrast, a second school of thought contends that choices regarding customer encounter strategies cannot be made independently from the service encounter information requirements and uncertainty surrounding a task (e.g. Larsson and Bowen, 1989; Huete and Roth, 1988; Siehl et al., 1992). This group suggests that service providers should make design tradeoffs between the store complexity level and the divergence allowed in the operating system.

Design for Self-selection

Design for self-selection (SS) is defined as the degree to which the store structure layout and structure support a **"**do-it-yourself" service environment for customer product selection. Customer self-selection is made possible by creating sub-tasks, each of which are simple and require little information processing (Buzacott, 2000; Galbraith, 1973) and when customers have control over their own information needs (Bateson, 1985) for buying store merchandise. For example, a supermarket may have a clearly marked aisle for laundry detergents which simplifies the sub-task of locating the product. The shopper has all the related products in the same area, so the sub-task of comparing competing products is simplified. However, a high-end furniture store will have only sample models available, but will provide server assistance to determine, for example, what upholstery fabric will match the customer's current color scheme. In these 'low contact, self-select' retail stores, shoppers themselves select, pick, and transport products.

Effective design for self-selection strategies may communicate information to the store's customers by using non-labor resources (Chase, 1978, pp.141-142), such as signs, tags, or technology. Huete and Roth's (1988) describe a 'service industrialization' concept where "technology and systems are substituted for people" (p.47). Our construct is different because we focus on the degree to which the self-selection customer encounter strategy helps complete product-selection tasks in store retailing environments. Retail self-selection involves the transfer of a physical good bundle, which has its own attached delivery processes and information content. In self-selection design environments, customers actively participate by selecting from the product-service bundle without much help from human contact (Bitner, Faranda, Hubbert, and Zeithaml, 1997). As a result, this design choice achieves high cost per transaction efficiencies (Xue, Hitt, and Harker, 2007; Goel, Jain, and Gupta, 2005; Huete and Roth, 1988), as the need for in-store labor contact decreases. Therefore, self-selection is the "leanest" customer encounter design choice given the low complexity of the surrounding service environment (Bitner, 1992, p.59).

Retail stores are designed for self-selection to improve the speed and cost-efficiency of each service encounter transaction by reducing the time servers spend analyzing customer informational needs during the service encounter (Huete and Roth, 1988). Therefore, there is less need for employee knowledge and training in retail service environments with low complexity or low service customization (Schmenner, 1986; Wemmerlov, 1990; Kellogg and Nie, 1995).

Design for self-selection is always more cost-efficient than providing human contact channels (Bitner, 1992; Bitner et al. 1997; Chase 1978); however, many customers prefer self-selection only when they have feel they have appropriate product knowledge and perceive time and efficiency gains (Xue et al., 2007; Bateson, 1985). High-contact customer encounter strategies, on the other hand, will provide both the customer and store server with an increased capability to mutually share rich information during the service encounter (Kellogg and Chase, 1995, p.1736).

Employee Task Empowerment

Front-line server empowerment can increase the information processing capacity at the customer encounter. Front-line ***employee task empowerment*** (TE) is defined as the level of control (discretion) provided to front-line employees in the retail service delivery process. Job task adaptability provides the organizational members the ability to respond effectively to unanticipated events (Menor, Roth, and Mason, 2001; Field, et. al, 2006, Miller et al., 2000). Similarly, employee task empowerment systematically improves the service employees' abilities to handle operational uncertainty and provide responsiveness (Bowen and Lawler, 1992; 1995). Server task empowerment decreases hierarchies of authority (dependence) and increases information processing capacity (Galbraith, 1974; Premkumar et al., 2005), which is needed to respond to heterogeneous customer encounter inquiries. Generally, customer encounter inquiries will require more human-contact to meet customer expectations (Chase, 1978; Huete and Roth, 1988; Buzacott, 2000).

Employee task empowerment is needed not only to diagnose a customer's initial service needs, but also to respond quickly to resolve and reduce the severity of possible service failures (Miller et al., 2000; Bowen and Lawler, 1995; Tucker, 2004).

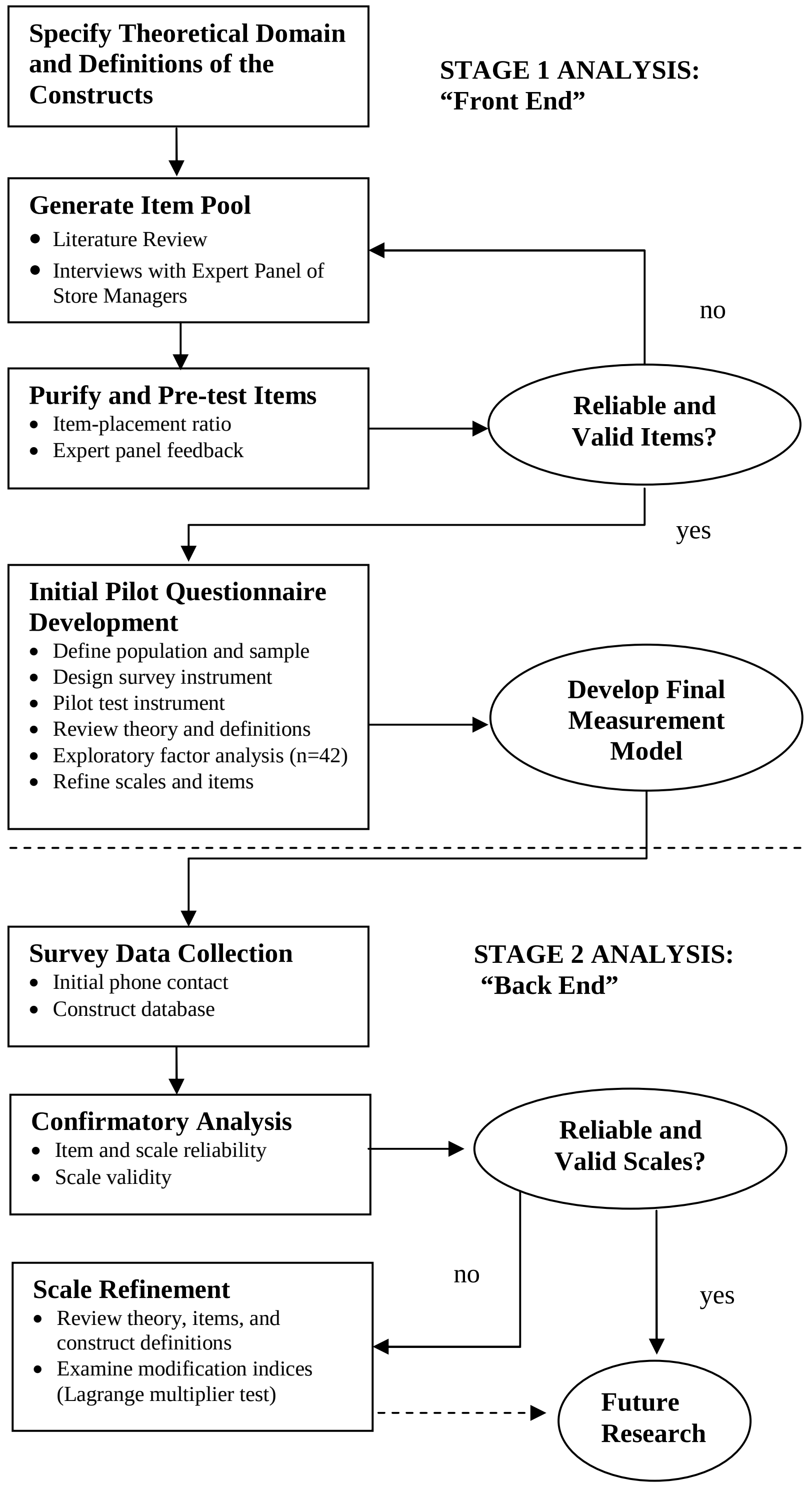
Empowered employees have the authority to investigate the customers' problems or analyze information in order to alter customer attitudes after a dissatisfying experience (Miller et al., 2000, p.388). When jobs are routine and rule-minded (standardized), as they may be in many retail store operating systems, front-line staff may feel powerless in their roles as defined by the organization. This results in front-line workers who are not able to handle any degree of task uncertainty in the store operating environment (Kanter, 1979; 1993), and may not be able to respond to a service failure. Nevertheless, survey findings show that over half of consumers are still "dissatisfied" even after the resolution of a service failure. Such dissatisfaction occurs because the incident is not handled in the appropriate amount of time or is handled incorrectly by those that do not have the information, authority, or ability to solve the problem (Zeithaml, Berry, and Parasuraman, 1990).

Structural power theory (Kanter, 1979) states that employee power is determined not by employee skills and knowledge, but by the defined job design position within the organization. However, open lines of information flow makes this granted power more productive (Kanter, 1979, p.65). Server task empowerment provides easy access to needed information for customers, and allows action on the customers' behalf so that task empowerment increases employee productivity (Kanter, 1979, p.65). As such, employee task empowerment is an important factor to allow for divergence (Shostack, 1987) in the store's customer encounter design strategy.

2.3 Multi-item Measurement and Scale Development

The measurement scale development was conducted by adapting the Menor and Roth (2009, 2007) two stage approach. An overview of our scale development and item selection process, as well as our methodological approach is given in Figure 2.2 and discussed in detail below.

Figure 2.2:
Application of Menor and Roth's Two-stage Approach for New Scale Development



Adapted from Menor and Roth, 2009, 2007; Roth, Schroeder, Huang, and Kristal, 2008

The unit of analysis for this study is the retail store, and the preferred respondent is the store manager, franchise owner, assistant manager, or store team leader, since they are closest to the actual design strategy execution and functions (Shim, Lusch, and Goldsberry, 2002).

2.3.1 Stage 1. Purification and Pre-testing of Measures

In Stage 1, items were developed for each construct described in Section 2 (See Appendix items – 7.1.1). Constructs and items tapping into them were originally constructed using literature reviews and in depth interviews with retail store managers, following an iterative process of scale pre-screening and purification. To "clean up" the "fuzzy front end" of this research (Menor and Roth, 2009 and Roth, Schroeder, Huang, and Kristal, 2008), we conducted rigorous pre-testing of the scales. Eight retail managers, with an average of nine years and a minimum of three years retailing experience, reviewed the preliminary items and scales for readability, face validity, and clarity. Their suggested changes were incorporated when deemed theoretically and practically appropriate.

Two scales in our conceptual model ("service production complexity" - Skaggs and Huffman, 2003, and "employee task empowerment" - Hayes, 1994) are culled from existing empirical literature and adapted to the retail design context. The remaining scales were newly developed for this study. The seven original items to measure the product difficulty of use (DU) construct are based primarily on feedback from the store manager interviews, as well as related literature. The six initial items used to measure product turnover (PT) are also based on interviews with store managers, since we could not locate an existing perceptual scale. The level of service production complexity (SC) was measured using Skaggs and Huffman's (2003) scale adapted to the retail operating context. Customer service encounter information requirements (IR) items were developed from store manager interviews and related studies by Buzacott (2000), Siehl et al, (1992), Mills and Morris (1986), and Mills and Turk (1986). The level of design for self-selection (SS) scale items utilize descriptions found in other studies of self-service consumers and service industrialization (Bateson, 1985; Huete and Roth, 1988; Bitner et. al, 1997). Finally, we used Hayes' (1994) eight-item employee empowerment questionnaire (EEQ) scale items, adapted to measure retail employee task empowerment (TE), using feedback from the store manager interviews. Hayes' eight item scale was used since because it has proven reliable in multiple service organization contexts (e.g. Melhem, 2003).

We initially pre-screened items and scales with 60 undergraduate students to establish face validity using an iterative item-to-construct placement process. For the final round of item-placements, a group of 26 evening MBA business students and five retail managers, each with experience or knowledge of retail service delivery systems, matched either 15 or 16 items respectively to one of the six construct definitions in Table 2.1. The "hits" or correct matching of the item to the construct definitions was used to measure the initial validity of the items (Moore and Benbasat, 1991). The item-placement ratio is the percentage of actual hits to the total number of potential hits. Scales that have high item-placement ratios are considered to have a high degree of construct validity and potentially high reliability scores. Any individual hit ratio below the 75% cutoff were dropped, modified, and/or retested as part of the item purification process. In the final round item-placements, depicted in Table 2.2, no construct hit ratio fell below the 75% cut-off value established in other scale development research (e.g., Moore and Benbasat, 1991, p.204; Stratman and Roth, 2002).

Table 2.2: Final Round Item Placement Ratios (Stage 1 – Initial Item Pool Development)

Theoretical Definition Classification	**Actual Construct Classification**							
	DU	PT	SC	IR	SS	TE	Total items	% Hits
Product Difficulty of Use (DU)	72	2	3	3	2	1	83	86.7%
Product Turnover (PT)	1	66	3		2		72	92.9%
Service Production Complexity (SC)	6	4	63	4	4		81	77.7%
Customer Service Encounter Information Requirements (IR)	1	5	3	64	6	6	85	75.3%
Design for Self Selection (SS)	1	3	3	4	72	2	85	84.7%
Front-line Employee Task Empowerment (TE)	1	2	2	3	1	77	86	89.5%
Total items	82	82	77	78	87	86	492	84.3%
	87.8%	80.5%	81.8%	83.1%	82.3%	89.5%		

2.3.2 Field Research

Having items with tentative reliability and validity, we developed and tested a pilot survey instrument to complete Stage 1. We then developed a hypothesized measurement model, and then conducted a full field study to confirm that model.

2.3.2-a Initial Pilot Testing of the Item Scales

Pilot testing was used to further calibrate and refine the newly developed scales (Anderson and Gerbing, 1991; Froehle and Roth, 2004). The items in Appendix 7.1.1 were used in an exploratory pilot study conducted in one region of South Carolina that contained two medium sized urban markets. A seven-point Likert scale with end points of "strongly agree" and "strongly disagree" was used for all responses.

A modified version of Dillman's (2000) total design method was followed to collect data from this pilot population. First, each store's retail manager was contacted by phone to get permission to mail the initial questionnaire. As shown in Table 2.3a, 296 store managers were contacted by phone in the pilot study. Phone numbers were obtained from the Local.com telephone directory database using the keyword "retail stores," and were validated with lists acquired from local Chambers of Commerce and Better Business Bureaus in these two market areas. Local.com is a geographic indexing database in which firm addresses, contact names, and phone information is recorded for individual strategic marketing areas (SMA). All the initial mailings included a cover letter, booklet, and a postage-paid return envelope. Ten days after the initial mailing, reminder postcards were sent to all potential respondents. We also personally visited 25 stores during the pilot study to hand-deliver questionnaires. The decision to do this was either based on the store manager's request, or because the listed location was convenient to visit from the survey administration site.

Table 2.3a-f: Demographic Details of Sample

Table 2.3a: Response Rate

	Pilot	Sample	
Original Phone Contacts	296	980	
Agreed to Receive Survey	114	522	
Returned Survey	46	182	
Usable	42	175	217
Usable response rate (from original)	*14.1%*	*17.8%*	
Usable response rate (from agreed)	*36.8%*	*33.5%*	

Table 2.3b: Store Sales

Total annual sales ($ millions)	Pilot	Sample
<1	11	24
1-5	27	110
5-10	3	14
10-20	1	12
20+	0	15
Total	42	175

Table 2.3c: Products Sold by Retailers

	Pilot	Sample	*Local.com Population*
% checking "yes" on products type sold[12]	n=42	n=175	*n=980*
Auto/Parts	8.8%	8%	*10%*
Furniture	17.5%	17.1%	*15.1%*
Electronics/Appliances	10.1%	12%	*9%*
Home Supply	6.9%	6.9%	*5%*
Food	22.1%	23.5%	*19.9%*
Health/Personal	15.7%	18.9%	*17.4%*
Gas/Convenience	8.8%	7.4%	*9.4%*
Clothing	24.4%	29.1%	*22.1%*
Sport/Book/Music	13.4%	14.8%	*12%*
General	30.9%	29.0%	*22%*

[1] Table does not sum to 100%, as retail managers could check "yes" to multiple product offerings
[2] Local.com/telephone directory classifications (for Population comparisons used primary classification listings)

Table 2.3d: Total number of store employees

Total store employees	Pilot	Sample
<10	33	88
10-15	6	30
15-20	1	10
20-25	0	8
25+	2	34
Missing	0	5
Total	42	175

Table 2.3e: Total years Manager worked at store

	Pilot	Sample
<2yrs	3	43
2-5yrs	10	51
5-10yrs	6	31
10-20yrs	9	26
20+yrs	13	24
Missing	1	0
Total	42	175

Table 2.3f: Total years worked as Manager at store

	Pilot	Sample
<1yr	2	32
1-2yrs	6	33
2-5yrs	11	31
5-10yrs	6	34
10+yrs	16	36
Missing	1	9
Total	42	175

Of those 296 store managers contacted by phone or in person during the pilot analysis, 114 agreed to receive the survey, and 42 usable responses were returned, for an overall response rate of 14% from the original sample and 37% from those that agreed (Table 2.3a). Component factor analysis with no rotation was used to initially pre-select items loading correctly on the intended constructs. Using component factor analysis in SPSS 13.0 with maximum likelihood extraction for each construct, we analyzed the non-rotated loadings of each item on its intended factor in the pilot sample, accepting all items with high correlations and no significant cross-loadings. Factor analysis with no rotation was used for item selection since the sample size of the first sample was too small (n=42) versus the number of items to use exploratory factor analysis with promax rotation (Fabrigar, Wegener, MacCallum, and Strahan 1999, p.294). The reduced number of items would still allow for adequate sampling for the six service design/information processing constructs of interest (Drolet and Morrison, 2001; Menor and Roth, 2007b, p.834), and further would eliminate the “noise” from poorly worded items that did not load well on the intended factor (Little, Lindenberger, and Nesselroade, 1999). This action was possible because the pilot sample has similar characteristics to the field sample (Noar, 2003, p.632), and the same target respondents and survey protocols were used for both the pilot and the final field samples. Items dropped during this stage are shown in Appendix 7.1.

Promax factor rotation was also used only to evaluate the loadings of two constructs in the pilot analysis - product difficulty of use (DU) and product turnover (PT). We examined the relevant items to determine if they loaded as separate factors or were part of a larger product offering complexity factor. They were found to be distinctly separate store operating complexity factors.

2.3.2-b Stage 2. Confirming the Hypothesized Factor Model

Our Stage 1 theory development and empirical work suggested that underlying constructs in our conceptual model were distinct factors related to retail store design strategy. Therefore, we posit that:

> **Chapter 2 - Hypotheses 1-6:** The items *1, … , n_i* reflecting the six intended constructs fit the data, where *i* represents distinct retail design strategy factors DU-TE (e.g., DU = product difficulty of use; PT = product turnover; SC = service production complexity; IR = customer service encounter information requirements; SS = design for self-selection; TE = employee task empowerment).

Using the guidance from the literature on latent variable modeling techniques described in Bollen (1989), Rosenzweig and Roth (2007, p.1319) and Froehle and Roth (2004, p.11), we developed a confirmatory measurement model to confirm our hypothesized model and initial research findings from both the theoretical and item-development process. The hypothesized measurement model represents the scales at the conclusion of Stage 1 in the instrument development cycle (Figure 2.2). This relationship can be further mathematically represented using both simplified (Equation 2.1) and matrix form (Equation 2.2) using standard modeling notation (format adapted from Froehle and Roth, 2004, p.11):

(Eq. 2.1) **Standard form:**

$$y = \Lambda_y \eta + \varepsilon$$

(Eq. 2.2) **Matrix form[2]:**

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{22} \\ y_{23} \end{bmatrix} = \begin{bmatrix} \lambda_1 & \lambda_2 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & \lambda_{22} & \lambda_{23} \end{bmatrix} \begin{bmatrix} \eta_{DU} \\ \eta_{PT} \\ \vdots \\ \eta_{SS} \\ \eta_{TE} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{22} \\ \varepsilon_{23} \end{bmatrix}$$

2.3.3 Stage 2. Field Study Data Collection

To examine if the hypothesized measurement model would hold up under empirical scrutiny, a retail store sample was selected from among multiple major urban centers in South Carolina and the surrounding states using the same Local.com telephone directory database as in the pilot study to contact store managers. We centered our sample around major market areas in the Southeast US because it allowed us acquire a more complete range of retail store types, as opposed to re-sampling the same dominant

[2] For clarity, many of the model latent constructs, item indicators, covariances, and error terms are not shown in the matrix (…).

retailers that would appear in multiple SMAs nationally (e.g. Wal-Mart). This database provided the phone numbers and addresses of 1,120 publicly traded and privately owned retail stores, excluding wholesalers and direct to consumer retailers. All stores would be classified as "retail trade distribution" by the North American Industry Classification System (NAICS). This grouping includes all public and private merchandise retail firms, including chain retailers such as Wal-Mart. Prior studies have indicated a general reluctance on the part of retail managers to participate in survey research or to provide data about sales, customers, or competitive position (Oppewal and Timmermans, 1997, p.43). In addition, prior survey work has shown that an adequate response rate from the store manager population is difficult to obtain (e.g., Shim et al., 2002). These issues were addressed in two ways in both the pilot and field sample questionnaires: 1) the cover letter and mail questionnaire emphasized the confidentiality and anonymity of the respondent, and 2) each store manager was personally contacted by phone using a pre-approved script to acquire their permission to mail the questionnaire and to obtain their preferred mailing address.

The same data collection protocol was used for this sample as in the pilot study. The phone calls verified the accurate contact information for 980 retail stores from the initial list and of these 980 contacts, 522 store managers allowed the survey to be mailed to them. From these 522 store managers, we received 175 returned surveys (34% response rate from agreed, or 17.8% overall response rate). Repeated store offerings (e.g. two or more store chain types) constituted less than 10% of the overall field sample; and no single store brand appeared more than three times in the sample[3]. The complete store demographics for both the pilot study analysis and the field sample survey are given in Tables 2.3a – f. While the pilot sample had a larger percentage of smaller stores in terms of sales (probably because of SMA size differences between pilot and field samples), it was determined that the two samples (pilot and field) were a similar mix of product offerings, store types, and respondent profiles. The cross-sectional sample included a large range of retailers in terms of annual sales (Table 2.3b), product offering (Table 2.3c), number of employers (Table 2.3d), retailing experience (Table 2.3e), and management experience (Table 2.3f).

Non-response bias (e.g. the potential that the sampling frame is somehow not representative of the population (Churchill, 1979)), was addressed in two ways. First, we examined the descriptive data (e.g., Sales, Store type, Manager tenure) of late respondent survey results versus early respondents and found no significant differences ($p<.05$) in the two data sets (early vs. late) across these measures (Armstrong and Overton, 1977). Additionally, we compared 'store type' frequencies from our sample to a random sample of our original Local.com database contact list and found no statistical differences between the two samples.

Self-report bias or common method variance (CMV) could contaminate the data (Podsakoff and Organ, 1986, Froehle and Roth, 2004, p.11) since one individual responded to multiple measurement scales and may not have distinguished between the

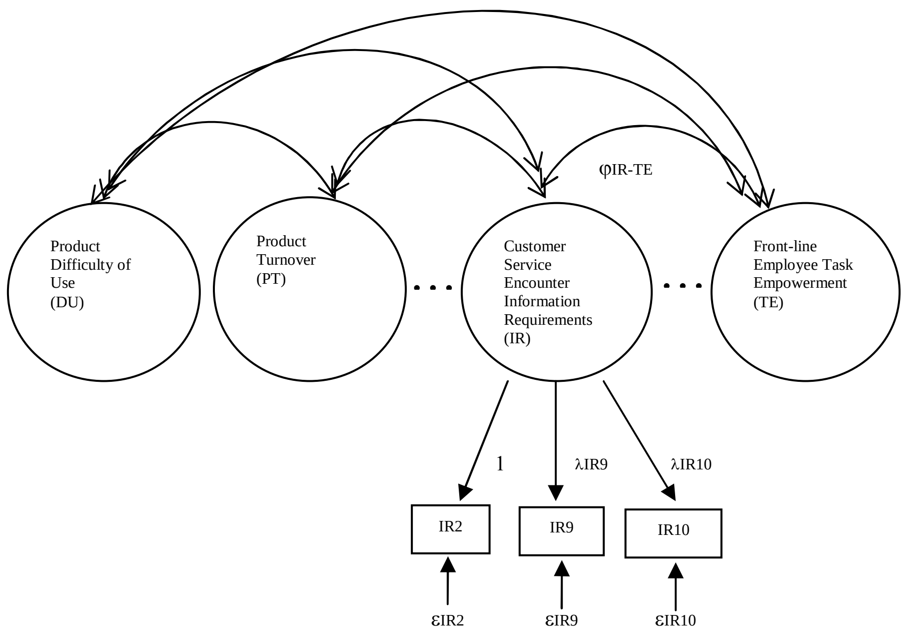
[3] We compared our final CFA measurement model with another analysis that excluded 16 repeated store 'formats'. No significant difference ($p<.05$) was found in any item-to-factor loadings for either sample.

constructs. Therefore, we applied several common tests to evaluate CMV. First, using Harmon's one-factor test for CMV (Podsakoff and Organ, 1986), we tested whether all the relevant items loaded onto a single factor using principal components extraction with no rotation for all items retained in our final model. This procedure identified six factors, with no one factor explaining more that 25% of the total item variance. While this does not rule out the presence of CMV, it is unlikely to be problematic (Podsakoff and Organ, 1986). The data was further tested for CMV using Lindell and Whitney's (2001) method, in which a theoretically unrelated factor (in this case, a 'seasonal traffic' measure) is correlated to the principal constructs. The average correlation among 'seasonal traffic' and the six constructs was r=.027 (average p-value=.44). Since a high correlation among any of the study's main constructs and 'seasonal traffic' would be an indication of CMV. We concluded that there was no direct evidence of CMV.

2.3.4 Confirmatory Analysis of Store Design Constructs

A confirmatory factor analysis (CFA) using EQS 6.1 (Bentler, 2005) was conducted using the independent field sample (n=175). Since we had one two-item scale for product turnover we used the "two-indicator rule" (Bollen, 1989). Figure 2.3 illustrates the CFA measurement model design.

Figure 2.3: Graphical Representation of the Measurement Model



Above is an illustration of the measurement model for the confirmatory factor analysis (CFA). For purposes of visual clarity, only 4 of the 6 latent constructs are shown, and only the three indicators for "customer service encounter information requirements" (IR) are shown. (See Appendix for items)

λ= CFA factor loadings.
ε = error terms of the indicators.
φ = covariances between latent constructs (discriminant validity was tested iteratively, measuring the $\chi 2$ difference of the baseline model where this is error term is freely estimated versus the model where it is constrained to "1" or unity.)

The confirmatory results from the first measurement model (Model 1) are shown in Table 2.4. While the fit indices indicate marginal overall fit (X^2=372.68, CFI=.91, RMSEA=.07 [90%CI: .05-.08]), some misfit is evident since many of our fit indices fall right at or below the recommended cutoffs for model acceptance (Hu and Bentler, 1999). Therefore, we also use robust estimation statistics to look for possible non-normalities in the data (Byrne, 2006, p.138). The reported robust statistics at the bottom of Table 2.5

(S-B X^2 =328.82, CFI=.924, RMSEA=.06 [90%CI: .04-.07]) suggest that the initial model (Model 1) had some multivariate non-normality or kurtosis, as robust results indicated somewhat better fit than the original model.

To examine if Model 1 could be improved, we conducted further tests which resulted in dropping four items from the model – IR6, SS2, TE7, and SC4. Two items – IR6 and SS2 – had low, albeit significant loadings ($p<.05$) on their intended factor. A Lagrange multiplier (LM) test showed that these two items exhibited cross-loading, so they were dropped from their respective scales. Further LM tests to simultaneously analyze the largest contributors to model misfit (see Byrne, 2006, pp.82-86) suggested that two task empowerment scale items (TE6 and TE7) had correlated error terms. The items were reviewed and it was determined that they were interpreted by respondents as being highly similar (same) items, so TE7 was dropped. A LM test also showed that (SC4) exhibited factor cross-loadings and it was dropped.

Since covariance item (LM) modification techniques tend to generate inconsistent results across multiple samples (MacCallum, 1986, p.109), we conducted a parallel specification search procedure using two equally sized sub-samples of the same dataset (MacCallum, Roznowski, and Necowitz, 1992). The results indicated cross-loading problems for the three problematic indicators (SC4, SS2 and IR6) in both subsets, which helped confirm our decisions.

Table 2.4: Stage 1 –Results of final pilot Exploratory Factor Analysis (Model 1) (n=42**)**
SPSS: Maximum likelihood extraction, Not rotated (except for scales where noted in text)

Items: measured as degree of agreement with item on a 7-point scale (1-strongly disagree, 4-niether agree nor disagree, 7-strongly agree)		Factor Loading
Most of the products that we sell in our store…		
Product Difficulty of Use [b] (DU)		
DU1	..are easy to use. [a]	.74
DU6	..are easy for the average customer to understand. [a]	.73
DU7	..have features that are well understood by customers before they enter the store. [a]	.68
Product Turnover [b] (PT)		
PT9	..lose value the longer they stay on the shelf.	.59 [c]
PT11	..lose their appeal over time.	.59 [c]
Service Production Complexity (SC):		
The way our store produces its overall service offering for customers….		
SC1	..requires a large number of different processes to be performed by clerks and/or sales people during the service.	.85
SC2	..results in high levels of dependency between processes.	.71
SC3	..requires coordination across our entire organization.	.82
SC4	..requires multiple steps to complete the transaction.	.90
Customer Service Encounter Information Requirements (IR)		
IR2	To satisfy customers, we must obtain information from them during the service.	.67
IR6	Our customers expect us to be able to handle inquiries about products.	.65
IR9	Our customers ask many questions before they make a product selection.	.99
IR10	Our customers need a lot of help in selecting products.	.84
Design for Self-Selection (SS)		
SS2	Our store's overall design assumes that customers already know a lot about the products that they are purchasing.	.83
SS3	Our store's use of layout and fixtures make it easy for customers to select and transport products for themselves.	.68
SS9	Our store allows customers to pick products from the shelves themselves.	.73
SS10	Our stores design is mostly a "self-select" environment.	.95
Front-line Employee Task Empowerment (TE)		
TE2	Our employees have the authority to correct problems as they occur.	.81
TE3	Our employees are allowed to be creative when they deal with problems at work.	.90
TE4	Our employees do not have to go through a lot of red tape to change things.	.71
TE5	Our employees have a lot of control over how they do their job.	.74
TE6	Our employees do not have to get management's approval before they handle problems.	.70
TE7	Our employees are encouraged to handle problems by themselves	.70

[a] reverse coded item
[b] Promax rotation on product complexity factors "product difficulty of use" and "product turnover" indicated no loading >.1, so these constructs show evidence of unidimensionality.
[c] On a two item scale, α is simply the correlation between the two items

Table 2.5 – Stage 2: Model comparisons with recommended values[1]

Fit statistic	One Factor Model[2] (Initial measures)	One Factor Model[2] (Final measures)	Model 1: Initial Measurement model	Model 2: Modified Measurement model	Recommended values
χ^2 – not adj.	1452.07	1066.04	372.68	174.79	
d.f.	230	152	216	138	
χ^2/d.f.	6.31	7.02	1.73	1.27	< 3.0
RMSEA	.18	.19	.07	.04	≤ 0.05 [a, b]
(90% CI)	(.17-.18)	(.18-.20)	(.05-.08)	(.02-.06)	
NFI	.24	.26	.81	.88	> 0.8 marginal fit and > 0.9 good fit [b]
NNFI (TLI)	.19	.20	.89	.96	
CFI	.27	.28	.91	.97	
GFI	.52	.57	.91	.91	
AGFI	.42	.46	.87	.88	
SRMR	.17	.17	.07	.06	< 0.09 [b]
Robust Statistics [c]					
S-B χ^2	1297.62	932.03	328.82	158.90	
N-NFI	.21	.23	.91	.98	> 0.8 marginal fit and > 0.9 good fit [bc]
CFI	.28	.32	.92	.98	
RMSEA	.16	.17	.06	.03	≤ 0.05 [a, b,c]
(90% CI)	.15-.17	.16-.18	.04-.06	.00-.05	

[a] Brown and Cudek (1993).
[b] Hu and Bentler (1999).
[c] Bentler (2005), Byrne (2006)

[1] We compared our final measurement model with another model excluding the 16 repeat store 'formats' (same chain store type), and found no significant chi-square difference (p<.05) in the two models for item-factor loadings.
[2] Both the initial items and the reduced item model were compared with a one factor model (where all items loaded onto one common factor) to evaluate model improvement.

The revised measurement model (Model 2) was re-tested and compared with the original model (Table 2.5). The second model fit statistics (X^2 =174.79, CFI=.971, RMSEA=.039 [90%CI.02-.06]) were significantly improved, suggesting that it was a good measurement model (Hu and Bentler, 1999). The LM test showed no significant correlated error terms with the latent constructs, suggesting that the latent factors (constructs) were unidimensional (Byrne, 2006). All the CFA results, descriptive statistics, factor loadings, and reliability statistics of this final model are reported in Table 2.6. Note that all factor loadings remained significant ($p<.05$) and large ($>.50$). The construct correlations, the average variance extracted (AVE) and scale reliabilities were given in Table 2.7. Note that all but one scale, product-difficulty of use, surpassed the .50 AVE cutoff established in the literature (Fornell and Larcker, 1981), and all reliability statistics met or exceeded the .7 cutoff (Nunnally, 1979).

Table 2.6 – Stage 2: Final (Model 2) items, item means, standard deviations, item loadings, and t-values from CFA (n=175)

Items: measured as degree of agreement with item on a 7-point scale (1-strongly disagree, 4-niether agree nor disagree, 7-strongly agree)		Mean	S.D.	CFA Loading [a]	t-value
Most of the products that we sell in our store…					
Product Difficulty of Use (DU)					
DU1	..are easy to use. [b]	1.96	1.36	.56	-----
DU6	..are easy for the average customer to understand. [b]	2.15	1.31	.57	5.44
DU7	..have features that are well understood by customers before they enter the store. [b]	2.50	1.52	.83	5.56
Product Turnover (PT)					
PT9	..lose value the longer they stay on the shelf.	3.35	2.20	.68	-----
PT11	..lose their appeal over time.	3.27	1.90	.78	-----
Service Production Complexity (SC):					
The way our store produces its overall service offering for customers….					
SC1	..requires a large number of different processes to be performed by clerks and/or sales people during the service.	4.62	2.17	.83	-----
SC2	..results in high levels of dependency between processes.	4.62	2.01	.85	11.72
SC3	..requires coordination across our entire organization.	5.24	1.89	.80	11.09
Customer Service Encounter Information Requirements (IR)					
IR2	To satisfy customers, we must obtain information from them during the service.	4.63	1.96	.60	------
IR9	Our customers ask many questions before they make a product selection.	4.95	1.65	.91	8.10
IR10	Our customers need a lot of help in selecting products.	4.47	1.70	.83	8.07
Design for Self-Selection (SS)					
SS3	Our store's use of layout and fixtures make it easy for customers to select and transport products for themselves.	5.43	1.69	.64	8.71
SS9	Our store allows customers to pick products from the shelves themselves.	5.49	2.00	.84	11.04
SS10	Our stores design is mostly a "self-select" environment.	4.97	2.23	.87	------
Front-line Employee Task Empowerment (TE)					
TE2	Our employees have the authority to correct problems as they occur.	5.30	1.60	.77	-------
TE3	Our employees are allowed to be creative when they deal with problems at work.	5.41	1.44	.85	11.59
TE4	Our employees do not have to go through a lot of red tape to change things.	4.78	1.85	.64	8.52
TE5	Our employees have a lot of control over how they do their job.	5.13	1.71	.70	9.45
TE6	Our employees do not have to get management's approval before they handle problems.	4.32	1.94	.73	8.63

[a] Standardized coefficients, all loadings are significant at $p < .05$.
[b] Reverse-coded item, item measure reversed by subtracting response value from 8.

Table 2.7 – Stage 2
Inter-construct correlations, *average variance extracted*, and scale reliability [a]

	Seasonal Traffic (Marker Variable)	DU	PT	SC	IR	SS	TE	Composite Reliability
Product Difficulty Of Use (DU)	-.04	*.43*						.74
Product Turnover (PT)	-.03	.02	*.53*					.69 [b]
Service Production Complexity (SC)	-.10	**.18***	.12	*.68*				.87
Customer Service Encounter Information Requirements(IR)	.07	**.44***	-.11	**.25***	*.58*			.86
Design for Self-Selection (SS)	-.10	**-.25***	.12	.07	**-.40***	*.61*		.89
Front-line Employee Task Empowerment (TE)	.05	-.03	-.13	.06	**.23***	**-.21***	*.53*	.88

[a] The lower half of the matrix shows the estimated correlations between the latent constructs, the diagonal shows in italics values for the average variance extracted (AVE) for each construct.

[b] For two item scales, composite reliability is simply the correlation between the two items

* Correlation between factors is significant at p<.05

The discriminant validity of the final measures (Model 2) was tested using a series of pairwise tests where the covariances (φ) between each pair of constructs was fixed to "1" and compared to the freed covariance using a X^2 difference test (Bollen, 1989). Every covariance, when fixed to one, resulted in a significant increase ($p<.05$) in the overall model X^2 statistic over the baseline model as shown in Table 2.8. This analysis supported the discriminant validity of our final measurements of the latent factors. We report all item correlations, variances, and covariances in Table 2.9.

Finally, we verified that each of the three store operating complexity factors were conceptually distinct by modeling them as a reflective second-order factor using CFA. Our post-hoc analysis revealed that even though the loadings were positive they do not significantly load on a latent second-order factor. So while these scales are all store operating complexity factors, they are not part any second-order store operating complexity construct. Taken together, the results from our analysis confirmed that each of the store design strategy factors used in the final measurement instrument were conceptually distinct (Chapter 2: H1-H6 supported).

Table 2.8– Stage 2
Discriminant validity analysis – Chi-square difference test [a b]

	DU	PT	SC	IR	SS
Product Difficulty Of Use (DU)	--	--	--	--	--
Product Turnover (PT)	203.85	--	--	--	--
Service Production Complexity (SC)	191.04	180.77	--	--	--
Customer Service Encounter Information Requirements(IR)	188.65	206.34	179.18	--	--
Design for Self-Selection (SS)	223.14	179.68	180.49	241.51	--
Front-line Employee Task Empowerment (TE)	226.45	208.59	189.06	188.61	214.51

[a] The lower triangle of the matrix reports the χ^2 statistic for constrained correlation paths between each pair of latent constructs. The χ^2 statistic for the baseline model is $\chi^2 = 174.79$ (χ^2 *.05, critical*=3.8, df = 1).
[b] All constrained pairs are significantly different from the baseline model (p<.05)

2.4 Discussion of Chapter 2 Results

This paper used organization information processing theory (OIPT) to develop a new conceptual model for retail store design strategy and developed multi-item scales to measure each of the salient constructs. A rigorous two-stage approach was used to develop and validate a hypothesized measurement model, which was confirmed in the second stage using data collected from retail stores in the Southeast United States. This study contributes to the theory and practice of retail service management in a number of ways. First, it answers calls in the service management literature (e.g. Chesbrough and Spohrer, 2006; Roth and Menor, 2003) for a more scientific approach to expand the body of knowledge around services (e.g., service science) by developing empirically verified construct measurement instrument. Second, these scales and instrument provide retail managers and academics a means to weigh design strategy tradeoffs. Third, the conceptual and measurement model allows for future research that forms the theoretical nomological network of construct relationships, as well as test whether or not conformance with the retail store design strategy conceptual model leads to more satisfied employees and more effective store delivery systems.

The use of OIPT in services literature suggests that task uncertainty for both the customer and the server are major issues in determining the effectiveness of the retail store design strategy, and that the organizational design structure assists in gathering and processing the information needed to manage uncertainty (Siehl et al., 1992, p.538). We suggest that managers affect operating complexity through the selection of their product offering and the complexity of their service production processes. Once these decisions are made, the service encounter information requirements are assessed. The amount of information needed then determines what constitutes an effective customer encounter design choice. The two design variables managers can manipulate in the customer encounter are the degree to which the store is design for self-selection and the degree to which server job designs are empowered.

The empirical validation of the hypothesized model using confirmatory methods allows for a more rigorous testing of service design strategy relationships. The model needs further development and testing to establish causal relationships among the constructs (see Chapter 3). However, the instrument developed here can potentially be used to evaluate customer satisfaction for store systems at different levels of complexity. It also could provide valuable feedback to retail store managers about their product assortment and service production processes, in relation to information processing needs and design choices. As proposed by Boyer and Swink (2008), an additional use of these new measurement scales would be to replicate and examine existing service design matrices (e.g. Buzacott, 2000; Huete and Roth, 1988).

Finally, while marketing and service operations research has discussed the application of OIPT principles to service encounter co-production, most of these discussions are conceptual taxonomies or case-based studies with little empirical validation or definitional rigor. By developing validated, empirical measures from an information processing-based framework, we provide an opportunity for researchers to empirically examine OIPT relationships across different service contexts. By developing and defining these constructs for retail store design strategy, we provide a platform for examining future strategic design issues in this industry.

There are limitations to this study. First, the measurement instrument was developed to gather only the retail store managers' view, which may limit their applicability to some contexts (e.g. employee empowerment). Nevertheless, this limit can be addressed in future research validating the scales with both employees and customers. An additional limitation is that store operational complexity is measured using only three separate factors – service production complexity, product difficulty of use, and product turnover. While these constructs have been widely discussed in the service production literature, it is possible that other factors may contribute to retail store operating complexity. Third, this research examines only two customer encounter strategies – design for self-selection and employee task empowerment. Additional design variables (e.g. employee knowledge and experience) need to be tested. Finally, it is possible that the customer community and segmentation may affect operational complexity in different ways, so that the store's physical location or the demographic characteristics of the customer base may allow the store to effectively manage multiple operating systems under one roof (e.g. Store within a store). While the scales evaluated here provide a valuable first endeavor, their scope can be expanded both in terms of the items and constructs, and to incorporate customer viewpoints. This would allow validation of the instrument from both the store and customer perspective.

Future research should also further refine and augment the final scales shown in Table 2.6. While our final revised model had good psychometric properties, the preliminary model had four cross-loading or bad items. Since our sample size was too small to conduct a traditional split sample calibration-validation study (e.g., Anderson and Gerbing, 1988), future replication studies in the retail store environment are warranted (Boyer and Swink, 2008).

While this model and instrument were developed for retail stores to evaluate the different constructs that make up design strategy management, it is possible that the constructs and measures can be modified and applied to other information rich service environments, (e.g. financial services; healthcare, etc.). For example, these constructs and measures may also be valuable to managers and academics studying customer relationship management (CRM), employee training, and knowledge-sharing mechanisms in retail store environments.

2.5 Chapter 2 Conclusions

This research proposes a theory-based, retail store service design strategy framework (Figure 2.1), and develops related construct and operational measures that may be useful in future research. These scales were then validated for use in-store retail environments, where customers come to the store to make product purchases. The conceptual model can provide a priori guidance about what service combinations will be effective, or if the realized service design strategy reflects what was intended in the original service concept idea. The instrument and resulting measures can also be used by managers to examine their existing designs vis-à-vis the model and to calibrate the relative performance of their design choices. These activities should give managers insight about whether their operating complexity is generating higher margins, and whether they need to make system design changes to manage task and informational uncertainty in their stores.

Our measurement study integrates theories from prior service design literature and OIPT, and uses a two-stage approach to create new measures to evaluate retail store design strategy. These measures explicitly incorporate store operational complexity factors as well as retail service design strategy decisions, and will allow managers to examine how adjustments to product line and service production complexity affect service encounter information processing. Our model factors were developed to examine the associations of operating complexities with service encounter information requirements, store self-selection, and server task empowerment strategies. By developing the conceptual model using an OIPT lens and confirming the hypothesized model, we argue that an effective retail store service design strategy is one which coordinates the customers' purchase decision by giving them access to the information that they need to select products. We hope that this research provides a foundation for both retailers and practitioners to better understand and evaluate the design strategies they use to enhance customer service encounters and retail store experiences.

CHAPTER 3

Linking Customer Information Requirements, Retail Store Design Strategies, and Satisfaction: A Structural Model Analysis

3.1 Purpose of Chapter 3

> Three of the TVs are dark in Wal-Mart's electronics department, where the only two clerks in sight stock the shelf and disappear. At nearby Target, the digital camera desk is unmanned, and there's no staff roaming electronics. In Circuit City, a clerk concedes it's his first day on the job and first week in the country. But over at Best Buy (BBY) three clerks staff the "Geek Squad" counter, and another hovers nearby, poised for questions, which he handles with ease.
>
> (Jayne O'Donnell, *USA Today*, July 22, 2008)

In this study, we posit that retail service organizations gather and process customer information through store design strategies that are strategically linked with customer service encounter information requirements and expectations. The above example of store visits in the consumer electronics industry illustrates the importance of managing customer information expectations with an effective customer encounter design choice. In three of these four cases, the complete self-service store model did not satisfy the customers well because the complex nature of electronics service-product offering was not well-integrated with customer encounter strategies that would manage the customer's information needs (Siehl, Bowen, and Pearson, 1992). For example, the product offering difficulty of use in the consumer electronics segment typically requires a more complex delivery system strategy to manage the increased heterogeneity of customer requirements expected in the service (Menor, Roth, and Mason, 2001, p.277).

Yet, operations management research notes that retail service concepts (e.g. service intentions) are not always in sync with actual delivery system design strategies (Goldstein, Johnston, Duffy, and Rao, 2002; Roth and Menor, 2003; Chapter 1). In this chapter, we use service operations theory and organizational information processing theory (OIPT; Galbraith, 1973; 1974) to develop a structural model to analyze both retail store delivery design strategy relationships and their impact on both employee and customer delivery satisfaction.

Retailing is "the business of providing goods and services to customers for their personal or household use" (Ghosh, 1990, p.51; Chapter 1). Customers perceive value-added service encounters in retail 'bricks and mortar' store designs that make the customer's product-selection choice easier (reduce uncertainty) by providing the appropriate level of service encounter information processing to complete service delivery tasks (Mills and Turk, 1986). The store design strategies of retailers should also provide the necessary supporting infrastructure (job design), structure (service layout), and coordinative (integrative) resources required to effectively manage customer encounter behaviors (Voss, Roth and Chase, 2008; Roth and Menor, 2003; Roth and Jackson, 1995).

Store operating complexity factors will also affect customer service encounter information requirements in the design system. Retail stores may manage complex product offerings, products with high turnover rates, or they may have complex service delivery processes. A good retail store design strategy recognizes the impact each of these factors will have on customers, and will try and resolve their disparate information needs in the service encounter (Mills, 1986). However, empirical research examining the strategic design links between store operating complexity factors, customer service encounter information requirements, and the customer encounter choices to enhance service encounter satisfaction is limited.

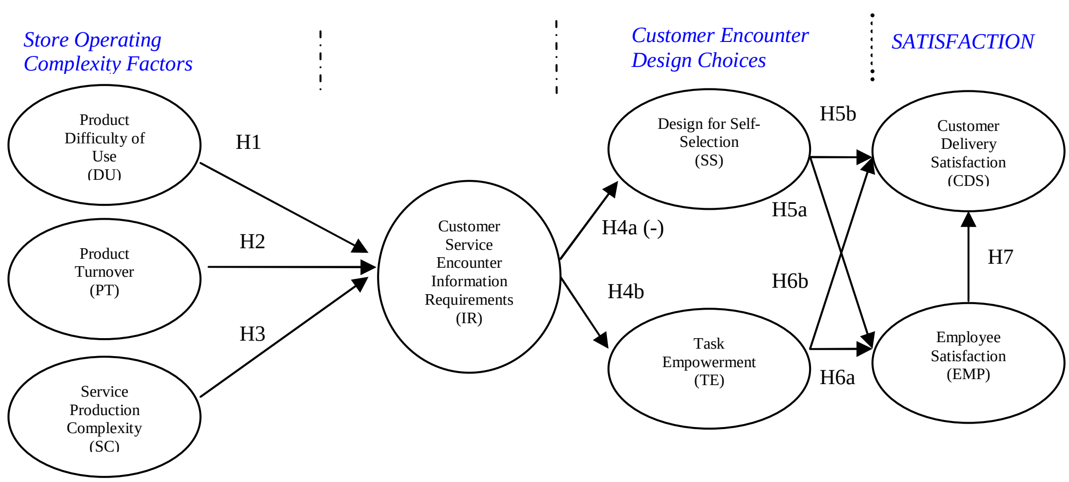
Key design constructs grounded in service operations strategy and organizational information processing theories (Table 2.1 and Appendix 7.1.1) were empirically developed and validated in Chapter 2 to evaluate and measure the content elements of retail store design strategy. As in other services, store retailers strategically choose, build, and deploy resources to design service delivery system "architecture" (Roth and Menor, 2003; Roth and Jackson, 1995). Design architecture is made up of specific structural capital (store layout), infrastructural (employee job designs and policies), and coordinative resource decisions (Roth and Jackson, 1995). Retail firms use these resources to manage the customer-server interactions in their store operating systems. While the importance of linking service delivery system architecture choices with environmental conditions is generally acknowledged (e.g. Roth and Jackson, 1995, Roth and Menor, 2003; Fitzsimmons and Fitzsimmons, 1999), there is no empirical testing of what design choice is best for managing customer information needs in product-selling retail store environments.

Organizational information processing theory (OIPT) recommends what design choice is appropriate to manage customer service encounter information requirements, if one considers the important information processing role of the customer/co-producer in retail organizational systems (Siehl et al., 1992, p.538). Service design strategy literature acknowledges that a key difference between service and manufacturing production systems is the co-productive nature of services (Fitzsimmons and Fitzsimmons, 2001; Roth and Menor, 2003; Langeard, Bateson, Lovelock, and Eiglier, 1981; Lovelock, Vandermerwe, and Lewis, 1999). As co-producers in service systems, customers are part of a larger organizational design strategy to manage task uncertainty. In fact, customer information requirements are recognized as a key source of input uncertainty for service production systems (Sampson and Froehle, 2006, p.332) and for service encounters. OIPT recommends how organizations, in response to uncertainty (defined as the absence of information), might develop design strategies to handle system-wide information processing requirements (Galbraith, 1973; 1974). However, OIPT research in services has not empirically examined retail service design choices, or their integration into specific retail store design 'architecture' strategies (Roth and Jackson, 1995).

By developing a structural equation model (SEM) to examine retail design strategy relationships, we address several important questions. First, we investigate how operating complexity factors – product difficulty of use, product turnover, and service production complexity - are linked with customer service encounter information requirements and the customer encounter choices of retail stores. Our first research question asks: Do retail store operating complexity factors create customer service encounter information requirements? And, do customer service encounter information requirements motivate the retailer's choice of in-store customer encounter strategy (design for self-selection, employee task empowerment)? Next, we want to understand if integrating customer service encounter information requirements with specific customer encounter choices leads to better perceived customer delivery and employee satisfaction experiences. Our second research question asks: Does linking specific customer encounter choices with service encounter information requirements improve employee and customer delivery satisfaction? Finally, we investigate store size effects by asking: Do the proposed retail design strategy relationships vary based on store size (large/small)?

In the next section, we discuss the structural model (Figure 3.1) and related Chapter 3 hypotheses investigating retail operating complexity factors, the resulting customer-server information needs, and the retailer's customer encounter strategy choices to manage customer service encounter information requirements.

Figure 3.1: Retail Store Design Strategy Structural Model (SEM) Hypotheses



H5a,b and H6a,b will be tested for total, direct, and indirect effects on the satisfaction DVs

3.2 Structural Model and Theoretical Development

We used six design-related constructs culled from service operations and marketing strategy literature (from Chapter 2; Table 2.1) and developed two new satisfaction constructs to construct a retail store design strategy model based on organizational information processing theory (OIPT). The Figure 3.1 model incorporates the three key concepts of OIPT: 1) *uncertainty* (measured by three store operating complexity factors); 2) *information processing* (customer service encounter information requirements), and two appropriate; 3) *customer encounter choices* (design for self-selection, employee empowerment) to achieve the best organizational design performance (Premkumar, Ramamurthy, and Saunders, 2005) measured by both customer delivery and employee satisfaction. First, we argue that operating complexity factors create the need for customers to seek information processing capabilities in the store service encounter (Siehl et al., 1992; Mills and Turk, 1986). In retail stores, customers may internally process needed information from servers, tags, or signs to resolve product-selection task uncertainty (Mills and Morris, 1986, p.732). Our model examines the important links between these customer service encounter information requirements, store customer encounter choice, and the satisfaction of employees and customers with service delivery in retail store environments.

3.2.1 Store Operating Complexity Factors

Three important internal operating complexity factors to consider in store design strategy are the product difficulty of use, product turnover, and the service production complexity. First, *product difficulty of use* (DU) is the difficulty (or relative ease) of use of the store's product offering and assortment for customers (Chapter 2). The complexity produced by the stores product offering mix determines how much information or analysis is anticipated from servers in the design structure to resolve task uncertainty (Buzacott, 2000). *Product turnover* (PT) is the speed at which the store's product offering depreciates, spoils, or becomes out-of-date (Chapter 2), and is part of a merchandising effort to offer more frequent introduction and a range of products that are targeted to specific customers in the local market (Dawson, Findlay, and Sparks, 2008, p.214; Grewal et al., 1999), or it may be driven by the nature of perishability of the core product line in the store (Cattani, Perdikaki, and Maruchek, 2007). Finally, the *service production complexity* (SC) is defined as the "level of coordination (number and interdependence of steps) required to produce the retail service" (Skaggs and Huffman, 2003, p.778; Shostack, 1987; Chapter 2). The higher the number of steps in a store's service process, the more interdependence and coordination is necessary to resolve task uncertainty in service encounters (Skaggs and Huffman, 2003; Mills and Turk, 1986). The notion of service production complexity is largely derived from Simon's (1962; 1969) work on complex systems as those having a large number of steps/parts with highly interdependent relationships (Chapter 2).

An example of how operating complexity factors create uncertainty is seen in home theater stores, where the big screen television (TV) is a core product offering. In the home theater store, both product use and service process characteristics related to the product offering dictate what service encounter task uncertainty is present. The product may be newly introduced to the market or come with multiple complementary products, and may be bundled with service offerings such as home delivery, installation services, and warranties. The consumer faces uncertainty about which bundle of TV, complementary products and services to purchase, and seeks information to resolve this uncertainty (Mills, 1986). Uncertainty exists in this case of more complex products where specific choice options cannot be eliminated quickly (Campbell, 1988; IBM, 2005), and most managers recognize that increased product complexity can negatively affect their operating margins (Gottfredson and Aspinall, 2005).

Yet, operating complexity in the product/service offering may also be highly valued because of the customization benefits it provides to consumers (Shostack, 1984; 1987), and it may be associated with higher profit margins if managed effectively (Menor et al., 2001). Moreover, the supporting merchandise, expertise, and services offered for sale is one of the major factors influencing a customer's decision to shop at a particular store (Ghosh, 1990, p.77). So, retailers must match the level of product offering and service production complexity with the needs and expectations of customers in their retail segment. While retailers control their service processes and product offerings to some degree, once the store operating complexity factors are pre-established in the minds of customers, they are hard to change.

3.2.2 Customer Service Encounter Information Requirements

In store service encounters, operating complexity factors impact information processing needs for both servers and customers. *Customer service encounter* i*nformation requirements* (IR) are the degree to which customer requirements are unknown (to store servers), requiring information or analysis to complete a service transaction (Chapter 2). Service system structures can be classified based on the need for information or analysis to be performed in the service encounter (Buzacott, 2000; Siehl et al., 1992; Mills and Morris, 1986). If the store service delivery system fails to provide these information processing capabilities, it results in more time and effort than the customer may be willing to spend to complete service encounter tasks (Mills and Turk, 1986). In information rich and more complex service contexts, the need to process and transfer information between server and customer by providing the appropriate level of contact is key to satisfying service customers (e.g. Xue and Field, 2008; Kellogg and Chase, 1995). In addition, measures of service offering information content in the retail banking industry have been shown to effectively position and classify service delivery channel use (Huete and Roth, 1988). Yet, no studies directly measure service encounter information requirements in retail stores, or develop empirical models that explain store design strategy relationships.

Examining retail store operating complexity factors (product difficulty of use, product turnover, and service production complexity) and customer service encounter information requirements with an OIPT theoretical lens provides interesting insights for understanding retail store design strategy relationships. First, perceived complexity creates uncertainty and information requirements in any organizational system (Campbell, 1988). If store service delivery systems are part of an overall organizational design structure, then customers co-produce any service encounter task (Mills, 1986).

Customers bring more uncertainty into retail service encounters where there are store operating complexity factors caused by either the nature of the retail store's product/service bundle offering or its internal production processes.

3.2.3 Customer Encounter Design Choices

Increasing task uncertainty may be managed by designing store systems to more efficiently process customer information by: 1) creating slack resources to isolate information processing needs and/or 2) cutting across lines of authority (or reducing hierarchy dependence) to increase information processing capabilities (Premkumar et al, 2005; Galbraith, 1973). There are multiple store design strategies that retail service organizations use to manage customer information processing requirements. One is to create service designs that require less information processing in customer encounters (i.e., designing for self-selection), and another is increasing information processing capability of servers by providing front-line employees with job task empowerment (Galbraith, 1973; 1974, Honold, 1997).

Design for Self-selection

First, retailers can design their internal delivery systems to process information by creating self-contained tasks that create slack resources (Galbraith 1973; 1974) through design for customer self-selection. *Design for self-selection* (SS) is the degree to which the store structure and layout supports a customer-based "do it yourself" service environment (for product-selection) – from Chapter 2. If the sub-routines required to complete product-selection tasks are relatively simple, than this part of the service delivery can be performed by customers (de-coupled) through designing for self-selection, rather than by human-server contact (Buzacott, 2000; Hefley and Murphy, 2008). This practice frees human resources to focus on improving transactional efficiency (Chapter 2). If customers feel that they have personal control over service encounter tasks, then they will perceive time and efficiency gains by performing these simple tasks for themselves (Bateson, 1985). However, getting consumers to use more cost-efficient self-selection channels will depend on understanding the customers' need for human contact to process rich (or more complex) information content (Kellogg and Chase, 1995); this can also be achieved by developing in-store systems, signs, or technology that can substitute for human contact (Xue, Hitt, and Harker, 2007; Froehle and Roth, 2004) by communicating information about store products and service options.

Employee Task Empowerment

Empowered retail job designs give front-line employees the opportunity to eliminate dependence on hierarchy (Galbraith, 1974), give the necessary support to customers, and allow the system to recover from possible service failures (Miller, Craighead, and Karwan, 2000). We define front-line store *employee task empowerment* (TE) as the level of control (discretion) provided to front-line workers in the retail service production process (Hayes, 1994; Argyris, 1998; Buzacott, 2000; Chapter 2). It is the natural tendency of organizational systems to create hierarchies or pre-programmed tasks to manage complexity (Galbraith, 1973; 1974; Premkumar et al., 2005). Retail job design strategies that provide employees with the discretion and authority to effectively coordinate information in more uncertain task environments increase the ability of the design system to process information in a timely manner (Chapter 2). Store managers are often the hierarchy of dependence in retail settings, providing problem-solving and analysis when transactions fall outside the routine (Shim, Lusch, and Goldsberry, 2002). As such, only store managers are presumed by retail organizations to hold the knowledge or judgment to override company policies or procedures (Davidson and Fielded, 1999).

In an effort to manage part-time and lower paid workers and to meet cost objectives, retail stores have been characterized by job designs with routine tasks, lack of investment in employee cross-training, and an organizational emphasis on management authority to control in-store activities (Zeytinoglu, Lillevik, Seaton, and Maruz, 2004). Also, larger retail organizations may wish to provide more empowerment to workers, but may not how to do so cost-effectively (Argyris, 1998). Honold (1997) argues that the sum of the empowerment literature is that employee empowerment must be incorporated and defined into the organization's overall design strategy. Therefore, achieving systemic task empowerment is largely a result of the organization's readiness to embrace front-line employee empowerment programs, and it is not often achieved in the short-term (Honold, 1997, p. 202-203).

Power structure theory (Kanter, 1979; 1993) suggests that front-line employee task empowerment is not so much dependent on the employee's abilities as on the "position that the person occupies in the organization" (Kanter, 1979, p. 66). Therefore, it is only by being granted systemic authority through their job design to mobilize and act on customer information, that retail workers will have any real power to manage task-level decisions (Kanter, 1993). Hayes (1994) developed the employee empowerment quotient (EEQ) questionnaire scale that has been used across a number of different service operations quality contexts to examine the efficacy of service task-based empowerment programs (e.g., Melham, 2004).

3.3 Chapter 3 Hypotheses Development

By linking the appropriate design choice (Roth and Menor, 2003; Roth and Jackson, 1995) with customer information requirements, the system better satisfies internal employees and external customers (Premkumar et al., 2005, Rogers and Bamford, 2002). Building on these theoretical insights, we investigate the key store design strategy relationships using our structural model.

3.3.1 Store Operating Complexity Factors – Affects on Customer Information Requirements

Our model store operating complexity factors– product difficulty of use, product turnover, and service production complexity - affect the customer service encounter information requirements in retail store delivery systems. Internal uncertainty within an operating system typically comes from the information intensity caused by either process or product-related factors (Zhang, Melcher, and Li, 2004; Simon, 1969). Service operations research argues that customer involvement in the service process and the product offering strategy are key sources of internal operational uncertainty in service delivery system settings (Field, et al., 2006, p.153).

Product difficulty of use: The store's *product difficulty of use* affects the amount of information that must be processed in the service encounter (Chapter 2). In retail store service delivery systems, product offering difficulty of use drives the need for information from the perspective of the co-producer/customer (Oppewal and Timmermans, 1997; Bettencourt, 1997). This type of product-driven complexity may vary considerably from retailer to retailer and it is an important consideration in designing any transaction-based system (Zhang and Reichgelt, 2006; Gottfredson and Aspinall, 2005). Product offering difficulty of use indirectly creates heterogeneity in customer needs that will determine the system requirements for server contact or interaction (Menor et al., 2001). Similarly, Buzacott (2000) argues that increasing variety of customer demands or requests needs a service system structure that is also more complex and dynamic, and that anticipated customer-server information needs should drive what type of design structure is most appropriate. However, little empirical research focuses on the relationship of product offering properties (versus process properties) and the transactional structure of service organizations (Zhang, Melcher, and Li, 2004). However, Malone, Yates, and Benjamin (1987) use the term 'product description' complexity (p.486) – to describe the amount of information that has to be communicated about a complex product to an end-user. They argue that it is a major contributor to the amount of task uncertainty in any production system. As such, the extant research suggests that products requiring complex descriptions of product features and benefits will increase shopper task uncertainty, requiring more information processing in the service encounter.

H1: Product difficulty of use (DU) is positively associated with customer service encounter information requirements (IR) in retail stores.

Product turnover: Another indicator of store operating complexity that affects information processing is the store's product turnover (Chapter 2). A retailer's product mix may be comprised of thousands of different items and is part of the store's overall merchandising strategy (Ghosh, 1990). Some items in the product mix are consumer staples with very predictable demand patterns that are familiar to customers. Nevertheless, retailers in many segments are under pressure to carry a large percentage of high turnover products in order to satisfy a wide range customer needs and to meet competitive demands (Ghosh, 1990, p. 347). The range planning and the number and frequency of new items a retailer introduces into the store has also been shown to increase urgency in the buyer and retailer to clear out slower selling lines through sales which require negotiating pricing and terms (Betts and McGoldrick, 1995). If a retail store has a large number of products with short product life cycles, this may contribute to overall complexity if more perishable items require information about customer demand (Chen and Watanabe, 2007) or internal systems to manage product variety, layout, and process changes (Ketzenberg and Fergusen, 2008).

While operations strategy literature has long history of discussing the importance of linking short product life cycles with task uncertainty and more complex production designs (e.g. Hayes and Wheelwright, 1979), high turnover products also generate customer uncertainty and information needs in service encounters (Siehl et al., 1992). For example, studies of online groceries indicate that more perishable product offerings are perceived by customers as high risk because the customers want to make their own personal quality comparisons to resolve uncertainty (Cattani, Perdikaki, and Maruchek, 2007). Therefore, we hypothesize that the product-selection task uncertainty caused by high product turnover will necessitate more information processing in store service encounters.

H2: Product turnover (PT) is positively associated with customer service encounter information requirements (IR) in retail stores.

Service Production Complexity: Complexity theory (Simon, 1969) states that complex operating systems will be characterized by multiple interactions within an organizational system that are independently confined in some way. The level of service production complexity should also be connected to the original service concept idea (Goldstein et al., 2002). In the service value chain literature, the service concept (offering) is simultaneously considered along with production process decisions (Heskett, Sasser, and Schlesinger, 1997). While the service concept and production processes are treated as distinctive components in service operations strategy literature, understanding the links between process design strategy and the original service intent is a critical research gap (Goldstein et al., 2002; Roth and Menor, 2003). High service production complexity may actually reflect customization benefits that are valued by consumers and this may lead to higher profits (Shostack, 1984; 1987), but the practical challenge for many retailers is that they may not know how effectively manage high service production complexity in a cost-effective and ongoing manner (Ghosh, pp.132-133; Menor et al., 2001).

Retail stores, like other service systems, increasingly offer multiple channels to interact and gather information about customers (Patricio, Fisk, and Falcao e Cunha, 2008; Xue et al., 2007). Internal task uncertainty in these cases is directly linked with the number of customer-server interactions and interdependent information needs (Skaggs and Huffman, 2003, Field et al., 2006). As such, coordinating multiple sets of server interfaces increases the customer's burden for information-seeking as they must navigate a complex store service process and multiple servers to get what they want. Therefore, we expect that service production complexity also increases the customer information processing requirements in retail store service encounters.

H3: Service production complexity (SC) is positively associated with customer service encounter information requirements (IR) in retail stores.

3.3.2 Customer Information Requirements and Design for Self-selection

The use of design for self-selection as a customer encounter strategy is possible if sub-routines can be de-coupled into simple sets of activities that allow customers to perform most product-selection activities without the help of server contact or interaction (Chase, 1978; Bateson, 1985). Design for self-selection is a part of a self-service environment, where customers perform all (or most) of the product-selection service delivery tasks (Chapter 2). Service organizations pursue self-service strategies primarily for cost and efficiency reasons (Bitner, et al., 1997; Chase, 1978). There are also customer time-efficiency gains in self-service systems (Patricio et al., 2008; Bateson, 1985), which they prefer if tasks are simple and clear to them. For example, Buzacott (2000) argues that in simple sets of service encounter tasks are more efficiently performed by customers. Conversely, when customer service encounter information processing is high, and information is harder to exchange, using self-service channels of delivery effectively is limited by the frustration customers' who want more interaction from severs (Xue and Field, 2008). In these cases, the right store system design strategy choice will be to provide more labor (human contact) to manage the high customer service encounter information requirements (Chase, 1978; Kellogg and Chase, 1995). Customers who already know about the store's product/service offering will be more willing to participate in self-service systems (e.g. Bateson, 1985; Xue, et al., 2007) because they have no uncertainty about product-selection decisions.

Swedish furniture retailer IKEA is an example of a store delivery system design that effectively integrates operating complexity factors, customer service encounter information requirements, and design for self-selection. The use of flat-packaging and unassembled products allows customers to transport furniture home, and requires little need for store servers to process service encounter information for home delivery, customization, or manage financing arrangements for customers, and it is also very cost-efficient (Moon, 2004). At IKEA, even first-time customers bring knowledge of the product and service offering into the store service encounter, and the store's layout effectively communicates information about how (and by whom) the service will be delivered. High self-selection stores have simple internal store processes with no interdependency, low customer service encounter information requirements, and highly standardized job tasks for front-line employees.

Design for self-selection strategies, like IKEA, effectively manage low customer encounter information requirements throughout the store system (Buzacott, 2000; Campbell, 1988; Premkumar et al., 2005). This is most efficiently done by designing tasks that allow customers to easily select products without human server contact. We hypothesize that stores will use this type of customer encounter strategy more often when customer service encounter information requirements are minimal.

H4a: Customer service encounter information requirements (IR) are <u>negatively</u> (-) associated with design for self-selection (SS) in retail stores.

3.3.3 Customer Information Requirements and Employee Task Empowerment

Front-line employee task empowerment provides organizations the ability to adapt to operating task uncertainty (Menor et al., 2001; Field et al., 2006, Miller, et al., 2000). Empowered job designs also systematically improve of service employees' abilities to handle uncertainty and provide improved system responsiveness (Bowen and Lawler, 1992; 1995). In fact, job empowerment might actually be more important to satisfying store customers than training or employee knowledge because it makes the employee's knowledge actionable (Kanter, 1993). If typical customer encounter demands for information are uncertain, then restrictive job designs will be overwhelmed by hierarchy, and the system will not function effectively (Galbraith, 1974, p. 29).

While merchandise retailing has the general reputation for not providing front-line worker empowerment, there are several well-documented cases where retail empowerment programs have been implemented effectively. In the 1990’s, Japanese department store retailer Ito Yokado developed an employee empowerment program to manage customer perception and demand for stocked items in an extremely uncertain market environment (Wylie, Salmon, and Furukawa, 1994). In 2006, Best Buy, Inc. implemented a manager evaluation system to drive store-level decision-making in its ‘customer-centricity’ retail stores with some success (Lal, Knoop, and Tarsis, 2006). On the other hand, the rewards, training, and incentives to empower service workers may not always be desirable for retailers, if customers do not require or want intervention when making product-selection decisions (Bowen and Lawler, 1995).

Despite anecdotal evidence that employee empowerment programs have been met with mixed success (Argyris, 1998), there has been little empirical testing of their effectiveness in retail store service design. Organizational theory suggests that firms will remove hierarchy dependence by empowering workers to use information, provide task discretion, and use their skills and training to be responsive to random events. This will increase the store system’s information processing capability (Galbraith, 1973). Therefore:

H4b: Customer service encounter information requirements (IR) are positively associated with front-line employee task empowerment (TE) in retail stores.

2.3.4 Customer Encounter Choices and Satisfaction

So, when do the strategic design choices of retail organizations lead to improvements in customer and employee satisfaction with store purchasing experiences? If little information is required to complete store product-selection tasks, customers will engage in self-selection and will not need empowered employees, wanting instead a customer encounter focused on transactional efficiency (Bateson, 1985). However, retail practitioners report that poorly deployed designs for self-selection may actually cause negative service consequences by not providing enough customer support (Bonde, 2004). So a good design for self-selection strategy will make the customers product-selection decisions easier by providing transactional information through tags, store layout, or automated systems (Froehle and Roth, 2004; Ghosh, 1990). This effort should also make employees lives easier so that they can focus on other more productive store activities.

H5a: Design for self-selection (SS) is positively associated with employee satisfaction (EMP) in retail stores.

H5b: Design for self-selection (SS) is positively associated with customer delivery satisfaction (CDS) in retail stores.

On the other hand, front-line employee task empowerment increases the capability of the store to process more customer information in more uncertain operating environments (Buzacott, 2000; Miller et al., 2000). Power structure theory suggests that empowered employees will do what is in the best interest of satisfying customers, because employee job designs are not restricted by process rules or regulations (Kanter, 1993). Research finds that empowered employees in services are also more satisfied employees, because front-line service workers generally want to feel that they are being effective at doing their jobs (e.g. Spence-Laschinger, Finegan, Shamian, and Wilk, 2004). However, it is hotly debated question whether empowered service employees are more effective at handling customer service encounter information requirements, or if empowerment gives employees the personal satisfaction and feeling of competence that allows them to do their jobs well (Honold, 1997; Quinn and Spreitzer, 1997; Spence-Laschinger et al., 2004).

Service operations research studying employee empowerment can be easily incorporated into our understanding of the OIPT proposed design strategies to eliminate hierarchy dependence (Galbraith, 1973). If high customer service encounter information requirements are linked with more empowered store employees, then the overall system should be more effective (Premkumar et al., 2005). This increase in retail service organization effectiveness will result in employee and customer satisfaction with store service delivery.

H6a: Front-line employee task empowerment (TE) is positively associated with employee satisfaction (EMP) in retail stores.

H6b: Front-line employee task empowerment (TE) is positively associated with customer delivery satisfaction (CDS) in retail stores.

3.3.5 Store Employee and Customer Delivery Satisfaction

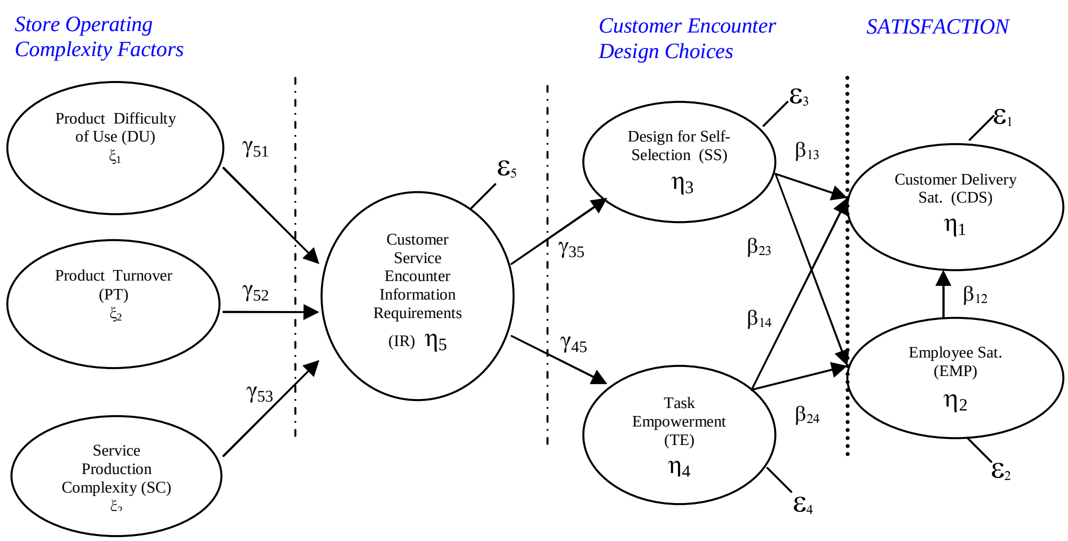
The service and quality management literature suggests a strong positive association will exist between employee satisfaction and customer delivery satisfaction in retail stores. For example, Douglas and Fredendall (2004) examine the Deming management model of total quality across service industries, finding a positive association between measures of employee fulfillment and customer satisfaction. Service-profit chain literature finds a positive internal service quality relationship link from employee satisfaction to employee productivity to customer satisfaction and loyalty (Heskett et al., 1997; Loveman, 1998). While these relationships have not been examined specifically in the retail store design strategy context, our final hypothesis tests this well-documented relationship.

H7: Employee satisfaction (EMP) is positively associated with customer delivery satisfaction (CDS) in retail stores.

3.4 Method

Using our previously validated scales, store manager interviews, and our readings of service strategy and organizational design literature (Chapter 2), we developed a structural model (Figure 3.2, Model 1) to test six of the hypothesized relationships (H1-H4b, H7). To understand how customer service encounter information requirements (H5a-H6b) affect customer encounter design choices and satisfaction, we also used a meditation model (Figure 3.3, Model 2) to examine the direct, indirect, and total effects of each customer encounter choice (self-selection, empowerment) with each of our two dependent variables (employee satisfaction, customer delivery satisfaction). The survey sample included 175 public and private retail stores in the Southeast United States, excluding wholesalers and internet retailers (Chapter 2). The survey respondent was the retail store manager, franchisee, or store owner. The summarized results of the prior scale development process, validation procedures, descriptive results, response rates, and scale testing for the independent variables are discussed in Chapter 2**,** along with footnotes discussing specific scale development and sampling issues. Our list of stores came from the Local.com telephone directory covering geographic strategic marketing areas (SMAs) in the Southeast U.S.

Figure 3.2: Retail Store Design Strategy Structural Equation Modeling (SEM)



To test the above proposed structural model (Figure 3.2), we developed two additional measures of satisfaction for our dependent variables: employee satisfaction (EMP) and customer delivery satisfaction (CDS). Because it was impractical to directly gather employee and customer feedback for the entire retail sample, we operationalized EMP and CDS as latent multidimensional satisfaction constructs measured with multiple item perceptual measures of satisfaction from the retail store manager survey respondent. All items for each construct use seven-point Likert scales (Table 3.1).

Table 3.1: Multi-item Perceptual Measures of Satisfaction

Satisfaction Measures Model – CFA (χ^2 = 3.37; RMSEA = .000; CFI = 1.00; SRMR= .032)

Items: measured as degree of agreement with item on a 7-point scale (1-strongly disagree, 4-niether agree nor disagree, 7-strongly agree)		Mean	S.D.	Loading [a]	t-value
CDS- Customer Delivery Satisfaction[b]: *In general….*					
CDS1	Customer satisfaction with our service offering is higher than our competitors.	6.09	1.12	.54	___
CDS5	Our service delivery system is the most customer friendly for the products that we sell.	5.42	1.49	.66	5.787
CDS6	Our customers are highly satisfied with our store's level of service.	5.87	1.17	.81	6.182
EMP - Employee Satisfaction: *In general….*					
EMP2	Employee job satisfaction is high.	5.54	1.34	.85	___
EMP3	Employee turnover is lower than competitors.	5.12	1.79	.61	___

a Standardized coefficients, all loadings are significant at $p < .05$.
b Equally weighted CDS measure was compared to a sub-sample (n=21) of objective customer-reported data at the location level where it is was available (5-star scale). Overall results (r=.466, p=.033).

To compensate for the store managers' limited ability to assess customer and employee satisfaction at the store location, more perceptual items were validated with more objective items in the survey (Ketokivi and Schroeder, 2004). For example, in the case of employee satisfaction (EMP), store managers were asked for an objective measure of employee turnover versus competitors. With the customer delivery satisfaction (CDS) scale, store managers were asked to compare the customer satisfaction performance to competitors.

To further provide content validity for the customer delivery satisfaction (CDS) scale, we gathered secondary source data from three online customer rating services (Local.com; BizRate/local.com; PalmettoBizBuzz.com) for those stores with sufficient data online (n=21). By sufficient, we mean that we disqualified any respondent store in the field sample that did not have more than 3 postings for customers across multiple databases in order to avoid single respondent biases, database type bias, or one-time disgruntled employee postings for a particular store. Each of these rating services uses a similar 5-star evaluation method to measure overall customer satisfaction with the retail store. While the result is not a perfect measure of customer delivery satisfaction, we expect to see a positive association between the store manager's perception of customer delivery satisfaction (CDS) and the actual 5-star customer satisfaction ratings. The results show that, despite the small validation sample size (n=21), our construct measure of customer delivery satisfaction (CDS) was significantly (p=.033) and positively correlated (r=.47) with the same-store online customer satisfaction ratings (Table 3.2).

Table 3.2: Customer Delivery Satisfaction (CDS) Measures (Manager Reported) vs. Objective Customer Satisfaction Scores at Location Level (n=21)[1]

n=21 matches	CDS (1-7)	Stars (1-5)
Average	**5.4**	**4.448**
Std. Dev	**1**	**0.508**
Pearson Correlation	0.47	
Sig. (2-tailed)	p=.033	n=21

[1] Correlations between '5-Star' data and TE (.08), SS (.23), and EMP (.32) were positive but all insignificant (p>.10) for the small subsample of stores (n=21) where it was sufficiently available.

Next, we evaluated the reliability and validity of our scales for EMP and CDS. Using confirmatory factor analysis (CFA) in EQS 6.1, we found that the two satisfaction measures exhibited good fit and convergent validity **(**χ^2 =3.37; RMSEA =.000; CFI=1.00; SRMR=.032). As with the measures developed in the earlier study (see Chapter 2), we conducted a χ^2 difference test between the two latent constructs and a constrained measurement model (Bagozzi, Yi, and Phillips, 1991), and found that the two satisfaction constructs exhibited good discriminant validity (p<.01). As a result of these analyses, it appeared that the two satisfaction measures were reasonable measures of the constructs of interest, and we incorporated them into our retail design strategy structural model (Model 1) as the dependent variables.

3.5 Analysis

To examine our model hypotheses, we first analyzed the fit of the sample data to the proposed design strategy model (Figure 3.2) using structural equation modeling (SEM) in EQS 6.1 statistical software (Bentler, 2005). Following Shah and Goldstein's

(2006, p.160) suggestions, we report multiple measures of fit (Table 3.3). First, the $\chi 2$ goodness-of-fit statistic; second, the absolute fit indices, including the root mean squared error of approximation (RMSEA); third, a general category measure of incremental fit indices, including Bentler's CFI, Bentler and Bonett's N-NFI in our analysis. To judge the effects of non-normality of individual items (Chapter 2), we also report 'robust' statistics to evaluate model fit (Byrne, 2006; Satorra and Bentler, 2001).

Table 3.3: Overall Model Statistics (Structural Model vs. Mediation Model)

Fit statistic	Model 1: Structural Model	Model 2[d]: Mediation Model	Recommended values
χ^2 – not adj.[1]	346.01	341.40	*Non sig. $\chi 2$ difference
d.f.	244	242	
χ^2/d.f.	1.42	1.41	< 3.0
RMSEA	.05	.05	≤ 0.05 [a, b]
(90% CI)	(.04-.06)	(.04-.06)	
NFI	.82	.82	> 0.8 marginal fit and
NNFI (TLI)	.93	.93	
CFI	.94	.94	> 0.9 good fit [b]
SRMR	.07	.07	< 0.09 [b]
Robust Fit Statistics (Satorra and Bentler, 2001)			
S-B χ^2	302.53	297.73	
N-NFI	.95	.95	> 0.8 marginal fit and
CFI	.96	.96	> 0.9 good fit [bc]
RMSEA	.04	.04	≤ 0.05 [a, b,c]
(90% CI)	.02-.05	.02-.05	

[1]no statistical difference between the two models (@ $p<.05$, X^2crit < 5.99, df=2)

[a] Brown and Cudek (1993).
[b] Hu and Bentler (1999).
[c] Bentler (2005), Byrne (2006)
[d] See Appendix 7.3 - Figure 7.3.1

The overall fit indices indicate that the proposed structural model (Model 1) fits the data reasonably well (X^2=346.00, CFI=.936, RMSEA=.049 (90% CI:.036to.06)). Figure 3.3 shows the parameter estimates and significance of each hypothesized path.[4] First, the product offering difficulty of use (DU) is positively and strongly associated with customer service encounter information requirements (DU→IR; γ_{51}= .41, p < .01), providing evidence to support H1. However, the relationship between product turnover (PT) and customer service encounter information requirements (IR) is non-significant and negative (PT→IR; γ_{52}= -.14, p > .10), providing no statistical support for H2. The final indicator, service production complexity (SC), has a positive and statistically significant association with customer service encounter information requirements (SC→IR; γ_{53}= .20, p < .05). The results support Hypotheses 1 and 3 which predict a positive effect of product difficulty of use and service production complexity on customer service encounter information requirements. Moreover, the three factors together explain roughly 23% of the total variance of customer service encounter information requirements (Table 3.4).

[4] Podsakoff, MacKenzie, and Lee (2003) recommend a number of tests (pp.890-891) for Common Methods Variance (CMV) including using a control common methods factor; however, they state that "potential problems may be encountered with identification of the model" (p.891). Our complete model failed to adequately converge (was underidentified) when including the common methods factor. Following the guidelines of Podsakoff et al., (2003), we tested the predictors and the specific criterion variables separately (p.895) to show the same model relationships existed when controlling for the methods factor. Given that our latent constructs showed no evidence of CMV problems using either the Harmon one factor test or the partial correlation test (completed in Chapter 2), we felt that CMV was not materially affecting the parameter estimates in the structural model analysis.

Figure 3.3: Structural Model Results (N=175) – Model 1
(Standardized Maximum Likelihood Parameter Estimates for multi-item latent constructs)

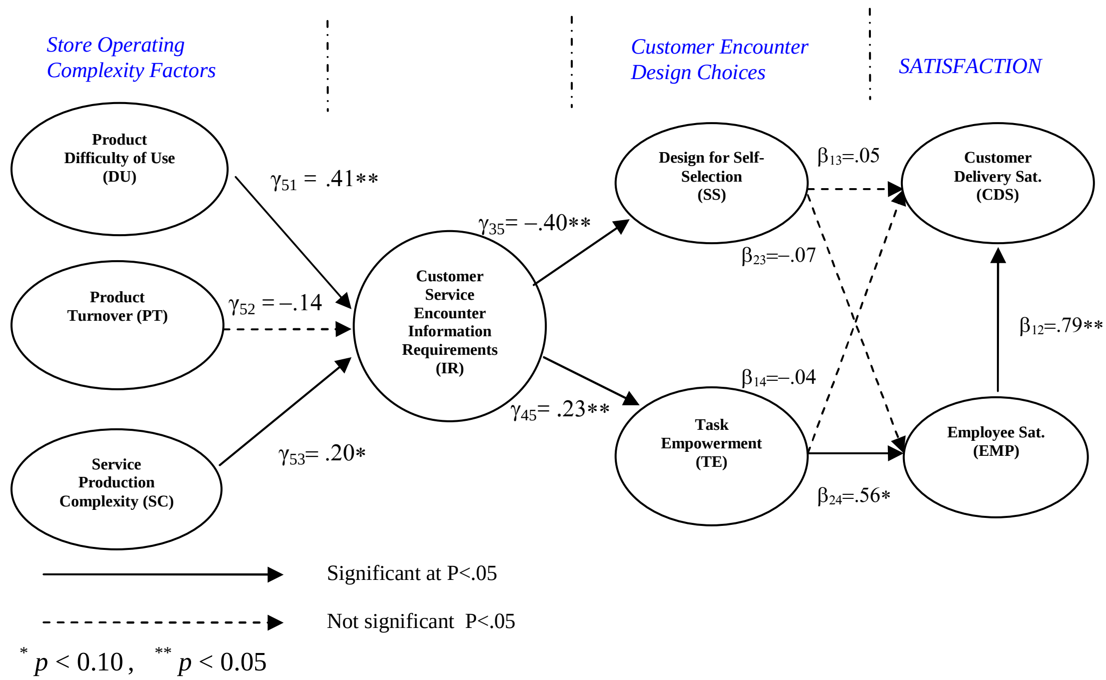


Table 3.4: Simultaneous Equations for Model 1
Standardized Estimates for latent constructs (EQS 6.1 output)

						R^2
$\eta 5$ = IR	=	.20*SC	+ .41*DU	- .14*PT	+ .88 $\varepsilon 5$	.23
$\eta 4$ = TE	=	.23*IR	+ .97 $\varepsilon 4$			.05
$\eta 3$ = SS	=	-.40*IR	+ .92 $\varepsilon 3$			.16
$\eta 2$ = EMP	=	-.08*SS	+ .56*TE	+ .82 $\varepsilon 2$		.32
$\eta 1$ = CDS	=	.05*SS	- .04*TE	+ .79*EMP	+ .65 $\varepsilon 1$	.58

The next series of hypotheses examines the effect that customer service encounter information requirements (IR) have on the customer encounter choices (SS and TE) in retail store systems. Hypotheses 4 a-b are initially supported. Customer service encounter information requirements (IR) are *negatively* associated with design for self-selection (H4a: IR→SS; γ_{35}= -.41, p < .01), also suggesting that stores use design for self-selection more when store encounter information requirements are low. In addition, customer service encounter information requirements (IR) are positively associated with store employee job empowerment strategies (H4b: IR→TE; γ_{45}= .23, p < .01). As such, these results provide evidence that store customer service encounter information requirements motivate the retailer's choice of customer encounter design, and that these strategies are consistent with extant OIPT and service operations management (SOM) theory.

Using the existing model (Model 1) we then tested H7, which suggests a positive association between the two satisfaction variables in our study. Employee satisfaction (EMP) is positively and strongly associated with the overall assessment of customer delivery satisfaction (EMP→CDS; β_{12}=.79, p<.01). This result supports consistent empirical findings in the service profit chain and quality literature on the important role that service employees play in satisfying customers (Heskett et al., 1997; Douglas and Fredendall, 2004).

To test H5a-H6b, and answer the remaining research questions related to design-satisfaction associations, we decomposed the mediated impact of customer service encounter information requirements (IR), and each design strategy choice (SS and TE) on employee (EMP) and customer delivery (CDS) satisfaction into an unmediated direct effect (D.E.), mediated indirect effect (I.E.), and total effect (T.E.). We did this by adding two paths to the proposed structural equation model (Bollen, 1989; James, Mulaik, and Brett, 2006; Menor, Kristal, and Rosenzweig, 2007, p.567-569) from the IR variable to each of the satisfaction variables (EMP and CDS). This additional model is called the mediation model (See Appendix Figure 7.3.1 – Model 2), for analyzing total, direct, and indirect effects. A mediator is evaluated based on the extent to which it accounts for the changes to the relationship between two variables (Baron and Kenny, 1986; Menor et al., 2007, p.568). Using our mediation model, we wanted to understand the mediated direct effect that each customer encounter choice (design for self-selection and employee task empowerment) was having on each of the satisfaction dependent variables, while still accounting for the customer service encounter information requirement (IR) relationship.

The statistical results reported in Table 3.5 yield several interesting results describing the associations between each customer encounter design choice (SS and TE), and employee (EMP) and customer delivery satisfaction (CDS). The mediation control model (see Appendix 7.3.1) also showed good overall fit with the data but was not statistically better than the proposed structural model (χ^2=341.40, CFI=.937, RMSEA=.049(90% CI:.036to.06). When analyzing the model for the direct, indirect, and total effects, we found that while customer service encounter information requirements (IR) are positively associated with both store employee (IR→EMP: Total effect =.16, $p < .1$) and customer delivery satisfaction (IR→CDS: Total effect =.24, $p < .05$). However, the direct, indirect, and total effects (see Table 3.5) reveal the different nature of each relationship.

Table 3.5:
Direct, Indirect, and Total Effects of Exogenous and Prior Endogenous Variables: Standardized Maximum Likelihood Parameter Estimates for multi-item latent constructs (N = 175)

	IR	SS	TE	EMP	CDS
Customer Service Encounter Information Requirements (IR)					
Total Effect	—	-.41**	.23**	.16*	.24**
Direct Effect (D.E.)	—	-.41**	.23**	.00	.18*
Indirect Effect (I.E.)	—	—	—	.16*	.06
Design for Self Selection (SS)					
Total Effect	—	—	—	-.18*	-.07
Direct Effect	—	—	—	-.07	.13
Indirect Effect	—	—	—	-.11	-.20**
Employee Task Empowerment (TE)					
Total Effect	—	—	—	.52**	.40**
Direct Effect	—	—	—	.56**	-.04
Indirect Effect	—	—	—	-.04	.44**
Employee Satisfaction (EMP)					
Total Effect	—	—	—	—	.79**
Direct Effect	—	—	—	—	.79**

Note: Statistical significance was calculated using the Sobel test outlined in MacKinnon et al. 2002
* $p < 0.10$, ** $p < 0.05$

Customer service encounter information requirements (IR) are indirectly associated with employee satisfaction (EMP) (I.E. = .16, $p < .05$) via the paths: IR → TE → EMP (I.E.=.14, $p < 0.05$) and IR → SS → EMP (I.E.= .03, $p > 0.10$). Given that only the first path is statistically significant (p<.05), we conclude that the customer encounter choices of retail stores (SS, TE) only partially mediate the relationship between customer service encounter information requirements (IR) and employee satisfaction (EMP). Coupled with the strong direct effect of employee empowerment (TE) on employee satisfaction (D.E.=.55, $p < 0.01$), it appears employee task empowerment leads to overall higher levels of employee satisfaction across retail stores.

In addition, we find that customer service encounter information requirements (IR) have a positive, and statistically significant total effect on customer delivery satisfaction (Total effect = .24, $p < .05$), Still, a statistically weak direct effect remains (D.E.= .18, $p<.10$) even after controlling for the mediating effects of design for self-selection (SS) and employee task empowerment (TE). This finding would seem to indicate that retail stores with higher customer service encounter information requirements (IR) generally perceive that customers are still more satisfied (CDS) with their store's service delivery, even when controlling for the customer encounter design choices indicated in the model and employee satisfaction (EMP). This may be because store managers feel that the information or service they provide to customers provides additional value-adding (problem-solving, supporting) capabilities for customers (Chase, Jacobs, and Aquilano, 2004) not captured in either customer encounter choice (SS, TE), or by employee satisfaction (EMP).

Our evidence suggests that the customer encounter design choices pursued by retail stores may play an important role in driving higher perceived customer delivery satisfaction (CDS) by either hindering or improving store employee satisfaction (EMP). In terms of indirect effects, two paths link the strategic design choices considered in this study with customer delivery satisfaction: TE → EMP → CDS (I.E. = .44, $p < 0.01$) and SS → EMP → CDS (I.E. = –0.20, $p < 0.01$). Employee task empowerment (TE) has a positive total effect on customer delivery satisfaction (Total effect.= .39, $p < 0.01$). However, this total effect is completely mediated by store employee satisfaction (EMP). On the other hand, design for self-selection (SS) has a negative indirect affect on customer delivery satisfaction (I.E. = -.20; p<.05). This is because design for self-selection negatively affects employee satisfaction (Total effect = -.18; p<.10). The direct effect of SS on CDS is actually positive in the mediation model (D.E. = .13, p>.10), but it is not statistically significant as we hypothesized.

The overall model results provide support for hypotheses 6b, as employee task empowerment appears to mediate the effects of IR on EMP. There appears to be no initial support for 5a, 5b or 6b, as design for self-selection (SS) is not positively associated with either employee satisfaction (EMP) or customer delivery satisfaction, and the positive total effect that employee task empowerment (TE) has on customer delivery satisfaction (CDS) is completely mediated by employee satisfaction (EMP). Finally, to examine if the overall model (Model 1) holds up under empirical scrutiny and eliminate alternative explanations for our findings, we examined other model paths for significance. We found that <u>no</u> additional model path parameters between any of the latent constructs were significant at p<.05.

3.5.1 Controlling for Store Size Effects

We repeated the procedures discussed above using path regression analysis in EQS 6.1, with maximum likelihood estimation (Model 3) to 1) validate the model and 2) to conduct an analysis on two store size group sub-samples (Kline, 2005). We used a multiple group path analysis approach (Kline, 2005, p.289-294) to avoid adding additional parameters to the model and weakening the statistical results because of the small sample size and the large number of items. First, we used an equally weighted average of items to develop a single item measure for each latent variable in the original structural model. The regression results for the path model (n=175) were similar to those observed for 1) the same proposed (Figure 3.3 – Model 1) structural model (n=175) and 2) the mediation effects model. Table 3.7 also shows that the overall path model exhibited adequate statistical fit. Parameter estimates in the path model were directionally the same, had roughly the same statistical effect size and significance; this analysis provided support that the original SEM findings were simulated by the path model analyses.

Table 3.6: Model Statistics (Multi-group Path Model Comparisons)

Fit statistic	Overall Path Model (Replicated SEM Model)	Multi-group Path Model (Store Size Groups)	Recommended Values
χ^2 – not adj.	21.65 (p=.06)	33.22 (p=.16)	
d.f.	13	26	
N-NFI	.87	.89	>.90
CFI	.94	.95	>.90
RMSEA	.06 (.00-.1)	---	<.05
SRMR	.06	---	<.09

We then examined if store size group membership would change the initial model findings. For competitive reasons, store managers are reluctant to share specific data on local store sales or profit measures. So, store size-related data (sales and number of employees per store) had to be collected in ordinal ranges on the survey. If a store was above the sample median in both number of employees and sales in the ordinal scale, it was classified as a ‘large store’ (n=85); otherwise, it was included in a ‘small store’ sub-group (n=90). The large stores group also consisted of about 68% (n=58) chain-owned stores, while the small store sample was about 33% (n=30) chain-owned stores.

First, an initial two-sample means analysis of the store groups showed that overall reported customer delivery satisfaction (CDS) factor scores from the large store group were significantly lower than for the small store group (t = -2.876, p=.003). For each store size sub-sample (large/small), multi-group path regression results showed the same Model 1 and mediation model (Model 2) relationships discussed in section 3.4.1. Standardized parameter estimates, errors, and critical ratios are reported in Table 3.7.

Table 3.7: Two-group Path Model Results - Standardized parameters, errors, and t-values - Maximum likelihood estimates (N = 175)[1]

					Structural (SEM) Model Parameters Overall (N=175)		**Path (ML Regression) Model Parameters To Test 'Store Size' Effects Model 3 Groups: a) Large Stores (N=85)**			**b) Small Stores (N=90)**		
Structural Model (Model 1)					S.E.	t-value	D.E.	S.E.	t-value	D.E.	S.E.	t-value
DU	IR	H_1	+	γ_{51}	.17	3.79	.41	.14	4.11	.23	.23	2.38
PT	IR	H_2	+	γ_{52}	.07	-1.60	.01	.08	.12	-.20	.07	-2.10
SC	IR	H_3	+	γ_{53}	.05	2.37	.15[1]	.09	1.49	.23[1]	.12	2.38
IR	SS	H_{4a}	-	γ_{35}	.09	-4.04	-.46	.09	-4.72	-.26	.14	-2.52
IR	TE	H_{4b}	+	γ_{45}	.09	2.62	.04	.10	.32	.28	.09	2.78
Mediation Effects Model (Model 2)					S.E.	t-value	D.E.	S.E.	t-value	D.E.	S.E.	t-value
SS	EMP	H_{5a}	+	β_{23}	.07	-.86	-.01[1]	.10	-.09	-.07[1]	.07	-.88
SS	CDS	H_{5b}	+	β_{13}	.05	1.45	.01	.07	.15	.19	.06	1.99
TE	EMP	H_{6a}	+	β_{24}	.06	6.12	.42[1]	.41	4.28	.42[1]	.11	3.84
TE	CDS	H_{6b}	+	β_{14}	.06	-.73	-.03	.08	-.38	.18	.09	1.24
EMP	CDS	H_7	+	β_{12}	.09	4.63	.55	.08	5.46	.27	.08	3.21

[1] No significant group differences for unstandardized coefficient estimates
Significant p<.05

While most parameter estimates across store group samples were consistent with those estimated by the structural and mediation effects model, there were some revealing group differences. First, in the large stores path model, the path IR→TE was not statistically significant (D.E. = .04, $p > .05$). In the small stores path mediated model, the path SS→CDS was statistically significant (D.E. = .19, $p < .05$). Therefore, it appears that conformance with the proposed structural model varies based on retail store size (large/small).

3.6 Discussion of Chapter 3 Results

Table 3.8 summarizes all of our findings across the multiple statistical analyses. Overall, we found at least some support for all but three (Chapter 3: H2, H5a, H6b) of the ten hypothesized relationships in Chapter 3. We also found that retailer conformance to the model varies by retail store size (sales and employees). In general, smaller stores were more in line with the proposed model (Model 1) and also reported higher overall customer delivery satisfaction (CDS) scores.

Table 3.8: Summary table of p-values for individual statistical tests of Hypotheses*

Hypothesis	**Overall Model (SEM)**	**Store Size (Multi-group Path)**		**Overall Conclusions**
	(n=175)	**Large (n=85)**	**Small (n=90)**	
H1: DU→IR	P<.05	p<.05	p<.05	Supported
H2: PT→IR	N.S.	N.S.	p<.05 (-)	Not Supported
H3: SC→IR	P<.05	p<.10	p<.05	Supported
H4a: IR→SS (-)	P<.05 (-)	p<.05 (-)	p<.05 (-)	Supported
H4b: IR→TE	P<.05	N.S.	p<.05	Partially Supported
H5a: SS→EMP	N.S.	N.S.	N.S.	Not Supported
H5b: SS→CDS	N.S.	N.S.	p<.05	Partially Supported
H6a: TE→EMP	P<.05	p<.05	p<.05	Supported
H6b:TE→CDS	N.S.	N.S.	N.S.	Not Supported
H7:EMP→CDS	P<.05	p<.05	p<.05	Supported

N.S = not statistically significant (p<.10)

Our first research question asked if retail store operating complexity factors were associated with customer service encounter information requirements. While two of the three store operating complexity factors – product difficulty of use (DU) and service production complexity (SC) - were found to be positively and significantly associated with customer service encounter information requirements (IR), product turnover (PT) was significant and negatively associated with IR only in small store settings. Additional analysis (Table 3.9) revealed that high PT scores tended to be concentrated in very transactional segments, such as small convenience stores and small/high-volume apparel retailers, which also tended to be part of a retail chain. While we do not want to read too much into this finding for the small store group, product turnover may actually indicate a highly transactional environment relying on scale efficiency that has fewer information requirements in some retail segments. Collectively, the store operating complexity factors do have a significant total effect on customer service encounter information requirements (R^2=.23).

Table 3.9: Store operating complexity factors: Segment score ranks
(#1 (highest) - #10 (lowest))

% checking "yes" on products type sold[1]	Freq	STORE OPERATING COMPLEXITY FACTORS DU Rank	PT Rank	SC Rank
Electronics/Appliances	21	1	2	2
Auto/Parts	14	2	10	1
Sport/Book/Music	21	3	7	3
Furniture	30	4	9	6
Health/Personal	33	5	5	9
Home Supply	12	6	8	4
Clothing	51	7	3	8
Food	41	8	6	10
Gas/Convenience	13	9	1	7
General	51	10	4	5

[1.] Freq' does not sum to n=175 as retailers could check "yes" to multiple product offerings

DU = Product Difficulty of Use
PT = Product Turnover (Depreciation)
SC = Service Production Complexity

Our evidence further suggests that retail customer service encounter information requirements (IR) significantly motivate retailers' customer encounter design choices – design for self-selection (SS) and designs that provide front-line employee task empowerment (TE). Overall, customer service encounter information requirements are negatively associated with design for self-selection strategies and positively associated with employee task empowerment strategies. By examining each alternative model path for significance we are able to show that customer service encounter information requirements completely mediate any direct effect between the store operating complexity factors and the customer encounter design choices of retail stores. This evidence supports the proposition that retail store designers are motivated to choose customer encounter designs based customer service encounter information requirements that they anticipate and not any other design strategy factor included in the model.

Next, we examined if customer service encounter information requirements along with either design for self-selection or employee empowerment design choices positively affected employee and customer delivery satisfaction. Here the results were mixed. We found that employee task empowerment has a direct positive association with store employee satisfaction, and a positive indirect effect on perceived customer delivery satisfaction. In addition, we find evidence that employee task empowerment is a critical driver of employee satisfaction in retail stores, and that this may be its most important contribution to store design strategy, given that employee satisfaction fully mediates the positive relationship (total effect) between empowerment (TE) and customer delivery satisfaction (CDS). While design for self-selection strategies (SS) are negatively associated with employee satisfaction, these negative indirect effects are confounded if customer service encounter information requirements and employee task empowerment are accounted for as control factors.

While most of the Chapter 3 hypotheses are supported, we find stronger support for the proposed model in smaller store settings. Applying our multi-group path model, we found that in large stores customer service encounter information requirements are not significantly associated with job designs promoting front-line employee task empowerment. Perhaps, this is because larger stores do not understand how to both manage empowered store employees, and still maintain control of the desired performance outcomes (Argyris, 1998; Eisenhardt, 1985). Alternatively, large retail stores may be so dominated by design for self-selection strategies and a focus on transactional efficiency (Ghosh, 1990), that job task empowerment strategies are not pursued to a large degree. However, we do find that design for self-selection is more effective at increasing overall customer delivery satisfaction in smaller stores than in these larger store settings. While the results may be an artifact of the different nature of our store sub-samples, our comparisons of customer delivery satisfaction scores indicate that smaller stores score higher as a.group. Ultimately, our evidence suggests that the strategic design decision to not empower store employees (and rely exclusively on design for self-selection) – as seen many large retail stores - may lead to lower customer delivery satisfaction, by negatively effecting the environment in which employs work (employee satisfaction). Chain ownership may mitigate these results to some degree because customers often enter into chain retail stores with more knowledge of the service delivery process, and these chains may also provide more convenience to customers. In addition, these stores may be offering the products at a price point customers perceive as more valuable. These specific tradeoffs need to be further studied.

This study does help explain the role that store employees play as information processors in retail store delivery systems. OIPT suggests that removing dependence on hierarchy increases system information processing capabilities, improving overall effectiveness and satisfaction. However, our analysis in retail store settings suggests that employee task empowerment improves customer delivery satisfaction to the degree that it creates more satisfied store employees. While there is a strong total effect of empowerment on customer delivery satisfaction, it does not appear that job design empowerment alone drives customer delivery satisfaction. Rather, employee task empowerment may be providing indirect benefits to store customers by giving front-line employees the ability to perform what Siehl et al. (1992, p.552) calls ‘rites of integration’ with customers by showing emotional warmth having the confidence to emotionally connect with and perform for them in a positive way.

In this analysis, we also find evidence in smaller retail stores that designing for self-selection has a positive direct effect, and may have positive customer satisfaction benefits by reducing unnecessary task complexity for store employees when information processing is not an issue. It is unclear why large stores do not see the same satisfaction benefits from design for self-selection strategies, unless the standardization of job tasks creates a work environment in these cases that is boring for store employees and this causes them to perform poorly (Ghosh, 1990; Zeytinoglu et al. 2004). Nevertheless, this finding provides an opportunity for more research.

In the small store case, our results may simply suggest that smaller stores are more adaptive to uncertainty than are large stores. While these findings do not directly speak to the importance of scale or cost-efficiency in larger retail store systems, they do suggest that smaller-sized stores have a perceived strategic service delivery advantage with respect to satisfying customers. In the case of small stores, this may also be because they provide a better information processing capability by placing more skilled employees close to the customer encounter, or may provide a more personalized human service experience (Voss et al., 2008; Cook, Bowen, Dasu, Stewart, and Tansik, 2002).

3.7 Chapter 3 Conclusions

Before discussing the contributions of this study, let us discuss some of its limitations. First, we used perceptual items from the store manager to measure customer delivery and employee satisfaction. While we attempted to compensate by using objective measures of satisfaction and secondary source data to validate our scales, we did not use multiple respondents or gather primary data from store's customers or employees. Future research should try to utilize more direct customer and employee feedback to further validate the model. In addition, we limited the study scope by examining only design for self-selection and employee task empowerment customer encounter design choices. It is possible that other strategies recommended by OIPT, including those that leverage information and communication technology to provide better customer information management or coordinative capabilities (Premkumar et al., 2005), would be effective or interact with these strategies in a positive or negative way. Finally, we did not have sufficient sample size to conduct a split sample structural model design for examining different retail store types, although we attempted to compensate by testing store size effects using a path regression analysis across different sub-sample groups of store sizes. Since the results for store size and ownership type share a lot of common membership across the sample groups, we are not able to determine if some cross-group variation was primarily due to ownership structure issues or managing the size of the store. Future research should further investigate this point..

This study makes several theoretical and practical contributions to the field of retail store design strategy and management. First, our structural model demonstrates how organizational design theory explains retail store design decision-making. This study also integrates organizational theory within a service production understanding of design strategy that is grounded in the resource based view (Roth and Jackson, 1995). Our evidence provides insight and understanding to the question: How do retailers manage, choose, and deploy store design architecture? By developing and empirically testing the proposed model, we examined several hypothesized design relationships in an important service industry setting. For researchers and practitioners, this study provides a platform for future research related to information-processing and customer encounter strategies in retailing, such as the use of customer relationships management (CRM) strategies, employee development and satisfaction training, use of in-store information and communication technologies, and customer training programs. Other satisfaction variables such as the ‘customer value proposition’ may also perform mediating roles, for example, between design for self-selection and customer delivery satisfaction (Vargo and Lusch, 2004). Incorporating each of these strategies into the model would provide valuable insight on the effectiveness of information systems, role of the customer, and employee cross-training in the retail trade industry. For practitioners and service scientists, we incorporate the role of human store servers and job design strategies to understand overall store design strategy relationships in the age of interactive technology promoting the use of self-service in store retailing environments (Hefley and Murphy, 2008; ifM and IBM, 2007). By providing new empirical support for the relationship between employee and customer satisfaction in retail store settings, we establish a nomological network of store design relationships across retail store operating complexity factors, customer service encounter information requirements, customer encounter design choices, and employee and customer delivery satisfaction.

In answering the research hypotheses, this chapter provides new insight into several important relationships to consider when designing retail store systems. Namely, that store product offering difficulty of use and service production complexity are positively associated with retail customer service encounter information requirements, which in turn are associated with the customer encounter design choices of retailers. Furthermore, we find evidence to suggest that when customer service encounter information requirements are linked with specific customer encounter design choices this can improve both employee and customer delivery satisfaction, and that store employee satisfaction plays a key mediating role in these design strategy relationships. Finally, we find that the model relationships vary by store size with respect to the motivation for customer encounter choices and their perceived impact on satisfying customers.

Retail stores provide an interesting context in which to study organizational designs and delivery system architecture strategies. As both a vendor of tangible products and associated services, merchandise retailers offer a unique perspective to study service delivery design strategy and what constitutes a “value-added” service offering. As researchers and practitioners develop a more scientific approach to analyze service production systems, it is critical that we examine different theoretical and industry perspectives of service encounter management and enhancement. By looking at retail service store design strategy relationships from an organizational information processing perspective, we hope this study provides a stimulus for conducting similar research in this area.

CHAPTER 4

Evaluating Store Design Responsiveness to Product Line Margin Changes:
An Empirical Analysis of U.S. Public Retailers

4.1 Purpose of Chapter 4

The purpose of this study is to investigate and measure ‘bricks and mortar’ retailers’ strategic store system design responses to product line gross margin changes over time. As discussed in previous chapters, delivery system design strategy is defined in the service operations management literature as the specification of the roles of people (e.g., service workers), capital, and the specific process by which a service is created and delivered (Chase and Bowen, 1991; Goldstein, Duffy, Johnston, and Rao, 2002; Roth and Jackson, 1995). Borrowing from inventory management research methods and terminology (Rumyantsev and Netessine, 2005; 2007b), we coin a term called ‘design responsiveness’ to describe and measure the co-movements of key delivery system design strategy decisions with product line gross margins over time. Specifically, we develop design responsiveness measures and use dynamic panel data analysis techniques to evaluate if retailers that simultaneously manage co-movements in product line margins, labor intensity, and capital intensity (investment) in their store systems year to year achieve superior operational performance.

We use panel data from the Compustat financial database, 10-K, and S&P company reports for “bricks and mortar” store retailers for the period 1994 – 2006 to develop an econometric model that links retail store design strategy decisions with financial operating performance. We also examine if designing store delivery systems to be responsive to product line gross margin changes improves operational performance (ROA). Specifically, our measurement proxy for design responsiveness is the percent change in a customer contact-related store system design practice (e.g. managing either store labor intensity or capital intensity [over time]) – versus the percent change in product line gross margin [over time]). Similar to studies examining inventory and sales co-movements (Rumyantsev and Netessine, 2005; 2007b), we posit that responsive retailers align product margins and their store system design strategies over time to achieve superior operating performance. Therefore, the degree to which firms either increase or decrease labor or capital intensity in their store systems at a faster rate than product line gross margins leads to worse financial operating performance year to year. We believe that our exploratory findings bring insight as to whether retail store systems should be designed to be responsive, or should become even more efficient relative to product line gross margin changes over time.

An example of store system design responsiveness can be seen in the U.S. consumer electronics retail segment. Throughout the 1990's, Best Buy Company, Inc. utilized a predominantly a self-service (low labor intensity) store system design strategy. During this period, Best Buy stores specialized in selling accessories, games, and personal computers in a rapidly declining product line margin environment and competed primarily on price and cost-efficiency. By 2001 - 2002, mass merchants Costco and Wal-Mart had moved aggressively into the consumer electronics segment using an even more cost-efficient store selling system. In response to the emerging threat, Best Buy's management recognized that it had to reformulate its store system design strategy to sell a portfolio of higher margin goods and services to remain competitive (Lal, Knoop, and Tarsis, 2006, p.3). Meanwhile, other segment competitors (e.g., Circuit City, CompUSA) were de-emphasizing human contact in their store systems in order to increase operating margins and compete with the mass merchants on scale and cost-efficiency. On the other hand, Best Buy bundled a higher margin product and service offering (Lal et al., 2006, p.4; O'Donnell, 2008) and invested in more store labor and capital to sell a variety of complex digital products and related services. While these store system operating changes were initially met with skepticism, Best Buy has far outperformed its segment competitors over recent years (O'Donnell, 2008).

Service/product bundle offering strategies do not often align with delivery system design strategies in practice, providing an opportunity for service operations management research (Roth and Menor, 2003; Chapter 1-2). This is particularly true in store retailing, as retail investment analysts have struggled to craft meaningful measures that link strategic design-related factors to financial accounting returns and operational performance (Gage, *Forbes*, 2007). Moreover, academic literature has argued that poor service performance persists because service firms generally do not link their service concept intentions with actual design architecture choices (Goldstein et al., 2002; Roth and Menor, 2003, Chapter 1-3). Linking the service product offering and the delivery system design strategy is a critical determinant of service delivery capabilities and sustainable performance (Roth and Menor, 2003; Huete and Roth, 1988). Yet, we argue that the alignment of product line margin and store system design strategy is a dynamic and strategic process that is not well-understood by either retail practitioners or academics.

Retailers simultaneously manage both product offering and service delivery functions (Murray and Schlacter, 1990) in their store systems. Because they offer both tangible products and supporting store services, retailers have different operating and environmental characteristics than other types of services - e.g. hospitals or banks. ‘Bricks and mortar’ store retailing has also received little specialized attention in the service design strategy literature. Notable exceptions include work by DeHoratius and Raman (2007), examining manager job design and incentive structures at Tweeter Electronics stores; and Fisher, Krishnan, and Netessine (2006) who examine retail store execution measures among stores in a single chain retailer. In 2001, the journal *Manufacturing and Service Operations Management* published a focused issue (Vol. 3, No. 3) on ‘Retail Operations Management.’ However, the focus of this series of papers is on more tactical applications of operations research techniques to solve assortment, logistic, and inventory optimization problems in retail store environments. Like other strategic issues surrounding services (Menor, Roth, and Mason, 2001, p.275), retail store design strategy and management has not been a key focus area of academic empirical research.

Nevertheless, the merchandise retailing sector is becoming a more critical component of the U.S. economy, employing the largest number of American workers and constituting over $1.3 trillion in domestic economic output (U.S. Bureau of Economic Analysis 2007, http://www.bea.gov/industry, 9/6/2008). It is also a particularly aggressive and dynamic industry, with any strategic move (like a product price cut), typically requiring an immediate response from other retailers to either improve their competitive position or to even survive (Ghosh, 1990, p.37). Moreover, U.S. retailers have spent over $30 billion annually in capital investment (mostly on technology systems or better store locations) to improve internal and external process performance (Fisher and Raman, 2001). Yet, reports of the financial benefits of these types of strategic capital investments have been mixed over the last decade, as retail firms are still characterized by high failure rates and low customer service (McGurr and DeVaney, 1998), but have also been attributed to industry improvement in some inventory and cost-efficiency measures (Chen, Frank, and Wu, 2007).

The industry trends seen in store retailing overall may also be attributed to the rise of Wal-Mart Stores, Inc. and other mass merchants who have leveraged their economies of scale and cost-efficient store design systems to put pressure on gross margins in some product line segments. These changes have forced competitors to respond to mass merchants by either imitating their operating and store design strategies (Boyd and Bresser, 2008), or by investing more labor or capital resources in their store systems (like Best Buy) to support the complexity of offering a wider variety of higher-margin products and related store services (Menor et al., 2001; Lal et al., 2006).

This research fills an important gap in practitioner and academic understanding of store system design strategy by empirically examining and measuring the elastic effects of retail store system design choices with product line margins over time. It uses multiple measures of retail design responsiveness and publicly available secondary source data.

Our operationalization of design responsiveness is a co-movement measurement of the percent change in both labor and capital intensity in a retailer's store system relative to the percent change in product line gross margins year over year. We argue that successful retail firms simultaneously and actively align store system design strategies with product line margin changes. This continuous alignment may either be the focus of new retailer strategies to provide new products or services (Ghosh, 1990, p.47), or a competitive response to new entrants into their segment (Boyd and Bresser, 2008; Ghosh, 1990). We then develop an empirical link from retail store system design strategy choices to financial operating performance using an econometric model. Finally, we discuss if retailers should design store systems to be responsive to product offering margins, or if they should always be designed to be more cost-efficient, reflecting a Wal-Martization of retail store design strategy (Boyd and Bresser, 2008).

To examine design responsiveness over a wide range of retail store systems, we propose a series of research questions. To answer these questions, we need to develop an empirical means to measure design responsiveness. Therefore, we ask: Can store design responsiveness be measured using publicly accessible data? Our next research question asks: Do retail firms pursue responsive store design strategies to product line margin changes? Finally, we propose hypotheses to examine if our measures of design responsiveness are associated with operational performance in the retail trade industry by asking: Does store system design responsiveness indicate better (or worse) firm operating performance?

The remainder of this paper is organized as follows. First, we identify the key issues surrounding design responsiveness by examining the service design strategy literature. Second, we discuss our design responsiveness measures, define the variables used, and present our empirical methods and research model. Third, we discuss our results. Finally, we address the study limitations and offer interesting areas for future research studying retail store design strategy.

4.2 Literature Review

Design responsiveness reflects the ability of the retailer to continuously align customer contact requirements with actual store system design strategies. Customer contact theory (Chase, 1978; 1981) has arguably become the dominant theoretical lens through which researchers have viewed service operations management (SOM) and design strategy. Generally, design strategies can be organized and positioned around the need for customer contact anticipated in the service delivery system (Chase and Tansik, 1983). Service management research has further suggested that customer contact needs are driven by both the customer perceived complexity and the information content of the service offering (Buzacott, 2000; Bitner, Faranda, Hubbert, and Zeithaml, 1997; Kellogg and Chase, 1995; Huete and Roth, 1988). More recent interpretations of customer contact theory have focused on management opportunities to use technology capital investment and location accessibility to substitute for human contact in service systems (Xue, Hitt, and Harker, 2007; Froehle and Roth, 2004; Boyer, Hollowell, and Roth, 2002).

The desire to maintain customer contact levels through automation and customer participation has also been seen in service science-oriented literature. Service science is a joint movement by academics and practitioners studying services to develop a more scientific approach to services management that recognizes the important differences between services and other types of production systems (ifM and IBM, 2007; Chesbrough and Spohrer, 2006). To date, service science research in operational design strategy has focused on using technology or capital investment to automate processes and reduce labor intensity, lowering cost and increasing economies of scale (Hefley and Murphy, 2008). The dominant service science view is that by using technology capital to manage complex product-selling environments, processes can be more fully automated, thereby increasing cost-efficiency (IBM, 2005; Chesbrough and Spohrer, 2006). However, customer service experiences are also an important strategic service design consideration (Voss, Roth, and Chase, 2008), and it is possible that automation/self-service can have negative associations with customer service level, satisfaction, and retention (Fornell, 2007).

Automation in service design strategy generally means developing self-service channels for product/service delivery. Service organizations pursue self-service design strategies primarily to increase cost-efficiency (Bitner et al., 1997; Chase, 1978). While many service segments effectively rely on customers to perform most service delivery tasks (think fast food self-service – see Buzacott, 2000), this is only possible if customers can effectively perform these tasks without help. Alternatively, when service processes and products are more complex, opportunities to use self-service channels of delivery are less preferred by customers (Xue and Field, 2008). More labor (human) contact helps to manage additional service encounter complexity (Chase, 1978; Kellogg and Chase, 1995), but investments in technology and/or increased channel accessibility can mediate direct human contact requirements (Froehle and Roth, 2004; Boyer et al., 2002). The degree to which a customer can manage the complexity of a transaction in a service delivery process - through prior product knowledge, location convenience, or information clarity - determines their willingness to participate in self-service channels (e.g. Bateson, 1985; Xue et al., 2007; Bettencourt, 1997).

Service design strategy literature grounded in the resource based view (RBV) of the firm (Wernerfelt, 1984; Barney, 1991), argues that organizations strategically choose, build, combine, and deploy human and capital resources in building service delivery system "architecture" that adapts to customer contact needs (Roth and Menor, 2003; Roth and Jackson, 1995). This design "architecture" is made up of the specific structural (buildings, equipment), infrastructural (policies, job design, and labor management), and coordinative resource choices (Roth and Jackson, 1995). While empirical studies of retail design architecture are lacking, the importance of continuously aligning service delivery system design capabilities with product/service offerings is generally acknowledged (e.g., Roth and Jackson, 1995; Roth and Menor, 2003; Fitzsimmons and Fitzsimmons, 1999).

In contrast to simply designing service systems to be more cost-efficient (more self-service) in all cases, some service design research states that firms follow a progression in aligning resource competencies with product markets (Heskett, Sasser, and Hart, 1990; Menor et al., 2001). For example, both Menor et al. (2001) and Roth and van der Velde (1992) find that increasing banking product complexity has resulted in higher operating margins, and the need for retail banks to deploy more flexible service design architecture. Agile banks are those most likely to invest in more human capital to manage increasing product offering variety, and they also operate in more complex and higher-margin service environments and better satisfy customers (Menor et al, 2001, p.286). Moreover, there are immediate financial impacts from not being responsive (or adapting) to customer contact needs. Fornell (2007) uses the American Customer Satisfaction Index (ACSI) to find that poor customer service quickly leads to negative financial returns. In total, these findings confirm customer contact theory by suggesting that more complex systems need high levels of human contact, substitutable technology, or customer location convenience to manage product and service-bundle complexity over time.

The field of operations management (OM) has established important connections between margin management, product-service offering complexity and variety, and the most responsive production design strategy. OM research suggests tan important link between product line variety, gross margin, and operating complexity (e.g. Gaur, Fisher, and Raman, 2005; Randall and Ulrich, 2001; Hayes and Wheelwright, 1979). More human skill (know-how), not just technology investment, is necessary to manage more dynamic product-service offering environments (Menor et al., 2001; Pheffer, 1994). A strong association between complex products, higher margins, and operating design strategies suggests that product line complexity can be a root cause of profit stagnation if not managed effectively (Gottfredson and Aspinall, 2005). Nevertheless, Gaur, Fisher and Raman (1999) find that a strong positive association exists between retail product line gross margins and firm performance.[5] Retailers can improve store margins through effectively using their store labor and capital resources, especially if the appropriate incentive structure is in place to manage product-selling activities (DeHoratius and Raman, 2007), and store labor staffing requirements are met (Fisher et al., 2006).

Responsive firms may also be better at adapting quickly to changes in market demand conditions, resulting in higher profits (Randall, Morgan, and Morton, 2003). Retail firms, in particular, may need responsive store design architectures to facilitate quick changes because of the competitive nature of the industry. As such, we want to make clear that our concept of design responsiveness is a proxy measure for the operational alignment of product line margin and retail store design strategy co-movements over time, not a direct measure of agility or the strategic intent. Therefore, we make several assumptions in developing our research model. First, our assumption that gross margins and design strategies are linked is grounded in the understanding of the retail investment analyst community that product line margin peaks often indicate strategic design shifts in retailing (Gage, *Forbes*, 2007), and in the research streams listed above, which examine customer contact and service delivery automation across service industries. Second, we acknowledge that little retail industry literature examines retail store system design strategy, or develops much empirical measurement related to service strategy at all (Menor et al., 2001). Finally, we recognize that the systematic and

[5] Gaur, Fisher, and Raman (1999) do not examine the co-movement of gross margin and design strategy. Rather, they examine a measure of GMROI to show the positive association of product line gross margins on retail stock returns.

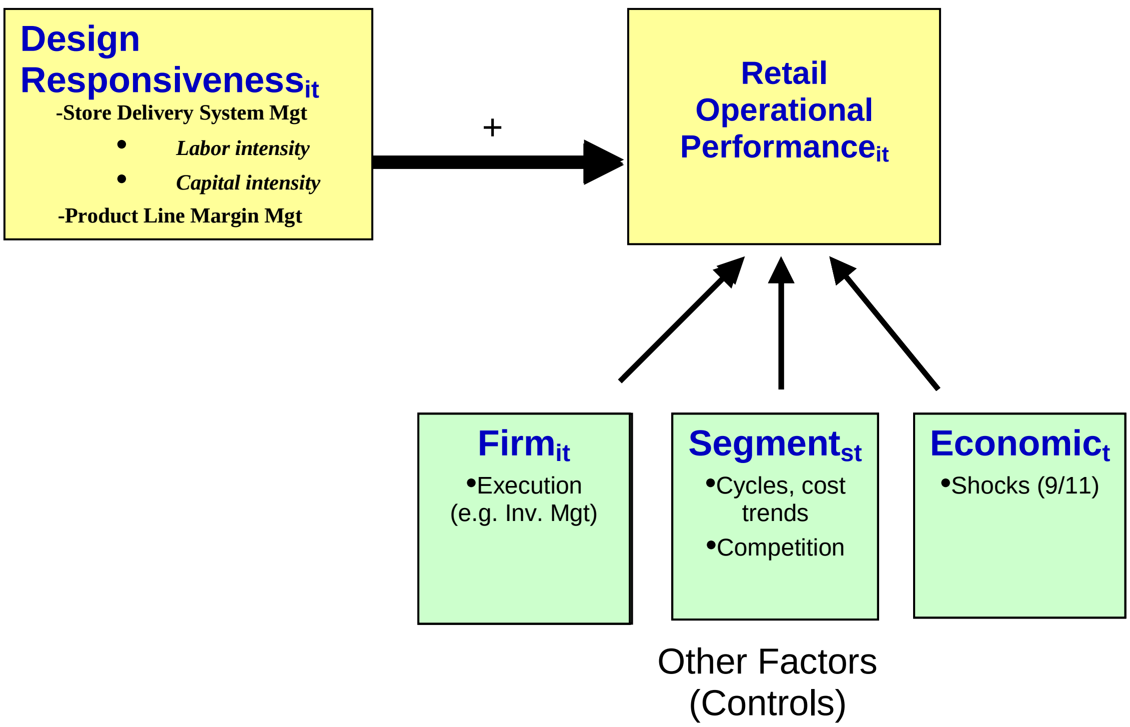
dynamic relationships between service operations strategy, product line or service context, and performance measurement are not well developed (Soteriou and Zenios, 1999; Menor et al., 2001). This paper contributes to a greater understanding of these relationships by analyzing the dynamic and competitive changes in the retail industry landscape (Boyd and Bresser, 2008) by using dynamic panel analytical tools and techniques. While we must rely on secondary databases and proxies to measure strategic design shifts, we take safeguards to stay theoretically and practically grounded in the actual product offering and systems design strategy issues that retail firms face.

The next section presents the conceptual model and discusses our measurement of design responsiveness. Our measurement approach comes from inventory management literature examining inventory and sales co-movements across multiple industries, including retailing (Rumyantsev and Netessine, 2005; 2007a,b; Gaur et al., 2005; Chen et al., 2007). While this foundational work examines the alignment of sales with responsive inventory management policies, we believe that similar measurement techniques offer interesting insights to examine store design strategy and product line margin co-movements. As the misalignment of operating strategy and environmental conditions is characterized by negative performance impacts (Venkatraman and Prescott, 1990), it is important to have an empirical means to examine the co-movement of retail design strategic decisions and product line margin management to discover what retail firms should do. Next, we link our discussion of service design strategy literature to the research model.

4.3 Model Development and Hypotheses Formulation

Retail design responsiveness is the simultaneous management of the store system design strategy with product line margins over time (Figure 4.1). We posit that design responsive firms outperform unresponsive firms, after controlling for other firm-specific, segment-specific, and macroeconomic effects (McGahan and Porter, 2002, p.835).

Figure 4.1:
Conceptual Model – Factors Affecting Operational Performance in Store Retailing



Our model assumes that retail firms behave rationally in their strategic design decisions to maximize profits. Therefore, we assume that retail firm strategic design planning and decision-making can be seen in year to year relationships among key operational variables such as sales, gross margin, and in resource investment decisions about store system employee labor and store capital. Therefore, we identify and evaluate strategic design shifts across all retailers by examining the co-movement of gross margins with the amount of 1) store labor intensity, and 2) store capital intensity required to deliver upon the intended service concept, while still maintaining or expanding firm profits. Retailing firms determine to what degree they wish to provide customer contact in their store systems and what form this contact will take (Chase, 1978). We argue that the degree to which retailers simultaneously manage these contact-design choices with their product line gross margins will be a key indicator of financial performance, after controlling for other firm-specific, segment, and timing effects.

4.3.1 Measuring Design Responsiveness

Our proxy measures of store design responsiveness are grounded in both current and classical inventory management research methodologies to measure the elasticity of inventory supply and sales demand (Rumyantsev and Netessine, 2005; 2007b; O'Glove, 1987). However, we apply this logic to analyze annual changes in product line gross margin versus annual changes to store system designs by using store labor and capital intensity as proxy variables to understand those relationships. Our base equation for measuring design responsiveness is stated as follows for the store labor intensity design responsiveness variable:

(Eq.4.1) $$SL_t = \frac{L_t - L_{t-1}}{L_{t-1}} - \frac{GM_t - GM_{t-1}}{GM_{t-1}}$$

where L_t stands for period t store labor intensity, and GM_t stands for period t product line gross margins. A positive result (> 0) indicates store system labor intensity is increasing at a faster rate than gross margins, while a negative (< 0) result indicates that store system labor intensity is declining relative to gross margins. A score of zero would indicate complete design responsiveness, as changes in gross margin were matched with store system labor intensity shifts in the given year.

The degree of human contact (or conversely self-service level) used in the store delivery system strategy is measured with a *store labor intensity* (*L*) ratio, which is simply the number of employees per selling square foot. Self-service store design strategies requiring less human contact will typically require lower labor intensity to deliver the service and maintain profitability. Alternatively, firms increasing human contact levels in store systems will increase the labor intensity ratio in their store systems. Because more complex product offerings are associated with higher gross margins (Randall and Ulrich, 2001), we posit that higher levels of store labor intensity will need to correspond with higher gross margins to stay in alignment. Alternatively, failure of these store system designs to provide adequate human labor contact will ultimately result in negative performance impacts (Menor et al., 2001). Therefore, we state the following Chapter 4 hypotheses for both positive and negative responsiveness measures for store labor intensity:

H1: *When SL is <u>positive</u>, a higher measure of design responsiveness in store labor intensity will be associated with worse operational performance.*

H2a: *When SL is <u>negative</u>, a lower measure of design responsiveness in store labor intensity will be associated with worse operational performance.*

While some operations research has advocated that retail firms should pursue self-service design strategies only when selling simple, lower-margin products (Buzacott, 2000); other research challenges this notion by indicating that retailers have achieved disproportionate financial benefits through self-service designs to increase economies of scale and cost-efficiencies (Boyd and Bresser, 2008; Chen et al., 2007). Therefore, we also wish to examine the following alternative Chapter 4 hypothesis for a negative responsiveness measure for store labor intensity.

H2b*:* *When SL is <u>negative</u>, a lower measure of design responsiveness in store labor intensity will be associated with better operational performance.*

Similarly, substituting *K* for *L* provides the baseline equation for calculating design responsiveness for store capital intensity vis-à-vis product line gross margin changes:

(Eq. 4.2) $$SK_t = \frac{K_t - K_{t-1}}{K_{t-1}} - \frac{GM_t - GM_{t-1}}{GM_{t-1}}$$

where K_t stands for period t store capital intensity, and GM_t stands for period t product line gross margins. Store design strategies that leverage technology, store fixtures, or location investment are represented by the variable *store capital intensity* (K) – which is the ratio of store-invested capital per selling square foot. Operations management research states that a retail firm may wish to use technology capital to manage complexity or product variety (Gaur et al., 1999), or may wish to invest in new store locations that are more convenient for customers to access (Xue et al., 2007). Increasing store capital intensity may have two additional strategic purposes by either substituting for higher human contact, or by providing greater economies of scale and a more cost-efficient selling system for lower-margin, high-turnover products. Retail firms either purchase or enter into lease agreements for buildings, technology, or store fixtures to achieve customer contact objectives. A positive responsiveness measure for store capital intensity (> 0) indicates that a retail firm may be over-investing in store capital. Conversely, a negative capital intensity responsiveness measure (< 0) suggests that a retail firm was under-investing in store capital, possibly leaving itself vulnerable to more adaptive retailers with more robust selling systems or better store locations. Therefore, we state the following Chapter 4 hypotheses for both positive and negative measures for store capital intensity responsiveness:

H3: *When SK is <u>positive</u>, a higher responsiveness measure in store capital intensity will be associated with worse operational performance.*

H4: *When SK is <u>negative</u>, a lower responsiveness measure in store capital intensity will be associated with worse operational performance.*

4.4 Database Sample Description

Financial data was collected for the time-period 1994-2006 for the entire population of “bricks and mortar” U.S. public retailers listed on the stock exchanges NYSE, NASDAQ, and AMEX, from the Standard and Poor’s COMPUSTAT Annual Fundamentals database using Wharton Research Data Services (WRDS, http://wrds.wharton.upenn.edu). The year 1994 was chosen as the starting date of our analysis because it is the first full retail fiscal year of data after the end of the last retail recession. We identified product-selling retailers and their product line category based on the four digit Standard Industry Classification (SIC) sample selection criteria for “retail trade” outlined in Gaur et al. (2005), excluding wholesalers, e-commerce retailers, retail holding companies, bankruptcy years, and American depository receipts (ADRs). There were 487 retailers that report at least one year of financial data to the Securities and Exchange Commission (SEC) during the study time period.

To follow established practices in dynamic ratio analysis (Peterson and Fabozzi, 2006; Kremer, Rizzuto, and Case, 2000), we selected only firms with five or more years of complete financial data during the period, which reduced the industry field sample to 320 retailers. We then manually collected data on the number of stores and the gross selling space (square feet) for each retailer in each year from multiple secondary data sources. We primarily used 10-K (annual report) statements accessed through the SEC Edgar database (http://www.sec.gov/edgar). However, we supplemented and validated this 10-K data using retail statistics purchased from the U.S. Business Reporter Database (http://www.usbrn.com), and data from Standard and Poor’s Retail Industry Reports

(Also available in WRDS, http://wrds.wharton.upenn.edu). While the retail investment community encourages retailers to report store-level operating information it is not mandated by Generally Accepted Accounting Principles (GAAP), and many retailer annual statements do not report information on selling square feet or number of stores. Yet, we found that most retailers do report aggregate store-level operating data their annual statements. As Table 4.1 shows, only 88 retailers (out of the 320) do not report store-level information during the study time period. This left us with our final industry field sample of 232 retail firms and 2,039 observations.

Table 4.1:
Frequency table showing number of years of reported store level data (1994 – 2006)

Number years of complete store-level information	**Number of retailers**	**Number of observations**
Retailers 5+ yrs Financial Data	*320*	
0 (dropped)	-88	------
1-3	**21**	**48**
4-6	**58**	**287**
7-9	**38**	**301**
10-12	**44**	**480**
13	**71**	**923**
Final Industry Field Sample	***232***	***2,039***

The U.S. Department of Commerce assigns a four digit primary SIC code to each retail firm according to its primary industry or product segment. Retail firms may also span several segments and have other assigned secondary SIC codes, or they may move from one four digit primary SIC code to another because of product portfolio changes or S&P reclassification. To avoid small sample bias present in segment-level data in these cases, we followed the guidelines of Gaur et al. (1999; 2005) to identify 12 relatively distinct operating segments in the retail trade industry by using primary SIC code groupings. Table 4.2 lists the segments, groupings, and corresponding example firms for each segment.

Table 4.2:
Retailers reporting store-level information for square feet and # of stores (1994 – 2006)

SIC (4 digit)	Segment Group Name	# of Retailers	Examples
5211	Lumber and building materials stores	6	Home Depot, Lowes, National Home Centers
5311	Department stores	17	Sears, Macy’s, Dillards, J.C. Penny
5331, 5399	Variety stores	25	Wal-Mart, Target, Warehouse Clubs
5400 – 11	Grocery stores	35	Albertsons, Kroger, Safeway
5600 – 99	Apparel and accessory stores	64	Ann Taylor, Gap, Limited
5700 – 11	Home furnishings and equip stores	14	Bed, Bath, and Beyond, Linens-N-Things
5731	Radio, TV, and appliance stores	14	Best Buy, Circuit City, RadioShack
5734, 5735	Computer and computer software stores, Records and tapes	9	Babbages, CompUSA, Gamestop
5912	Drug and proprietary stores	7	CVS, Rite Aid, Walgreens
5940	Misc. stores- other	24	Staples, Barnes and Noble, Sports Authority, etc
5944	Jewelry stores	7	Tiffany, Zale
5945	Hobby, toy, and game	10	Toy’s R Us, Zany Brainy, Michaels, etc.
Sample Total		**232**	

4.5 Variable Definitions

We use the following notation for our model variables. From the Compustat Annual Fundamentals data, for firm *i* in year *t*, let S_{it} be the total sales for the firm (Compustat Fundamentals field ‘SALE’); $COGS_{it}$ be the cost of goods sold (COGS); AT_{it}

ending total assets for the period (AT); $LIFO_{it}$ be the LIFO reserve (LIFR); $INVT_{it}$ be the ending total inventory for the period (INVT); $OIBD_{it}$ be the operating income before depreciation (OIBDP); PPE_{it} be the ending net property, plant, and equipment for the period (PPENT); and EMP_{it} be the average number of employees for firm *i* calculated by averaging the ending number of employees (EMP) for year *t-1* and year *t* for each year *t*. From our 10-K and S&P collected data, let $SQFT_{it}$ be the average gross selling square feet for firm *i* calculated by averaging SQFT for year *t-1* and year *t*.

Several adjustments must also be made to make firm-level performance variables and ratios comparable. Retail firms often use different inventory valuation methods (e.g. FIFO versus LIFO methods) and this practice produces differences in firm to firm reporting of period-ending inventory (INVT) and cost of goods sold (COGS). We accounted for inventory valuation method differences by adding the LIFO reserve (Compustat field ‘LIFR’) into the ending inventory calculation for of a given fiscal year. In addition, the change in LIFO reserve from year to year was subtracted out of period-ending COGS (e.g., Kesavan, Gaur, and Raman, 2008). This practice ensures that resulting ratios calculated from these variables for the sample firms are comparable.

4.5.1 Dependent Variables

We use the retail firm’s return on assets (*ROA*) as the primary measure of operational performance for this study (Barber and Lyon, 1996; Rumyantsev and Netessine, 2005; 2007a,b; Gaur et al, 1999). We operationalize ROA as the operating income generated per dollar of total investment. Because performance measures using operating income ratios can vary based on firm scale or accounting treatments (Barber and Lyon, 1996, p.397), we control for any potential performance measurement bias by using return on sales (*ROS*) as an alternative measure of operating performance. We are also interested in the carryover associations of strategic design decisions on forward firm operational performance, so we also examine forwarded ROA (*ROAF*) for *t+1* year period. The basic formula for ROA in year *t* is calculated as follows[6]:

(Eq. 4.3) $$ROA_{its} = \frac{OIBD_{its}}{\left(AT_{i(t-1)s} + AT_{its}\right)/2}$$

4.5.2 Independent Variables

The joint movement of gross margins and store delivery system design strategies for labor and capital is measured using the design responsiveness elasticity measures SL_{its} and SK_{its} introduced in section 4.3.1. Table 4.3 shows the components and each design responsiveness measure. GM_{its} is simply Sales minus COGS, adjusted for the inventory valuation method. Our measure of L_{its} is stated as the ratio of the number of employees (*EMP*) to total gross selling square feet (*SQFT*) for all stores during the period. Our measure of K_{its} is the sum total of PPE_{its} and the net present value of five-year lease contracts (capitalized leases) using the notation $LC_{it,1}$ (MRC1), ….., $LC_{it,5}$ (MRC5) in

[6] Return on Sales (ROS) and Forwarded ROA (ROAF) are calculated in a similar fashion as regular ROA using OIBD in the numerator and sales and forward average assets respectively in the denominator.

Compustat[7]. To simplify the capitalized lease analysis, we used a discount rate *r = 9.3%* based on the average weighted average cost of capital (WACC) of the retailing industry reported from Value Line (A. Damodaran, Damodaran Online, http://pages.stern.nyu.edu/~adamodar, 9/3/2008).

Table 4.3:
Definition of Component Measures and Independent Variables

Component Measures	
Product Line Margin (Gross Margin)	$GM_{its} = \dfrac{S_{its} - COGS_{its}}{S_{its}}$
Store Labor Intensity	$L_{its} = \dfrac{EMP_{its}}{SQFT_{its}}$
Store Capital Intensity	$K_{its} = \left[PPE_{its} + \sum_{\tau=1}^{5} \dfrac{LC_{its}}{(1+r)^{\tau}} \right] \Big/ SQFT_{its}$
Store Design Responsiveness Measures (Co-Movements of Design Strategy Variables and Product Line Margins)	
Design Responsiveness – Labor Intensity	$SL_{its} = \dfrac{L_{its} - L_{i(t-1)s}}{L_{i(t-1)s}} - \dfrac{GM_{its} - GM_{i(t-1)s}}{GM_{i(t-1)s}}$
Design Responsiveness– Capital Intensity	$SK_{its} = \dfrac{K_{its} - K_{i(t-1)s}}{K_{i(t-1)s}} - \dfrac{GM_{its} - GM_{i(t-1)s}}{GM_{i(t-1)s}}$

** Note that COGS is adjusted for the LIFO reserve as stated above*

A positive (or negative) result any of our store design responsiveness measures would indicate that a firm was trying to increase (decrease) labor or capital intensity in their store systems at a faster rate than changes to product line gross margins. Since our hypotheses predict negative relationships between these variables and our operating

[7] Both Gage, *Forbes* (2007) and Kesavan, Gaur, and Raman (2008) discuss the importance of adjusting for capitalized leases when conducting capital analyses among different store retailers

performance measures, we follow the standard inventory co-movement methodology (Rumyantsev and Netessine, 2007b) by further defining variables to capture both directional positive (increasing) and negative (decreasing) co-movements for each design responsiveness variable listed in Table 4.3 above as follows:[8]

For *Store Design Responsiveness – Labor Intensity*,

$$SLinc_{its} = SL_{its} \times 1_{(SL \geq 0)} \text{ ; } SLdec_{its} = SL_{its} \times -1_{(SL \leq 0)}$$

For *Store Design Responsiveness – Capital Intensity*,

$$SKinc_{its} = SK_{its} \times 1_{(SK \geq 0)} \text{ ; } SKdec_{its} = SK_{its} \times -1_{(SK \leq 0)}$$

4.5.3 Control Variables

We use the following additional notation to operationalize our control variables. From our 10-K and S&P collected data, let N_{it} be the total number of stores open for firm *i* at the end of year *t*. In addition, to calculate average inventory (Inv_{it}) for our inventory management ratio, we take the previous annual period (*t-1*) inventory ending balance ($\text{INVT}_{i(t-1)}$ adjusted for the LIFO reserve) from Compustat Annual Fundamentals, add in the current period balance (INVT_{it} adjusted for the LIFO reserve), and take the average of the two numbers. So, our final measure of Inv_{it} for a given year is a calculated adjusted average of the prior ($\text{INVT}_{i(t-1)}$) and current year (INVT_{it}) ending balances.

[8] The notation used here assumes the variable is "0" otherwise. So, for "labor intensity" responsiveness: *SLinc* = SL*1 if SL >= 0; *SLinc* = 0 if SL <= 0; *SLde*c*-1 if SL < =0; *SLdec* = 0 if SL >= 0, etc.

From this data, we define the following additional independent variables in Table 4.4:

Table 4.4:
Definition of Control Measurement Variables

Control Variables	**Calculations**	**Related References**
	Firm-specific	
Firm size	$\log S_{its}$	Barber and Lyon (1996); Gaur, Fisher, and Raman (2005, 1999); Rumyantsev and Netessine (2005; 2007a,b)
Sales (revenue) growth rate (firm sales growth)	$RG_{its} = S_{its} / S_{i,t-1,s}$	Gaur, Fisher, and Raman (2005, 1999); Rumyantsev and Netessine (2007a,b)
Store growth rate (firm store growth)	$NG_{its} = N_{its} / N_{i,t-1,s}$	Gaur, Fisher, and Raman (2005, 1999)
Inventory management* (relative inventory)	$I_{its} = Inv_{its} / COGS_{its}$	Gaur, Fisher, and Raman (2005, 1999); Rumyantsev and Netessine (2005; 2007a,b), Fisher, Ramdas, and Zheng, (2001); Jayanthi, Roth, Kristal, and Venu (2009)
	Industry Segment	
Segment margin*	$SM_{ts} = [S_{ts} - COGS_{t-1,s}] / S_{(t-1),s}$	Rumyantsev and Netessine (2005; 2007b); Cheng (2005)
Segment sales growth rate	$SG_{ts} = S_{ts} / S_{(t-1),s}$	Rumyantsev and Netessine (2007b); Cheng (2005)
Competitive intensity (segment diversification or entropy)	$E_{ts} = \sum_{s=1}^{S} \rho_{ist} \ln\left(1 / \rho_{ist} \right)$	Jayanthi, Roth, Kristal, and Venu (2009), Palepu (1985)
	Economic (shocks)	
Fiscal Year	*fyear* = yearly dummy	Roodman (2006); McGahan and Porter (2002) STATA-'xi: …DV IV i.fyear, …'

** Note that here both COGS and Inv are adjusted for LIFO reserve as stated above*

Firm-specific control variables

We initially control for *firm size* (log of firm Sales*), sales growth rate, store growth rate*, and *inventory management. Inventory management* (I_{it}) is operationalized by using the ratio of average inventory (*Inv*) to cost of goods sold (*COGS*). Along with inventory turnover ratio (its inverse), this relative inventory metric has been widely used as a standard measure of inventory management effectiveness and supply chain execution in the OM literature (e.g. Gaur et al., 2005; 1999; Rumyantsev and Netessine, 2005; 2007a; Fisher, Ramdas, and Zheng, 2001; Jayanthi, Roth, Kristal, and Venu, 2009). We control for inventory management in order to account any association between retail inventory position and ROA in our model, an association that has been already established in the OM literature. Furthermore, inventory ratios are proven measures of retail inventory management effectiveness on an annual basis (e.g., Gaur et al., 1999; Rumyantsev and Netessine, 2005).

Industry control variables

We control for average *segment gross margin* (SM_{ts}) to make sure that a firm's product line gross margins are measured relative to the average gross margins of its industry (Rumyantsev and Netessine, 2005, 2007b). Furthermore, we use a *segment sales growth* (SG_{ts}) ratio, to control for sales trends within product line industry segments (Rumyantsev and Netessine, 2005; Cheng, 2005). Lastly, we control for the *competitive intensity* in the industry by using a measure of segment diversification or entropy (E_{ts}) which is stated as simply the transformed ratio of total sales for the market share leader in a given industry segment for a given year (Jayanthi et al., 2009). A higher score for E_{ts} would indicate a more diverse and competitive segment.

Time control variables

We use yearly dummies (*fyear*) to control for possible trends in profitability over time due to one-time economic shocks or industry cycles (Roodman, 2006; McGahan and Porter, 2002). This is done using the "xi:…. i.*fyear*" procedure in STATA.

4.5.4 Empirical Model Specification

We use the following base empirical model (Eq. 4.4.) to initially examine a retail firm's financial operating performance with store design responsiveness measures, while simultaneously controlling for other firm-specific, industry segment, and timing variables that may be present:

$$\text{(Eq. 4.4)} \quad \mathrm{ROA}_{it} = \mu_{it} + \varepsilon_{it} + b^{i}\,\mathrm{ROA}_{i,t-1} + b^{1}SLinc_{it} + b^{2}SLdec_{it} + b^{3}SKinc_{it} + b^{4}SKdec_{it} + b^{5}I_{it} + b^{6}NG_{it} + b^{7}RG_{it} + b^{8}logS_{it} + b^{9}SM_{ts} + b^{10}SG_{ts} + b^{11}E_{ts} + d^{1}fyear$$

where μ_i indicates the firm-specific error, $\varepsilon_{\mathbf{it}}$ is the remaining random model error, b^i is the coefficient for the temporal lag of the "ROA" dependent variable, b^1, b^2 , b^3 and b^4 are the directional coefficients for our firm-specific design responsiveness variables for store labor (*SL*) and capital intensity (*SK*) changes, b^5, b^6 , b^7 and b^8 are the coefficients for other firm-specific control variables, b^9, b^{10}, and $b^{11}$are the coefficients for segment-specific control variables, and d^1 represents our time control dummy variables (Rumyantsev and Netessine, 2007b; Roodman, 2006; McGahan and Porter, 2002). So, our hypotheses are confirmed if we see negative and statistically significant coefficients for b^1 to b^4 for our initial model. We also estimate the same model (Eq. 4.4) for a forwarded ROA dependent variable (*ROAF*) for the *t+1* forward time period, as well as for current period return on sales (*ROS*).

We take special care to analyze our results for sensitivity (Kennedy, 2003) to the different assumptions and variables included in the model. While our statistical power in excess of 98%, many of the underlying statistical assumptions are sensitive to the number of variables entered into the model and the number of instruments used versus the number of variables. Therefore, we used multiple statistical analyses to "test up" and "test down" the model (see Appendix 7.3.2) by adding some variables and removing those that are redundant or may not be necessary (Plummer, 2007; Kennedy, 2003). In addition, we examined alternative model specifications to determine if the number of instruments used in the model is necessary or appropriate (Roodman, 2008). Given that our base model specification had initially 11 variables to be estimated, it was important to examine if the number of parameters was necessary or appropriate for dynamic panel data model.

4.6 Research Design: Analytical and Methodological Approach

Our longitudinal research design uses dynamic panel data analysis techniques in STATA v10 to test our hypotheses. The use of dynamic panel models is "part of broader historical trend in econometric practice toward estimators that make fewer assumptions about the underlying data-generating process and use more complex techniques to isolate useful information" (Roodman, 2006, p.13) from large longitudinal panel data sets. A dynamic panel data model is "one containing a (temporal) lagged dependent variable (and possibly other regressors), particularly in the 'small T, large N' context" (Baum, p.232). The lagged dependent variable term is assumed to be correlated with the error term in the overall model, and this persistence bias becomes more acute as the number of observations in each time-period sample increases. This is of particular concern with our study dependent variables, as profit-derived ratios have been found to exhibit high levels of persistence in prior literature (Plummer, 2007; Oei, Ramsay, and Mather, 2008; Roberts, 2001; Waring, 1996). Therefore, it is both important and necessary to account for the persistent effects of the dependent variable using established generalized method of moments (GMM) estimation techniques (Hansen, 1982). We estimate all our dynamic models using the "xtabond2" command in STATA v10 (Roodman, 2006).

One method to account for persistence of the dependent variable lagged term (b^i) in our model (Eq. 3.4) is to use Arellano and Bond's (1991) technique[9] which takes the first difference of the base levels equation (Eq. 4.4) and creates a system of equations (one per period) that allows for applicable instruments to each equation term (Baum, 2006, p.233). The first differencing of the original levels equation effectively removes the individual (fixed) effects for each model variable, and the lagged difference term instruments for additional correlation with the overall model residual error. A key

[9] This Difference GMM estimator is executed using the "noleveleq" postestimation command procedure in STATA v10.

assumption of Difference GMM is “that there is no-second order serial correlation for the disturbances of the first differences equation” and they “follow a random walk” (Baltagi, 2005, p.136). However, a potential weakness of Difference GMM is that the lagged difference term created as an instrument in the A-B procedure may also be endogenous (serially correlated) with past, present and future errors if it is highly persistent (Plummer, 2007). In addition, there may be unbalanced panels with few observations in each time period that may “magnify” error variance in the model (Baum, 2006; Roodman, 2006, p.19). Either of these conditions would make the lagged difference terms less valid instruments for the variables of interest.

System GMM gives more “reasonable and precise estimates” (Baltagi, 2001, pp.143-144) versus Difference GMM when instruments are weak, by combining levels terms with differences terms to create new system of equations using all available instruments. This procedure allows System GMM to instrument the lagged dependent variable term and “any other endogenous variables with variables thought uncorrelated (orthogonal) with the fixed effects” (Roodman, 2006, p.16). Because it can take more full advantage of all future moment conditions (Arellano and Bover, 1995), System GMM is more efficient with degrees of freedom versus Difference GMM. However, the results may not strictly eliminate the firm fixed effects because variation from the levels equation is now introduced into the model instruments. Like Difference GMM, the System GMM estimator is sensitive to the number of instruments versus the number of parameters estimated in the model, and is subject to misinterpretation of results (Roodman, 2006; 2008). Unfortunately, the extant literature provides little guidance on how many instruments is “too many” (Roodman, 2006, p.13; 2008), but it does provide some guidance on how to test if assumptions embedded in these techniques are being violated (Plummer, 2007; Roodman, 2006).

4.6.1 Examining Assumptions in Dynamic Panel Data Models

We follow the guidelines from the related literature (Roodman, 2006, p.14; Plummer, 2007; Baum, 2006; Baltagi, 2001) to examine the assumptions embedded in both the Difference and System GMM estimators that we use in this study (see Appendix 7.3.1 for a full reporting of these tests). First, Roodman (2006, p.14) states that researchers should examine if the use of GMM is appropriate by examining if 1) “current realizations of the dependent variable (are) influenced by past ones” (i.e., the dependent variable is serially dependent and autocorrelated), and 2) there are “fixed individual effects in the dynamic” (i.e., variation within firms over time) that argue against the use of cross-sectional analysis and in-favor of panel data analysis. Since ROA, ROS, and ROAF are all profit-derived (and established to be highly persistent) dependent variables (Plummer, 2007, p.79), the use of dynamic panel models is deemed appropriate in our study. Nevertheless, we take special care to test for the important assumptions underlying the appropriate use of these models.

Serial Dependence

In longitudinal studies, serial dependence (or autocorrelation of error terms) in the dependent variable (DV) is often present. This is because ‘time’ interdependence is often assumed in panel data to be part of a business cycle or economic trending towards changes in the dependent variable result (e.g. ROA changes could be a result of a regional macroeconomic shock or effect). Since our model includes both individual (firm) and time-specific error terms, serial dependence of the dependent variable would cause the lagged time error term to be correlated with the overall model error term. This means that any error-derived estimates in the model (e.g. t-stats for coefficient significance) would consist of both firm-specific and time residual errors. Since we are trying to isolate only firm-specific fixed-effects related to design responsiveness, not accounting for the serial dependence in this model would lead to a biased interpretation of the coefficients. Our tests for serial dependence are based on Wooldridge's (2002) test procedures and are discussed in detail in Appendix 7.3.1 - A.1. We find evidence of serial dependence in all our dependent variables.

Endogeneity

Next, Roodman (2006, p.14) suggests that researchers should examine the assumption that "some regressors may be endogenous," and therefore, invalid. We test and report a series of diagnostic tests for endogeneity and instrument validity (Plummer, 2007, p.81): the Sargan/Hansen test, the difference-in-Sargan/Hansen test, and the Arellano-Bond statistics (AR1 and AR2), which are all given with the STATA "xtabond2" command[10]. First, the Sargan/Hansen test statistic (Sargan, 1958; Hansen,

[10] These diagnostic statistics are reported after using the 'twostep' procedure in STATA.

1982)[11] tests the null hypotheses that the variables used in the model instrumentation/specification are strictly exogenous (uncorrelated) with the overall model error term. A rejection of the null hypothesis would indicate that the model specification was invalid, and even a statistically weak rejection (p=.10) would call into question the model specification (Roodman, 2008, p. 11). On the other hand, too strong a rejection (p=1.0) might indicate that the model was overspecified with "too many instruments" (Roodman, 2008, p.1), suggesting that reducing the number of instruments in the model is warranted. Second, the difference-in-Sargan/Hansen test reports the difference between the reported model Sargan/Hansen test statistic (exogenous model) and an alternative specification of a completely endogenous model. But, because it uses the Sargan/Hansen test statistic "a high instrument count also weakens this difference test" (Roodman, 2008, p.11). Therefore, we also use the Arellano Bond statistics which examine the autocorrelation of errors in both the level one (AR(1)) and level two (AR(2)) differences equations. The model specification would be rejected if there was a statistically significant AR(2) statistic.

Collinearity and Heteroscedasticity Issues

Examining collinearity and heteroscedasticity among model-specific observations is also a critical assumption when using GMM estimation, as with any regression model. First, we examine collinearity of model variables using the "collin" command in STATA

[11] Both the Sargan and Hansen test statistics have tradeoffs (Roodman, 2008, p.11) with respect to instrument proliferation (e.g. the Sargan (1958) test statistic is not sensitive to the number of instruments, but assumes normally distributed data). Specifically, we report the Hansen (1982) test statistics because of the heteroscedastic error data structure and unbalanced panel design makes it the most appropriate test for our study (Roodman, 2008).

v10 (Plummer, 2007). With collinearity concerns, small changes in the data matrix may cause large changes in parameter estimates (Baum, 2006, p.85), so it is particularly important to interpret the variance inflation factor (VIF) and the condition number as part of the diagnostic testing (Plummer, 2007). A general "rule of thumb states that there is evidence of collinearity" (Baum, 2006, p.85; Plummer, 2007) if the largest VIF is greater than 10 or a condition number is greater than 30 (Plummer, 2007). Our initial group of variables had a condition number greater than 30 indicating that multicollinearity could be a concern for the full model (Appendix 7.3.1 - A.2). As part of our sensitivity analysis, we discovered that we could limit the effect of multicollinearity by removing any of the segment control variables (SM, SG, or E). We find that the decision to retain or remove any of these variables has no bearing on any of our firm-specific responsiveness estimates of primary interest, and we report results with and without the most problematic segment control variables (SM and SG) as part of our sensitivity analysis (see Appendix 7.3.2).

To examine if heteroscedasticity is a concern in our model, we used a modified Wald test statistic using the "xttest3" postestimation command in STATA (Greene, 2000; Baum, 2006, p.222). Residual variances in panel survey data "often display marked heteroscedasticity" (Greene, 2000, p.15) even if other sources of error disturbance are controlled for in the model. In particular, accounting-derived ratios often exhibit varying precision which causes unintended heterogeneity in the sample (Kennedy, 2003). For example, retailers may use different accounting treatments of depreciation so that the true dollar value of an asset may not be directly comparable to other retailers over time.

Greene (2000, pp.230-232) reports several methods to test for normality of errors in panel data including the Wald Test statistic; Baum's (2006) modified Wald test statistic has the advantage of adjusting for unbalanced panel designs (p.222), so it is particularly useful and easy procedure to run as a postestimation command in STATA. Like the standardized Wald test (Greene, 2000), this modified procedure tests the null hypothesis of homoscedasticity of errors. As is typical of panel data models of our type (Roodman, 2008, p.11), we find evidence of heteroscedasticity ($p<.01$), whether fit by fixed-effects or generalized least squared estimators (see Appendix 7.3.1 - A.3). Therefore, we use robust estimation of errors in our models (and related test statistics) to adjust for these scalar differences.

Stationarity

Finally, a key assumption of System GMM is that of the dependent variable is stationary (Plummer, 2007, p.82; Baltagi, 2001, p.143). The dependent variable is assumed to be stationary if the mean, distribution, and variance do not change over time periods (Plummer, 2007, p.82). Following Plummer's (2007, pp.82-83) and Baltagi's (2001, pp.235,240) guidelines, we report Fisher's test, which was further developed by Maddala and Wu (1999, p.636), to test for stationarity of each dependent variable. Fisher's test procedure examines summed log of individual panel unit root tests (p-values) and combines them into a common test statistic using the Fisher test command "xtfisher" in STATA. This statistic tests the null hypothesis of non-stationarity, and works well with unbalanced panel designs (Maddala and Wu, 1999, pp.636-637). We run this procedure for each of the dependent variables used in our model and find evidence (see Appendix 7.3.1 - A.4) that they are all stationary across time periods ($p<.01$).

4.7 Analysis

4.7.1 Descriptive Analysis

After validating the methodological assumptions, we used multiple statistical analyses to examine our results and to test our hypotheses. First, we used descriptive statistics to analyze our dependent variable and gross margin trends for our retail trade industry sample (Figure 4.2). While gross margin and return on assets results vary among retail industry segments, is it interesting to note that despite increased spending on technology and supply chain management capital during the period, the retail industry sample in aggregate did not see any real increase in ROA. However, Figure 4.3 shows that retailers have been active and quite volatile in their annual labor and capital investment decisions vis-à-vis gross margin changes during the period. While Figure 4.3 shows that the tendency for retailers was to decrease store labor intensity and increase store capital intensity at a faster rate than gross margin changes, there is no discernable or directional trend in either area. Finally, Figure 4.4a-b shows the normal distribution and spread of the dependent variable observations. It also shows that there is a great deal of heterogeneity among retail firms' financial operating performance.

Figure 4.2: Plot of Industry Gross Margin and Return on Assets by Fiscal Year

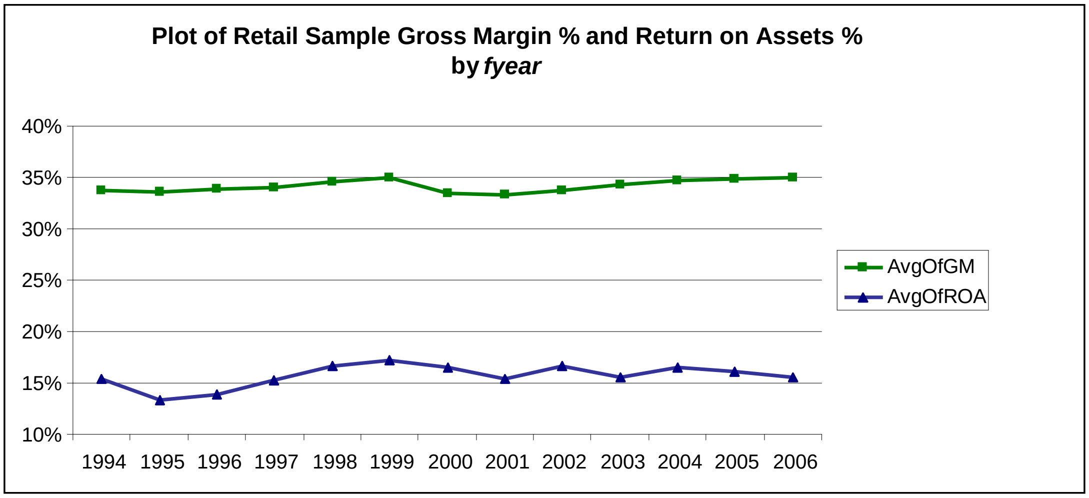


Figure 4.3: Plot of Design Responsiveness by Fiscal Year

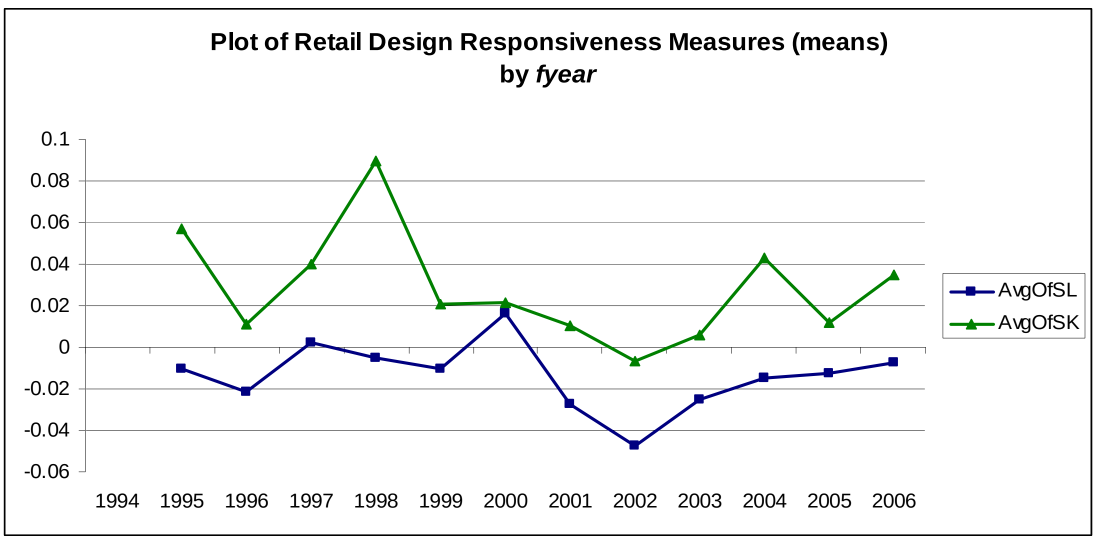
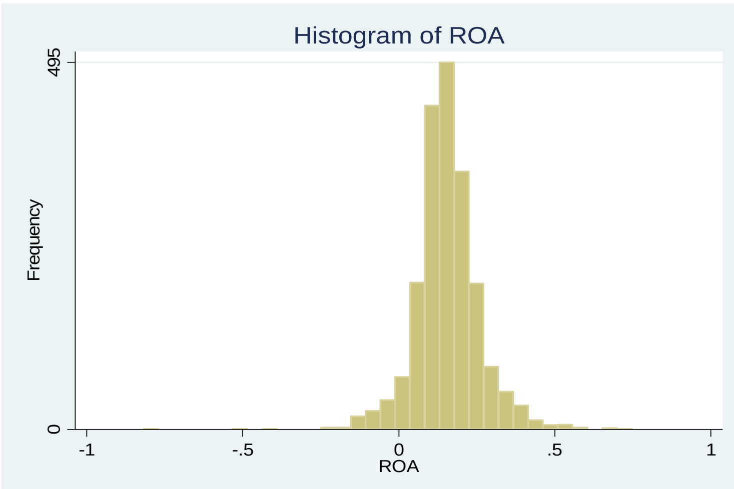
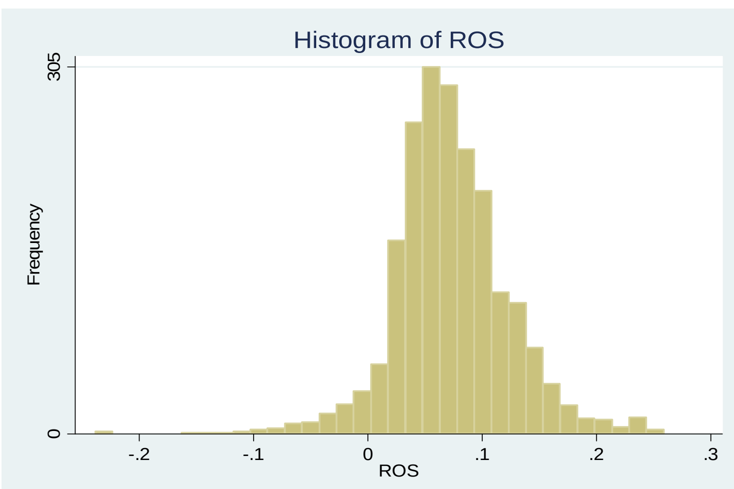


Figure 4a-b: Sample Distribution of Observations (Dependent Variables)

a)



b)



Next, we examined the descriptive data – mean, standard deviation, minimum and maximum value - for all of our model variables and their various components (Table 4.5). This was done to check for any outliers in the data and to validate and empirically ground our variable calculations. We analyze observations at either tail of the distribution to verify if the result was "real" or that it is not the result of measurement error. As a result of this review, we did not drop any observations or additionally transform their values. The average firm in the sample reported a mean ROA of 16% and an ROS of 7%. Annual firm sales averaged $5 billion dollars. Revenue and store growth averaged 11% and 10% per year respectively. In examining store system labor and capital intensity, number of stores, and selling square feet, we see additional evidence of the heterogeneity of the firms within the retail trade industry.

Table 4.5: Descriptive Statistics

Model Descriptive Variables	Mean	S.D.	Min	Max	Obs.
Dependent Variables					
Return on Assets (ROA)	.16	.11	-.82	0.75	2039
Return on Sales (ROS)	.07	.05	-.23	0.26	2039
Firm-Specific Controls					
Sales[1] (S)	$5,830	$19,171	$12	$345,977	2039
Firm Revenue Growth ratio (RG)	1.11	.18	.34	2.92	2039
Firm Store Growth ratio (NG)	1.10	.32	.28	4.81	2039
Relative Inventory (Inventory/COGS) ratio (I)	.29	.18	.04	1.37	2037
Segment Controls					
Segment GM% (SM)	.34	.05	.25	0.56	2039
Segment Revenue Growth ratio (SG)	1.07	.09	.55	1.57	2039
Competitive Intensity (E)	1.52	.59	.08	2.8	2039
Component Measures					
Gross Margin% (GM)	.34	.10	-.05	.70	2039
Operating Income before Depreciation[1] (OIBD)	$443	1388	-728	$23,283	2039
Number of Employees[2] (EMP)	38.0	110.9	.1	39	2023
Number of Stores (N)	730	1177	7	8,079	2039
Labor Intensity[3] (L – adj.)	3.2	3.1	.1	39	2023
Capital Intensity[4] (K)	$130.21	$153.05	$2.72	$3,489.95	2038
Gross Selling Square Feet[2] (SQFT)	18,242	50,817	27	782,287	2039
ACSI Satisfaction Score (ACSI) – for forward testing	74.5	3.5	66	84	188

[1] $ millions
[2] stated in 000's
[3] Labor intensity multiplied by 1000 in table to aid interpretation (e.g. 3.2 employees/ thousand square feet, L=.0032emp/sqft)
[4] Interpreted as $ of capital investment per selling square foot

The correlations of the model variables are listed in Table 4.6. ROS is highly correlated with ROA in our sample (r=0.85). As part of our testing-up and testing-down procedures and diagnostics (discussed earlier), we found that any of the segment control variables Segment GM% (SM), Segment growth (SG), or Competitive intensity (E) could be removed to reduce collinearity issues, without having any major impact on the coefficient results of interest (see Appendix 7.3.1 - A.1). All other descriptive statistics for the focal firm variables in Table 4.6 appear to be within the expected ranges.

Table 4.6: Correlations of Model Variables

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Return on Assets (ROA)	1											
2	Return on Sales (ROS)	.85	1										
3	SLinc	-.02	-.02	1									
4	SLdec	-.10	-.08	-.12	1								
5	SKinc	.00	-.00	.28	.04	1							
6	SKdec	-.19	-.15	-.06	.48	-.13	1						
7	Size (logS)	.16	.16	-.01	-.11	-.01	-.16	1					
8	Firm Revenue Growth ratio (RG)	.42	.34	.29	.00	.32	-.16	.00	1				
9	Firm Store Growth ratio (NG)	.23	.21	.05	.17	.16	-.05	.00	.54	1			
10	Relative Inventory ratio (I)	-.20	.01	.00	.03	.03	.07	-.30	-.08	-.05	1		
11	Segment GM% (SM)	.04	.24	.00	.02	.04	.06	-.33	.04	.05	.56	1	
12	Segment Revenue Growth ratio (SG)	.00	-.05	.02	.01	.05	.01	-.05	.14	.06	.05	.04	1
13	Competitive Intensity (E)	.14	.11	-.03	-.08	.00	-.01	-.10	.00	-.03	-.18	.06	-.05

4.7.2 Model Estimation using Difference GMM

We next tested our model using Difference GMM estimation procedures (Arellano and Bond, 1991) to control for endogeneity in our ROA dependent variable, and autoregressive correlations in our model. For our initial difference models, we treat all independent variables as exogenous. We report the Difference GMM model results excluding the constant term[12], because simulation research has shown that including the term causes transformation issues in interpreting the model results (Roodman, 2006).

[12] Difference estimation removes the constant term during the first difference transformation (Baum, 2006). While including a constant term tends to have a minor effect on results in practice (Roodman, 2006, p.37), we exclude it in our analysis to aid in interpreting the results.

Table 4.7 shows our four model estimations using ROA as the dependent variable. All four models in the table validate the use of Difference GMM, as the lagged term and the first-order AR(1) statistics show evidence of significant first-order serial correlation (p<.05). In contrast, the AR(2) test suggests no significant serial correlation among the second-order variable instruments. In column 1, we include all variables specified in the original model, including time-dummies. Column 2 shows the same model excluding the time-dummies. Columns 3 (with time-dummies) and 4 show the improved final model excluding the problematic segment control variables. Across models we see no initial evidence to support H1 or H2a, as increasing (*SLinc*) or decreasing store labor intensity responsiveness (*SLdec*) has no negative effect on annual *ROA* performance (p>.10). However, the models provide strong evidence to support the alternative hypotheses (H2b), as decreasing store labor intensity (*SLdec*) is positively associated (p<.05) with *ROA*, indicating that retail firms reducing labor intensity at a faster rate than gross margin changes achieve better operating performance. On the other hand, we do see evidence across models supporting H3 and H4, stating that increasing (*SKinc*) or decreasing (*SKdec*) store capital intensity responsiveness is negatively associated with *ROA* (p<.05). Decreasing store capital intensity (*SKdec*) also has about a 50% stronger negative effect on performance as increasing store capital intensity responsiveness (*SKinc*). We also analyze the firm and segment control measure effects on our operational performance variable. The positive effect of revenue growth (*RG*) and the negative effect of inventory management (*I*) on *ROA* is consistent with the literature. However, the other control variables show no significant direct associations with *ROA* in our empirical model.

These results were consistent when examining return on sales (*ROS*) – see Appendix 7.3.1 - Table A.5, column 1.

Our difference-in-Hansen tests show no evidence of endogeneity among the independent variables. While our Hansen and AR(2) test statistics (p>.10) provide sufficient evidence of no serial autocorrelation of residuals, simulation research suggests that these tests can produce misleading results when many variables are included in the model (Roodman, 2006; 2008). With this in mind, we use alternative estimation techniques to test the different model assumptions and the robustness of our empirical findings.

Table 4.7: Model Estimation Using the Difference GMM estimator, DV=ROA

ROA	1	2	3	4
time lag t-1	0.35 **	0.39 **	0.37 **	0.41 **
	[3.53]	[3.74]	[3.74]	[3.91]
Firm				
SLinc - Increasing store labor responsiveness	0.09	0.16	0.13	0.10
	[0.43]	[0.86]	[0.60]	[0.56]
SLdec - Decreasing store labor responsiveness	0.58 *	0.86 **	0.66 **	0.89 **
	[1.86]	[3.12]	[2.20]	[3.11]
SKinc - Increasing store capital responsiveness	-0.27 **	-0.26 **	-0.27 **	-0.29 **
	[2.10]	[2.16]	[2.05]	[2.20]
SKdec - Decreasing store capital responsiveness	-0.32	-0.46 **	-0.43 **	-0.44 **
	[1.43]	[2.64]	[1.97]	[2.59]
Size (logS)	0.07	0.10	0.07	0.08
	[0.44]	[1.45]	[0.45]	[1.45]
Revenue Growth (RG)	0.52 **	0.52 **	0.55 **	0.52 **
	[3.58]	[4.55]	[4.16]	[4.69]
Store Growth (NG)	-0.03	-0.08	-0.06	-0.05
	[0.41]	[0.79]	[0.62]	[0.47]
Relative Inventory (I)	-0.69	-0.65 *	-0.43	-0.52 *
	[1.48]	[1.88]	[1.24]	[1.80]
Segment				
GM% (SM)	1.54 *	-0.75		
	[1.85]	[1.14]		
Revenue Growth (SG)	0.13	0.10		
	[0.68]	[0.66]		
Competitive Intensity (E)	0.00	0.06	0.00	0.05
	[0.02]	[1.02]	[0.01]	[0.85]
Time				
Time dummies (included)	Yes	No	Yes	No
Observations	1555	1555	1555	1555
Number of Firms	218	218	218	218
Hansen Test (p-value)	.724	.500	.191	.500
Arellano-Bond AR(1)	-3.1 **	-3.3 **	-2.9 **	-3.3 **
Arellano-Bond AR(2)	0.6	0.3	0.9	0.0
F Test	5.8 **	7.6 **	7.0 **	9.3 **

Difference GMM estimates (Stata, xtabond2..nolevelseq); the lag of dependent variable is endogenous; all the independent variables entered as exogenous; absolute value of t statistics are in brackets;
robust standard errors
One-tailed tests: * Significant at 10%; ** Significant at 5%

4.7.3 Model Estimation using System GMM

Next, we used System GMM estimates to examine our model. According to our tests for serial dependence (Appendix 7.3.1 - A.1), the ROA profit lag term is strongly associated with the dependent variable error term. As such, System GMM estimation provides some advantages over Difference GMM, particularly as the coefficient term of the lagged dependent variable becomes more persistent ($\boldsymbol{b^i} \rightarrow 1$). Our panel data also has several characteristics that make the use of system GMM more attractive. First, we are generalizing to the universe of retailers using N=232 selected retail firms with sufficient data, so system GMM causes us to lose fewer degrees of freedom. Second, Difference GMM may over-fit models by using more instruments than is necessary if the number of variables is high (as in our case). Finally, the dependent variables in our model have been shown to exhibit highly persistent properties in prior economics and operations management research (e.g. ROA).

Table 4.8 reports six alternative models using System GMM estimation. Column 1 and 2 show the same model that was used in Difference GMM with and without time-dummies respectively. Each model treats the lagged dependent variable as endogenous and the rest of the independent variables as exogenous. The difference-in-Hansen, Hansen, and Arellano Bond test statistics all support the model instrumentation. The coefficient estimation results are very similar to the model using Difference GMM estimation. H2b, H3, and H4 are all statistically supported, while the other hypotheses were not supported. We also find similar results with respect to the firm and segment specific control variables relationships as seen in the first set of models. Next, we repeated our analysis for the *ROS* dependent variable and found that the results were consistent (see Appendix 7.3.1 - Table A.6, column 1). Therefore, there is empirical evidence in Model 1 and 2 that decreasing store labor responsiveness is associated with better operational performance, and that either increasing or decreasing store capital responsiveness is associated with worse operational performance.

Table 4.8: Model Estimation Using the System GMM estimator, DV=ROA

ROA	1	2	3	4	5	6
time lag t-1	0.37 **	0.43 **	0.60 **	0.60 **	0.49**	0.50**
	[3.21]	[4.01]	[7.43]	[7.40]	[4.28]	[4.38]
Firm						
SLinc	0.09	0.06	-0.05 **		-0.10**	
	[0.45]	[0.33]	[2.04]		[2.92]	
SLdec	0.38	0.64 **	0.08		0.09	
	[1.57]	[2.70]	[1.21]		[0.93]	
SL (non-directional)				-0.06 **		-0.11**
				[2.39]		[3.17]
SKinc	-0.27 **	-0.30 **	-0.04 **	-0.04 *	-0.01	-0.02
	[2.18]	[2.30]	[2.04]	[1.74]	[0.21]	[0.22]
SKdec	-0.43 **	-0.49 **	-0.13 **	-0.13 **	-0.24**	-0.25**
	[3.00]	[3.48]	[2.45]	[2.67]	[2.51]	[2.72]
Size (logS)	0.02	0.04	0.00	0.00	0.00	0.00
	[0.64]	[1.17]	[0.46]	[0.44]	[0.08]	[0.11]
Revenue Growth (RG)	0.62 **	0.58 **	0.18 **	0.18 **	0.25**	0.25**
	[5.39]	[5.89]	[5.13]	[5.15]	[3.80]	[3.82]
Store Growth (NG)	-0.11	-0.10	-0.03 **	-0.03 **	-0.04	-0.05
	[1.00]	[1.05]	[2.40]	[2.51]	[1.42]	[1.44]
Relative Inventory (I)	-0.29 *	-0.33 **	-0.09 **	-0.08 **	-0.17**	-0.17**
	[1.79]	[1.97]	[2.18]	[2.18]	[2.23]	[2.24]
Segment						
Competitive Intensity (E)	0.00	0.00	0.03 **	0.03 **	0.02	0.02
	[0.12]	[0.21]	[2.41]	[2.41]	[0.71]	[0.73]
Time						
Time dummies (included)	Yes	No	Yes	Yes	Yes	Yes
Constant	-0.46 *	-0.46 **	-0.13 **	-0.14 **	-0.12	-0.12
Observations	1784	1784	1784	1784	1784	1784
Number of Firms	226	226	226	226	226	226
Hansen Test (p-value)	.359	.411	1.00	1.00	.698	.710
Arellano-Bond AR(1)	-3.1 **	-3.5 **	-4.6 **	-4.5 **	-4.2**	-4.2**
Arellano-Bond AR(2)	1.6	0.8	-0.4	-0.4	0.5	0.5
F Test	13.2 **	19.8 **	26.7 **	28.0 **	22.0**	22.9**

System GMM estimates (Stata, xtabond2); the lag of dependent variable is endogenous; absolute value of t statistics are in brackets; robust standard errors;
Model 1 – 2 treat IVs as exogenous;
Model 3 – 4 treat IVs as follows: (I, logS - endogenous; NG, RG – predetermined);
Model 5 – 6 treat IVs as follows: (I, logS – endogenous);
One-tailed tests: * Significant at 10%; ** Significant at 5%

Column 3 and 4 models also use system GMM. However, we additionally instrument for independent variables that may be either highly endogenous or predetermined. We do this to test the robustness of our findings to alternative model specifications. Some economics and operations management empirical research suggests that both inventory (*I*) and sales (*logS*) variables may be highly persistent (Ramey and West, 1999; Rumyantsev and Netessine, 2005; 2007b). In addition, our growth rate variables (store growth and sales growth) are specified as predetermined variables.[13] Although there is limited research using these techniques in operations management, it appears appropriate to instrument for these conditions by treating *logS* and *I* as endogenous and *NG* and *RG* as predetermined variables.

Column 3 and 4 report the results of the analysis using instruments for the specified endogenous and predetermined variables. Column 3 results show that while H1 is supported in the respecified model, and H2b is not supported. Store capital intensity responsiveness hypotheses (H3 and H4) continue to be supported. The model fit statistics also show improvement, as the AR(2) statistics have a serial correlation closer to 0, and the Hansen and difference-in-Hansen results both indicate acceptable instrumentation. Because we found the change in the store labor intensity responsiveness results interesting, we further re-specified the model (column 4) by substituting our directional variables for store labor intensity (*SLinc, SLdec*) for the base non-directional store labor intensity elasticity variable (*SL*). This produced a statistically significant and negative

[13] There is debate in the econometrics literature on how to instrument growth rates. Generally, growth rates are instrumented as predetermined variables, but we found no specific instances where retail revenue growth and store growth were used as proxy variables. However, this treatment appears reasonable based on GDP studies, etc.

coefficient ($p<.05$), suggesting that increases in the variable resulted in negative financial operating performance. The control variable relationships to the DV also change in these models, as all coefficients except that for *logS* are statistically significant and directionally consistent with what is found in the literature. Since our Hansen test statistic was equal to 1.0 (Roodman, 2008)[14], we examined the sensitivity of our findings using only the specified endogenous variables (Column 5 and 6). These models confirm the results for the store labor intensity responsiveness variables (H1 supported) and the decreasing store capital intensity responsiveness variable (H4 supported), but do not statistically support H3, which suggests that increasing store capital responsiveness worsens firm operational performance. This is surprising given that H3 was supported in all other model specifications. Collectively, our evidence shows that many of the findings in base model, where we instrument only for the lagged DV, are very sensitive once we instrument for the other firm-specific control variables that may be endogenous. Therefore, our findings should be viewed with caution and within the context of how aggressively one specifies the firm-specific model control variables.

4.7.4 Forward Impact of Design Strategy Shifts

The final step of our analysis was to examine if any of the design responsiveness measures have carryover effects to the following period (see Appendix 7.3.1) for either profits (*ROAF*) or for forward customer satisfaction (*acsiF2*). We find no evidence that

[14] Roodman (2008) states while Hansen statistics of p=1.0 indicate acceptable instrumentation, these results should be viewed with caution and checked for sensitivity, as they may indicate that the model is over-specified.

any of our responsiveness measures have particularly strong carryover effects on forward ROA (*ROAF*) – see Table A.7. This finding indicates that the financial benefits of being design responsive are generally realized over the short-term timeframe, and that managing design responsiveness is an ongoing, year-to-year process for store retailers.

Because the negative impact of being unresponsive may be felt by customers in forward periods (Menor et al., 2001; Fornell, 2007), we additionally collected forward American Customer Satisfaction Index (ACSI)[15] data for 24 sample retailers (141 observations) where it was available during the study period. Because of the small portion of firms with available ACSI data in our sample, we base our findings on this much smaller subsample of data (see Appendix 7.3.1 - Table A.8). We found that both decreasing labor intensity responsiveness (*SLdec*) and increasing labor intensity responsiveness (*SLinc*) had significantly ($p<.05$) negative associations with forward year ACSI scores (*acsiF2*) for retailers. These results suggest that retail firms that reduce or increase labor intensity in their store systems at a faster rate than gross margins may see a negative impact on forward service delivery satisfaction scores. Perhaps this is because retailers sacrifice customer satisfaction for the benefit of short-term financial performance gains by reducing store labor intensity. On the other hand, both decreasing and increasing store capital intensity responsiveness (*SKdec*) had small albeit significant effects ($p<.05$) on forward ACSI scores. This finding may indicate that retail store customers are more satisfied with a personalized store experience that is not dependent on capital attempting to substitute for personal contact, or for store's making the extra

[15] ACSI data is reported in calendar years, so paired our full fiscal year COMPUSTAT results with the first full 12 months of forward data after the retailer's fiscal year ended.

effort to use this capital to improve prices or improve customer service through convenience. However, we note that ACSI scores are skewed toward larger, well-known retail firms and certain retail segments, and we accounting for only a subset of firms where these scores were available. Therefore, these results should be viewed with caution. Nevertheless, our results indicate that future research is needed to examine the forward impact of design responsiveness on retail customer satisfaction.

4.8 Discussion of Chapter 4 Results

This study contributes to retail store research and practice in a number of ways. First, we develop a statistical proxy for measuring store system design responses to gross margin changes in the retail trade industry for both labor and capital intensity. We then constructed an empirical model to analyze the impact of strategic design shifts on operational performance while simultaneously controlling for other firm-specific, segment, and temporal effects. A major benefit of our empirical model and analytical approach over other studies is that our model controls for the persistent effects of the dependent variable (e.g. ROA). Furthermore, our findings confirm that controlling for the persistence of *ROA* is both useful and necessary to fully understand the impact that relevant model variables are having on retail firm profits.

Our first research question asked if it was possible to develop an empirical method to measure strategic store design shifts in the retailing industry. Drawing upon the inventory management studies of Rumyantsev and Netessine (2005; 2007b), we constructed four elasticity measures to examine the directional co-movements of strategic design changes with gross margins for store retailers. Our empirical model then used firm-specific, segment, and time control variables culled from previous empirical studies to account for any non-design responsive effects that may be present. The results of our analysis validate findings from earlier studies on the impact that some these control variables may have on retail firm operating performance, particularly the impact of inventory management practices and revenue growth rates on operational performance. Our measures of store design responsiveness complement this previous work by demonstrating the importance of store labor and capital intensity management to operational performance, in addition to managing sales growth and inventory. Using our measurements of design responsiveness, we provide an empirical means to evaluate retail store design strategy shifts across different segments. Given the heterogeneity of retail store systems and the dynamics of retail markets, this is an important contribution.

Our second research question asked if retailers actually pursue responsive store design strategies. The results of our descriptive analysis revealed that retail firms do not manage the co-movements of design strategy and margins as often as might be expected. While we find that the mean responsiveness score for both store labor and capital intensity measures was centered on zero for all observations, there was a wide standard deviation and range of design responsiveness scores across the field sample (see Appendix A.9). Directionally, the tendency for retailers was to reduce store labor intensity at a faster rate than gross margins and to increase store capital intensity at a faster rate than gross margins. This finding provides some insight into the internal motivations of reported retail design strategic shifts towards greater cost-efficiency and economies of scale in store selling systems (Boyd and Bresser, 2008).

Our final research question asked how our measures of design responsiveness were related to retail firm financial operating performance. To answer this question, we made four hypotheses about the impact each of our measures would have on operational performance. Our first series of hypotheses (H1, H2a, H2b) stated that increasing or decreasing store labor responsiveness measures would have negative performance impacts. Our evidence suggests that in fact decreasing labor intensity responsiveness in the store system may improve short-term operating performance (Support H2b). In addition, we find that when we instrument for possible endogenous and predetermined variables, increasing store labor intensity responsiveness has negative short-term effects on retail operating performance (Support H1). This finding is consistent with literature arguing that retailers are becoming more like Wal-Mart in that they are increasingly relying on low-contact/self-selection store environments, more automation, and supply chain management to deliver products to customers, regardless of margin changes (or in recognition that margins will continue to decrease). These findings also confirm the general importance of actively managing labor intensity in retail store systems.

We find generally strong support for our hypotheses stating that both increasing and decreasing store capital responsiveness measures are associated with worse financial operating performance in retail firms (H3 and H4 supported). This finding suggests that retail store systems need to be deliberate in managing their property in conjunction with gross margin changes. This finding may also indicate that retail firms need to coordinate gross margin shifts with capital planning and forecasting efforts.

Finally, we examined whether increasing or decreasing responsiveness had any carryover effect on future financial operating performance or customer satisfaction scores. Here the results were mixed. We find that none of our responsiveness measures has any association with forward ROA (*ROAF*), so it appears that the financial operating benefits we describe are only realized in the short-term. However, the dynamic analysis of our retailer subsample found that either increasing or decreasing store labor responsiveness is negatively associated ($p<.05$) with forward customer satisfaction scores. In particular, our evidence indicates that if retailers reduce store labor intensity to achieve short-term profits, they may also see negative carryover effects on customer satisfaction scores. Therefore, failing to be responsive with store labor intensity may affect the long-term sustainability of the firm's service concept. Getting to the root cause of these relationships is important for future research.

It is also important to point out the limitations of this study. While our results are fairly robust to different panel data analysis techniques that control for the lagged dependent variable term (*ROA* or *ROS*), they are very sensitive to excluding or changing the assumptions about the endogeneity of different firm-specific control variables. While we found no evidence of endogeneity in the model diagnostic tests, it is possible that the large number of independent variables in this study could bias those tests. Nevertheless, each control variable was chosen because of its documented effects on retail operational performance, labor, and capital is grounded in the extant literature. We also analyzed the differences that changing the assumptions about endogeneity had on the model results and reported them. Nevertheless, more work needs to be done to establish the degree of endogeneity among retail sales growth, inventory management, and margin-related variables.

Our findings are also limited because of how certain model proxy variables were formulated. Our store capital intensity responsiveness variables, for example, may include investments in technology, store locations, fixtures, warehouses, or other items. It is difficult to determine if these components collectively influence the results, or if only certain components of capital intensity should be managed responsively. However, it might be possible to separate each of these capital items into separate responsiveness variables in future work if one could get access to more detailed capital data than is typically reported in company financial statements.

4.9 Chapter 4 Conclusions and Future Applications

Both the academic and investment analyst community suggest a deficiency in the area of retail store system design strategy measurement and theory. In this research, we create a statistical means for practitioners, industry analysts, and academics to evaluate the effectiveness of strategic store design shifts in retailing on financial accounting returns. We have hypothesized that retail firms should endeavor to keep their product line margins and store system design strategies aligned over time. We find strong support that increasing/decreasing store capital intensity responsiveness measures are associated with worse operational performance in most cases. For increasing/decreasing store labor intensity responsiveness measures, we find that decreasing store labor intensity responsiveness year to year may have positive financial benefits, and that increasing labor intensity responsiveness may have negative associations with ROA. However, these results are sensitive to the assumptions one makes about other model variables. We find that none of these measures have statistically significant carryover effects on ROA (*ROAF*). However, we do find that our decreasing/increasing store labor responsiveness measures may have strong negative associations, and that our decreasing/increasing store capital responsiveness measures may have slightly positive associations, with forward customer satisfaction scores.

Through our dynamic measures of store system design responsiveness, we believe that we provide a superior means to evaluate the performance of store system design strategy choices year to year using publicly available data. In contrast, more traditional measures used to evaluate retail design performance, such as same store sales, sales or gross margin per square foot, and profit per store, do not indicate the important strategic shifts, incorporate customer contact implications, or evaluate capital resource investment decisions that are critical to firm financial performance in dynamic retailing environments (Gage, *Forbes*, 2007).

Finally, this study provides a significant opportunity for future research examining design responsiveness and operational performance in services. While our research model examines only the retail trade industry, future studies could examine the strategic profiles of firms pursuing specific design strategy options in different service industries. For example, service firms may be equally successful at pursuing different design strategies to stay in operational alignment, or different design strategy combinations may be more effective in other service settings. This research effort may provide a superior design classification scheme than is currently seen in the extant service management literature. While we examine store systems in aggregate, future research could use portfolio theory in combination with design responsiveness measures to examine how chains manage multiple designs under common ownership. Finally, research could use our responsiveness measures to evaluate firm survival. For example, design responsiveness measures combined with traditional financial stability measures (Altman's Z, Fixed Asset Turnover, etc.) may help to explain and predict the long-term survival rates of retail firms.

In conclusion, this chapter improves both practitioner and academic understanding of the dynamics of retail design strategy shifts and their effects on operational performance. By focusing on the retail trade industry, we concentrate our performance measurement efforts on retail responsiveness metrics that are of direct relevance to retail design strategy. In developing an empirical means to show how customer contact can be managed through design decisions regarding store capital and labor intensity management, we provide a direct link to evaluate how retail design strategy responses affect financial operating performance in an ever important industry in the U.S. economy.

CHAPTER 5

Study Conclusions

"Looming on the horizon for every retailer is the long shadow of Wal-Mart"
(Suzanne Kapner, *Fortune*, April 27, 2009)

5.1 Study Implications and Contributions

Collectively, these essays argue for the importance of aligning store design strategy decisions with operational complexity to promote the long-term sustainability and survival of retail service firms. At the beginning of this study, we broadly asked if retailers must manage store design tradeoffs in aligning 'the service concept' with the 'design strategy?' This question was investigated by measuring the different elements of design strategy in retail services, and by examining how retail stores link specific customer encounter strategies to customer information processing requirements. Our evidence shows that retail stores must eventually align both information processing capabilities with a cost structure that is supportive of product line margins. The paradox for retail store managers and designers is that improving customer contact in the store often comes at a high price. Store retailers, then, must decide if the added cost of providing more customer contact is worth it. Our essays provide some insight into answering that question, as well as provide retail managers with a means to evaluate store design strategies for their specific operating environments.

First, we empirically investigated if the use of specific customer encounter strategies had any impact on customer delivery satisfaction measures. In Chapter 3, we found that customer service encounter information requirements are a significant motivator customer encounter design strategy choice – whether or not to empower store employees or to design for self-selection. In general, we confirmed that stores actually choose customer encounter strategies based on the customer information requirements they perceive. Our evidence reveals that model conformance varied by store size in that small stores were possibly more successful at using customer encounter design strategies to manage task uncertainty and enhance customer delivery satisfaction. While employee task empowerment was positively associated with customer delivery satisfaction, large stores did not widely use employee task empowerment as a means to generate additional information processing capacity. However, large stores relied heavily on design for self-selection strategies and employees were not judged to have the discretion to satisfy customers even when customer information requirements were considered. It might be that for large stores to effectively deploy design for self-selection strategies, they need to leverage the integrative abilities of technology to improve the in-store environment for employees or provide a quality control capability surrounding specific customer-driven performance measures. Therefore, in addition to providing an survey instrument that can be used by store managers to weigh the tradeoffs of store design strategies, we demonstrate the nomological network of store design strategy relationships using our structural equation model and empirically validated measures of customer delivery satisfaction.

In Chapter 4, we examined the dynamic nature of retail store design strategy choices over a 13 year period (1994-2006) by studying the strategic store system design responses of retail firms to product line gross margin changes. We provide empirical evidence that retail firms are better off from a financial operating performance perspective when they align store capital intensity changes with product margins year to year. Furthermore, we found that failure to invest in store capital (decreasing capital responsiveness) has a far worse negative impact on operating performance that does overinvesting in store capital vis-à-vis gross margins (increasing capital responsiveness). In addition, we find empirical evidence that providing more store labor intensity (a proxy for human contact) in declining product margin environments had negative impacts on firm operating performance. Taken together, these findings suggest that stores should maintain consistent investment in store capital and that they should manage store labor costs with a great deal of care. However, we did not find any carryover effects of any of our design responsiveness measures on forward financial operating performance. So the financial benefits to retail firms of reducing store labor intensity faster than margins are short-term, and these firms should be highly flexible when deploying store capital. However, we did find evidence that both decreasing and increasing store labor intensity at a faster rate than product offering gross margins did lead to worse forward satisfaction stores, with decreasing store labor intensity having the stronger effect in most cases. This may indicate that the failure to maintain adequate store labor intensity in the design system may lead to a service concept that is not supportable or unsustainable.

Our research findings further support the proposition of Boyd and Bresser (2008) and other retail strategy scholars who suggest that while it is generally assumed that retail firms will and should use fast responses when threatened by lower product line margins, the term fast should not be confused with “fastest possible response” in order to avoid being “too fast” or “too late” (p.1083). Rather, our evidence suggests that firms should be intentional in designing their store systems to be in sync with the information content of their product/service offering (Huete and Roth, 1988) so that they are both deliberate and flexible in managing product line margins along with the most appropriate store operating design strategy. Our evidence suggests that both small stores and firms with more flexible store design architectures can claim certain strategic design advantages if they can be responsive to environmental conditions and changes. Nevertheless, it is clear from our research that there is a short-term financial incentive to operating a leaner store system that can actively manage capital investment year to year. This would be particularly true if customer encounter information requirements are low, or if the customer value proposition relies heavily on price or cost-efficiency. In such cases, the retail firm behaves much more like a product delivery system in its store value proposition for customers. However, it is unclear if such strategies can be sustained unless capital can effectively substitute for human contact or retailers can maintain or improve their gross margin merchandising positions.

Much as Sampson and Froehle (2006) have proposed a Unified Services Theory in an effort to distinguish service from manufacturing production systems, there is value in distinguishing retail service from manufacturing production design strategies. Within the context of the retail trade industry, and focusing specifically on the store design channel, this study offers strategic insights that can be used by retail researchers to build toward a comprehensive theory of retail store design strategies. Our focus has been on how supporting design structures help facilitate and enhance the in-store service encounter experience, and determining what tradeoffs may be necessary in managing store design strategies to stay in alignment. We have provided definitional rigor, validated measurement, and performance evaluation methods in an important service industry setting by incorporating both marketing and service operations strategy theory to construct our models. For practitioners, we offer analytical tools that can be used to help explain and evaluate existing store design strategies and relationships. As store retailing is widely documented to be a highly competitive, risky, and dynamic business environment (McGurr and DeVaney, 1998; Ghosh, 1990), it can be assumed that retailers operate near their operating asset frontier. Therefore, retail firms may be more likely to suffer economic tradeoffs (Lapre and Scudder, 2004) as they attempt to maintain alignment between their intended service concept and their store design strategy and execution. As they face more competition from mass merchants and other retail channels, retail stores may be very sensitive to even subtle shifts in these areas. In this research, we hope to initiate a discussion on how retailers may effectively respond (versus react) to changes in their market segments through active planning and ongoing evaluation of their operating design strategies, thus ensuring the long-term viability of 'bricks and mortar' retail stores that are not like Wal-Mart or other mass merchants.

5.2 Areas for Further Retail Design Research

The rise of mass merchants (e.g., Wal-Mart) and internet retail giants (e.g., Amazon.com) pose a grave threat to retailers that rely too heavily on being a solely a product merchandise delivery system. Therefore, it would be too much to read into our findings that all retailers should conform to a "one size fits all" store operating strategy. Increasingly, evidence suggests that mass-merchants and internet retailers provide a competing channel for selling more complex product-service bundles and that customers come into stores to make product purchases with increasingly more product knowledge than they have had in the past (Boyer et al., 2002). Therefore, the ability of store retailers to differentiate from these other service delivery channels has become a more challenging endeavor. Nevertheless, this fact provides an important opportunity for future research to investigate how retailers can differentiate themselves from mass-merchant and internet competitors. In other words, are all retailers becoming Wal-Mart/Amazon.com, or is there another alternative?

While we have argued that product offering and service production processes are difficult to change once established, other research challenges this assumption. For example, retail marketing research has suggested that store retailers can differentiate their product offering and offer more private label merchandise in order expand product line margins. This potential strategy offers the opportunity for retailers to expand product line margins; however, it is unclear if the resulting store capital and labor intensity changes required offset this strategy. Given the large amount of marketing literature studying retail merchandising with private labels (e.g. see Dawson et al, 2008 for a review of much of this literature), a study examining the impact of private labels on operating complexity and store design choices is warranted.

In addition, more interdisciplinary research is needed to understand how retail design systems can differentiate and create the in-store experiences that cause customers to feel a sense of buyer loyalty to the store brand (Voss et al., 2008), rather than experience a 'generic' shopping environment in which differentiated value is simply determined by relative price. While marketing research has examined the role of retail atmospherics at evoking customer emotions and creating a sense loyalty in shoppers (Karande and Kumar, 2000; Babin and Attaway, 2000; Babin and Darden, 1996), more work is needed to understand how retail atmospherics can be brought to scale in retail systems or how emotions can be used to evoke product sales (e.g., Is the cost of providing atmospherics worth it?). For example, while Voss, Roth, and Chase (2008) have examined the design architecture choices of service destinations using the analogy of stagecraft; there is ample opportunity in this area to examine if chain retailers also can create a sense of service experience and cost-effectively replicate the "experience architecture" across their store network without it becoming 'generic retailing'.

While in this study we have explored the role of information processing on design choice and customer satisfaction, there are research opportunities to further examine the relative stickiness (generally defined as the cost to transfer a unit of information from a locus to a receiver) and scale of information processing in developing new retail store design channels (von Hippel, 1998, p.629). Service operations literature has explored how service firms might be organized to accelerate new service design development and innovation (Johne and Storey (1998) provide a comprehensive review). However, most of this research is primarily exploratory with limited empirical supporting evidence (Xue and Field, 2008). Understanding the difficulty and cost of a new service information transfer is critical to managing the dynamics of store design strategy, and it should be considered when firms evaluate strategically 1) how to develop a new service concept or offering and 2) how operational knowledge and information related to the new service offering will be transferred throughout the larger organizational design system.

Given that some of our evidence suggests that small retail store chains perform somewhat better on customer delivery satisfaction scores, an investigation of formalized processes for replicating and imitating service delivery systems across a larger chain system is warranted. For example, retail chain store services face challenges to internal integration because high labor turnover and outlet distance inhibits the knowledge creation process (e.g. typically annual employee turnover rates service industries in the 1990s were about 300%, with managerial turnover approaching about 50% - from Darr, Argote, and Epple, 1995). In addition, many retail stores have only seasonal needs for workers. Therefore, retail store chains often manage workers with limited experience and knowledge of business operations; a fact that may cause confusion regarding job duties and responsibilities (Ramaseshan, 1997; Zeytinoglu et al., 2004). These particular human resource dynamics suggest that internal integration, process standardization, and rapid learning may critically important to create economic scale in retail chain store settings (Darr et al., 1995). Similarly, given the evidence that empowerment has a critical effect at satisfying store employees and therefore customers, it would be interesting to empirically examine how successful empowerment programs can be deployed over a chain-wide store network.

Our collective research findings also build a platform for future work examining the long-term sustainability and survival of retail store service firms. At the time of this dissertation, the U.S. (and world) is experiencing the largest economic downturn since the Great Depression. It would be interesting to study the design characteristics of surviving (versus failing) retail firms during this period. There has been much work examining firm failure from the perspective of examining fixed asset productivity (Gaur et al., 1999), debt-leverage ratios, and related bankruptcy measures used to anticipate firm failure. However, there is relatively little work examining the evolution of store design strategy and its effects on creating a 'death spiral' for retail firms. Given that the commercial real estate landscape is now littered with empty storefronts, it would be interesting and valuable for research to examine the impact of not being design responsive has on firm failure, and how firms can break out of these conditions to grow and prosper.

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7

APPENDICES

7.1 Chapter 2 and 3 Additional Analysis

Initial Pool of Items Associated with Each Construct in this Study

-Measured as degree of agreement with item on a 7-point scale (1-strongly disagree, 4-niether agree nor disagree, 7-strongly agree)
-Item numbers after codes indicate the order in which the scale item appeared in the survey section

<u>Store Operating Complexity Factors (3 Scales)</u>

Product Difficulty of Use (DU)

The products that we sell in our store….

DU1…..are easy to use.[r]
DU6…..are easy for the average customer to understand.[r]
DU7…..have features that are well understood by customers before they enter the store.[r]
DU8.…are easy for the average customer to select without sales help.[r,a]
DU4….have many components. a
DU5….need other products or services (like delivery or installation) to be used correctly.[a]
DU3….have many features'

Product Turnover (PT)

The products that we sell in our store….

PT9…lose value the longer they stay on the shelf.
PT11…lose their appeal over time
PT2…have a short shelf life
PT10…have little salvage value
PT12…become outdated quickly.[a]

Service Production Complexity (SC) – (from Skaggs and Huffman, 2003)

The way our store produces its overall service offering for customers…..

SC1…..requires a large number of different processes to be performed by clerks and/or sales people during the service.
SC2…..results in high levels of dependency among processes.
SC3…..requires coordination across our entire organization.
SC4…..requires multiple steps to complete the transaction.[c]
SC5…..requires multiple servers (people) to complete one transaction.[b]

<u>Service Context (1 Scale)</u>

Customer Service Encounter Information Requirements (IR)

IR2 - To satisfy customers, we must obtain information from them during the service.
IR9 - Our customers ask many questions before they make a product selection.
IR10 - Our customers need a lot of help in selecting products.
IR1 - We require a lot of information from each customer to execute our store's service.[b]
IR3 - We spend a lot of time diagnosing customer needs.[b]
IR4 - We spend a lot of time matching customer needs to the appropriate service or product offering.[b]
IR5 - Our customers often have non-standard requests.[b]
IR6 - Our customers expect us to handle inquiries about products.[c]
IR7 - Our customers expect high levels of customized service.[b]
IR8 - Our customers shop the store to gather information about products and services.[b]
IR11 - Our customers expect to be treated as individuals.[b]
IR12 - Our customers often have unpredictable requests.[a]

<u>Customer Encounter Design Choices (2 Scales)</u>

Design for Self-Selection (SS)

SS3 - Our store's use of layout and fixtures make it easy for customers to select and transport products for themselves
SS9 - Our store allows customers to pick products from the shelves themselves.
SS10 - Our stores design is mostly a "self-select" environment.
SS1 - Our store design assumes that customers control most aspects of product selection.[b]
SS2 - Our store's overall design assumes that customers already know a lot about the products that they are purchasing.[c]
SS4 - Our store's overall design helps minimize the amount of time that customers spend selecting and purchasing products. [b]
SS5 - Our store infrastructure facilitates an easy shopping environment.[b]
SS6 - Our store uses signs to give information about products/services to customers.[b]
SS7 - Our store uses directional signage effectively.[b]
SS8 - Our store displays both products and available inventory in the same location.[b]

(Front-line) Employee Task Empowerment (TE) - (from Hayes, 1994)
Our front line store employees…..
TE2…have the authority to correct problems as they occur.
TE3 …are allowed to be creative when they deal with problems at work.
TE4 …do not have to go through a lot of red tape to change things.
TE5 …have a lot of control over how they do their job
TE6 …do not have to get management's approval before they handle problems.
TE1 …employees are allowed to do almost anything to do a high quality job.[b]
TE7 …are encouraged to handle problems by themselves.[c]
TE8 …can make changes on the job whenever they want.[b]

[a.] *removed in prescreening item refinement process*
[b.] *removed after pilot exploratory analysis*
[c.] *removed after sample CFA analysis (Lagrange multiplier (LM) test modifications for cross loadings and correlated errors)*
[r.] *reverse coded item*

Appendix Table 7.1.1– Stage 2 Item Statistics

Final item *correlations* (lower half triangle), *variances* (**diagonal**), and *covariances* (upper half triangle) matrix

	Marker	DU1	DU6	DU7	PT9	PT11	SC1	SC2	SC3	IR2	IR9	IR10	SS3	SS9	SS10	TE2	TE3	TE4	TE5	TE6
Marker	**4.04**	-.23	-.02	-.07	-.16	-.07	-.38	-.36	-.27	-.17	.28	.16	.01	-.35	-.54	.15	.20	-.03	.21	-.14
DU1	-.08	**1.86**	.62	.97	.10	.24	.03	.03	-.00	.45	.34	.44	-.13	-.12	-.05	-.25	-.41	-.39	-.14	-.43
DU6	-.01	.35**	**1.71**	.93	.03	.19	.17	.13	.15	.41	.42	.45	-.35	-.18	-.40	.01	-.06	-.17	-.28	.05
DU7	-.02	.47**	.47**	**2.30**	-.30	.07	.11	.17	.09	.86	.79	.92	-.61	-.59	-.70	.11	.06	-.03	.26	.15
PT9	-.04	.03	.01	-.09	**4.85**	2.25	.02	.11	.10	.10	-.54	-.70	.48	.62	.16	-.42	-.25	-.08	-.75	-.40
PT11	-.02	.07	.08	.03	.54**	**3.61**	.08	.10	.01	.04	-.11	-.04	.14	.26	.26	-.11	-.14	-.24	-.58	.15
SC1	-.09	.08	.48*	.34*	.10	.33*	**4.70**	3.09	2.69	.94	.69	.75	.38	.32	.01	.30	.38	-.15	.27	.05
SC2	-.09	.08	.33*	.52**	.48**	.37*	.71**	**4.06**	2.63	.71	.54	.61	.31	.23	.22	.01	.32	-.13	.21	-.05
SC3	-.07	-.01	.37*	.26*	.41**	.04	.66**	.69**	**3.58**	.61	.51	.45	.28	.17	-.04	-.16	.12	-.31	-.10	-.23
IR2	-.04	.17*	.16*	.29**	.02	.01	.22*	.18*	.16*	**3.83**	1.76	1.57	-.76	-.69	-1.12	.31	.26	.17	.66	-.35
IR9	.08	.15*	.19*	.32**	-.15	-.04	.19*	.16*	.16*	.54**	**2.72**	2.13	-.63	-.76	-1.33	.41	.54	.44	.59	.40
IR10	.05	.19*	.20**	.36**	-.19*	-.01	.20**	.18*	.14	.47**	.76**	**2.81**	-.75	-.86	-1.44	.39	.26	.24	.45	.28
SS3	.00	-.06	-.16*	-.24**	.13	.04	.10	.09	.09	-.23**	-.23**	-.26**	**2.86**	1.98	1.95	-.05	-.19	-.09	-.10	-.15
SS9	-.09	-.04	-.07	-.19*	.14	.07	.07	.06	.05	-.18*	-.23**	-.25**	.58**	**4.02**	3.34	-.35	-.55	-.41	-.61	-.41
SS10	-.12	-.02	-.14	-.21*	.03	.06	.00	.05	-.01	-.26**	-.36**	-.38**	.51**	.75**	**4.99**	-.50	-.56	-.59	-.49	-.75
TE2	.05	-.12	.01	.05	-.12	-.04	.09	.00	-.05	.10	.16*	.14	-.02	-.11	-.10	**2.56**	1.61	1.46	1.38	1.70
TE3	.07	-.21**	-.03	.03	-.08	-.05	.11	.11	.04	.09	.23**	.11	-.08	-.19*	-.13	.76**	**2.08**	1.47	1.55	1.64
TE4	-.01	-.16*	-.07	-.01	-.02	-.07	-.04	-.04	-.09	.05	.14	.08	-.03	-.11	-.14	.52**	.58**	**3.42**	1.80	1.47
TE5	.06	-.06	-.12	.10	-.20**	-.18*	.06	.06	-.03	.20**	.21**	.16	-.03	-.18*	-.09	.56**	.68**	.57**	**2.91**	1.45
TE6	-.04	-.16*	.02	.05	-.10	.04	-.01	-.02	-.06	-.00	.12	.09	-.05	-.10	-.15	.53**	.56**	.44**	.45**	**3.77**

* $p < 0.05$

** $p < 0.01$

[a] The marker variable is a measure of 'seasonal traffic' which should not be theoretically related to any of the model constructs.

7.2 Procedures for Item Development and Field Survey

7.2.1 Calling Script

Note to callers: It is important to try and get the names of at least two contacts (manager, assistant manager, sales manager, owner). We will still send the survey if only one agrees to participate.

Hi. My name is ___________, a college student at Clemson University. I am working with Researchers on a survey project of store managers (in the Upstate). I am calling store managers across the Southeast (Upstate) asking them to participate in a confidential survey, neither your name nor the store name will be on the survey. May I mail you a copy of this short survey?

[What is survey about?]

General questions about service delivery and customer satisfaction in retailing.

[Where did you get this number?]

Your business was selected at random from the phone book for the sample. All results <u>will be held confidential.</u> So, there is no risk to you or your business in participating.

[Store policy?]

Do you have a number I could call to get permission?

GET NUMBER OF CORPORATE CONTACT.

[YES] Could you give me the name of a Manager, Asst. Manager, Supervisor at your business so I could mail them the survey? (Try to get at least 2 contacts)

GET NECESSARY INFORMATION.

THANK THEM FOR PARTICIPATING.

[NO]

THANK THEM FOR THEIR TIME.

7.2.3 Procedures Used to Generate and Confirm Item Scales

(thank you to Dwayne Moore, Professor of Psychology, Clemson University, for his help on developing these procedures)

<u>Pilot Data Sample</u> (n=42) ------ Factor Analysis Packet

Step 1 – Conducted Factor Analysis with Maximum Likelihood (not Principal components) Extraction with no rotation for each construct*

Step 2 – Removed bad items one at a time based on factor loading component matrix. Simultaneously analyzed each factor structure for unidimensionality using parallel Scree test (Fabrigar et al., 1998)*

Step 3 –No LM test on the pilot study to check for cross-loadings.

(*Stage 1 Analysis completed with SPSS V13.0 statistical software - source code can be provided upon request)

<u>Field Sample</u>-(n=175) ----- 5 CFA Model packets (shockleymodelrun1 - shockleymodelrun5)

Step 4 – Used the results from steps (1-3) to generate CFA measurement model "shockleymodel1" – to confirm the item to constructs in the initial model

Step 5 – Used a Lagrange Multiplier test to examine for cross-loadings and unidimensionality of each construct (end of EQS output)

Step 6 – Made modifications based on chi-square differences in LM test one item at a time

-"**shockleymodel1**" is the initial model with item to factor loadings from Stage 1 (X^2-372,CFI-.91,RMSEA-.06)

-"**shockleymodel5**" is the resulting model after 5 LM modifications (X^2-174,CFI-.97,RMSEA-.04)

*EQS code, output, and diagrams are available for each model run.

7.2.4 Clemson University Retail Store Manager Survey

(Adapted from cover letter booklet form to shrink-fit in space allotted)

<u>COVER LETTER</u>

CLEMSON UNIVERSITY

April, 2006

Dear <*Business Manager Name*>,

Thank you for agreeing to participate in this survey. We are studying how retailers design service systems to improve customer satisfaction. The objective of this project is to increase our understanding of the drivers of customer satisfaction, so that retailers can more effectively design store selling systems. The research findings will be used in classes here at Clemson University.

Attached is a questionnaire that we would like you to complete. It asks a variety of questions concerning your store's design and policies. We hope that you will take the time to complete this important questionnaire (10 to 20 minutes). Your participation will help us to better understand what factors enable store service delivery systems to succeed, as well as what factors hinder success. A similar survey is being completed by other retailers in your area.

We emphasize that this is a research project. Your responses are confidential and we guarantee that your choice to participate and your responses will not be identified with you personally. In fact, we ask that you do not write your name on the questionnaire. We do not need to know who you are. Your participation is completely voluntary and you may withdraw at anytime without penalty or prejudice. There is no risk to you or your company in participating.

If you have any questions or concerns about this study or if any problems arise, please contact Larry Fredendall at Clemson University at 864.656.2016. If you have any questions or concerns about your rights as a research participant, please contact the Clemson University Office of Research Compliance at 864.656.6460.

Thank you for your participation,

Larry Fredendall
Clemson University
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Jeff Shockley
Clemson University
(864) 986-9232
tshockl@clemson.edu

BOOKLET COVER (Shrink to fit in space allotted)

Clemson University
Survey of Retailers

Please return your completed questionnaire
in the enclosed envelope to:

Retail Survey, Department of Management
Clemson University, Clemson SC 29634-1305

I. Please supply general information about yourself and your employer.

PART 1: Manager Information Your Title ________________

1. How long have you worked at this store?
   - ☐ Less than 2 years.
   - ☐ 2-5 years.
   - ☐ 5-10 years
   - ☐ 10-20 years
   - ☐ More than 20 years

2. How long have you been a Manager at this store?
   - ☐ Less than 1 year
   - ☐ 1-2 years
   - ☐ 3-5 years
   - ☐ 5-10 years
   - ☐ Longer than 10 years

3. Which of the following best describes your store's retail business (Check all that apply):
   - ☐ Motor Vehicle and Parts
   - ☐ Furniture and Home Furnishings
   - ☐ Electronics and Appliances
   - ☐ Building Materials, Garden Equipment, and Supplies
   - ☐ Food and Beverage
   - ☐ Health and Personal Care
   - ☐ Gasoline Station
   - ☐ Clothing and Accessories
   - ☐ Sporting Goods, Hobby, Book, and Music
   - ☐ General Merchandise

PART 2: Circle the degree to which you Agree or Disagree with the following statements about the **nature of products and services** at your store.

Strongly Disagree	Neither Agree nor Disagree	Strongly Agree

	The way our store produces its overall service offering for customers . . .	**SD** 1	2	3	**N** 4	5	6	**SA** 7
1*	..requires a large number of different processes to be performed by clerks and/or sales people during the service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	..results in high levels of dependency among processes.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	..requires coordination across our entire organization.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4*	..requires multiple steps to complete transactions.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5*	..requires multiple servers (people) to complete one transaction.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

	The products that we sell in our store….	**SD** 1	2	3	**N** 4	5	6	**SA** 7
1*	..are easy to use.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	..have a short shelf life	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	..have many features.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4*	..have many components.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5*	..need other products or services (like delivery or installation) to be used correctly.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6*	..are easy for the average customer to understand.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7*	..have features that are well understood by customers before they enter the store.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8*	..are easy for the average customer to select without sales help.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9*	..lose value the longer they stay on the shelf .	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10*	..have little salvage value.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11*	..lose their appeal over time.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12*	..become outdated quickly.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

*Items used in Chapter 2-3 construct development

		Strongly Disagree			Neither Agree nor Disagree			Strongly Agree
	Part 3: Circle the degree to which you Agree or Disagree with the following Statements about ***customer traffic*** at your store.	**SD**			**N**			**SA**
		1	**2**	**3**	**4**	**5**	**6**	**7**
	At our store, customer traffic is…..							
1	…evenly spread out over the day.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2	….evenly spread throughout the week.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3	….highly seasonal.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4	….easy to predict/forecast.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5	….highly dependent on the time of day.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6	….hard to anticipate.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7	….anticipated using reliable store forecasts.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

		Strongly Disagree			Neither Agree nor Disagree			Strongly Agree
	PART 4: Circle the degree to which you Agree or Disagree with the following statements about ***interactions with customers*** at your store.	**SD**			**N**			**SA**
		1	**2**	**3**	**4**	**5**	**6**	**7**
1*	We require a lot of information from each customer to execute our store's service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	To satisfy customers, we must obtain information from them during the service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	We spend a lot of time diagnosing customer needs.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4*	We spend a lot of time matching customer needs to the appropriate service or product offering.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
	Our Customers…							
5*	..often have "non-standard" requests.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6*	..expect us to be able to handle inquiries about products.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7*	..expect high levels of customized service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8*	..shop the store to gather information about products or services.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9*	..ask many questions before they make a product selection.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10*	..need a lot help in selecting products.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11*	..expect to be treated as individuals.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12*	..often have unpredictable requests	**1**	**2**	**3**	**4**	**5**	**6**	**7**

*Items used in Chapter 2-3 construct development

PART 5: Descriptive Information

1. What are your store's approximate annual sales ($ millions)?	2. How many employees (FTEs), on average, are employed by your store?
☐ 1 – 5 million ☐ 5 - 10 million ☐ 10 – 20 million ☐ More than 20 million	☐ < 10 ☐ 10-15 ☐ 15-20 ☐ 20-25 ☐ 25+

PART 6: Circle the degree to which you Agree or Disagree with the following statements about your **store's use of fixtures, layout, and information systems** (store infrastructure).

Strongly Disagree | **Neither Agree nor Disagree** | **Strongly Agree**

		SD			**N**			**SA**
		1------2------3------4------5------6------7						
1*	Our store design assumes that customers control most aspects of product selection.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	Our store's overall design assumes that customers already know a lot about the products that they are purchasing.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	Our store's use of layout and fixtures make it easy for customers to select and transport products for themselves.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4*	Our store's overall design helps minimize the amount of time that customers spend selecting and purchasing products.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5*	Our store infrastructure facilitates an easy shopping environment.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6*	Our store uses signs to give information about products/services to customers.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7*	Our store uses directional signage effectively.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8*	Our store displays both products and available inventory in the same location.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9*	Our store allows customers to pick products from the shelves themselves.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10*	Our store's design is mostly a "self-select" environment.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

*Items used in Chapter 2-3 construct development

		Strongly Disagree			Neither Agree nor Disagree			Strongly Agree
	Part 7: Circle the degree to which you Agree or Disagree with the following statements about ***store employee job designs*** in your store**.**	**SD** 1	**2**	**3**	**N** 4	**5**	**6**	**SA** 7
1*	Our employees are allowed to do almost anything to do a high quality job.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	Our employees have the authority to correct problems as they occur.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	Our employees are allowed to be creative when they deal with problems at work.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4*	Our employees do not have to go through a lot of red tape to change things.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5*	Our employees have a lot of control over how they do their job.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6*	Our employees do not have to get management's approval before they handle problems.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7*	Our employees are encouraged to handle problems by themselves.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8*	Our employees can make changes on the job whenever they want.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9	Our employees are allowed to deviate from standard warranty and return policies.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10	Our employees are allowed to deviate from standard shelf-stocking/merchandising procedures	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11	Our employees can do anything to improve customer service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12	Our employees have high task discretion.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13	Our employees set own targets and goals for their job.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

*Items used in Chapter 2-3 construct development

		Strongly Disagree			Neither Agree nor Disagree			Strongly Agree
	PART 8: Circle the degree to which you Agree or Disagree with the following statements about ***service performance*** at this store.	**SD**			**N**			**SA**
		1------2------3------4------5------6------7						
1*	Customer satisfaction with our service offering is higher that with our competitors.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2*	Employee job satisfaction is high.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3*	Employee turnover is lower than competitors.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4	Our service delivery system is the most cost effective way of providing this service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5*	Our service delivery system is the most customer friendly for the products that we sell.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6*	Our customers are highly satisfied with our store's service level.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7	For the products we sell, our service delivery system is the best possible system.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8	Our service delivery system is more cost effective than our competitors.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9	Our sales per employee are higher than our competitors.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

*Items used in Chapter 2-3 construct development

		Strongly Disagree			Neither Agree nor Disagree			Strongly Agree
	PART 9: Circle the degree to which you Agree or Disagree with the following statements **about your store.**	**SD**			**N**			**SA**
		1------2------3------4------5------6------7						
1	Our store uses automated or self-checkout.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
2	Our store uses central checkout.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
3	Our store uses multiple lines at central checkout.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
4	The income level of our customers is higher than the national average.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
5	Our store has one or more “stores within a store.”	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6	Customers must go to different areas of our store to receive different services.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
7	We use our store warehouse space to store excess inventory.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
8	Once products are unloaded from the truck, they go immediately to our sales floor.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
9	We offer packages of products or services in our store.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
10	Our workers are highly trained.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11	Our worker pay is above the industry average.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
12	Performance incentives are a significant chunk of our worker’s compensation.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
13	Our employees are trained to use scripts when interacting with customers.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
14	Workers in our store are responsible for qualifying customers to higher levels of service.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
15	Our store relies on in-store signs and point of purchase materials to communicate product information.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
16	Our store uses standard pricing to simplify transactions.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
17	We use a lot of information technology in our store.	**1**	**2**	**3**	**4**	**5**	**6**	**7**
18	Our workers are highly satisfied with their jobs.	**1**	**2**	**3**	**4**	**5**	**6**	**7**

Comments / Suggestions ____

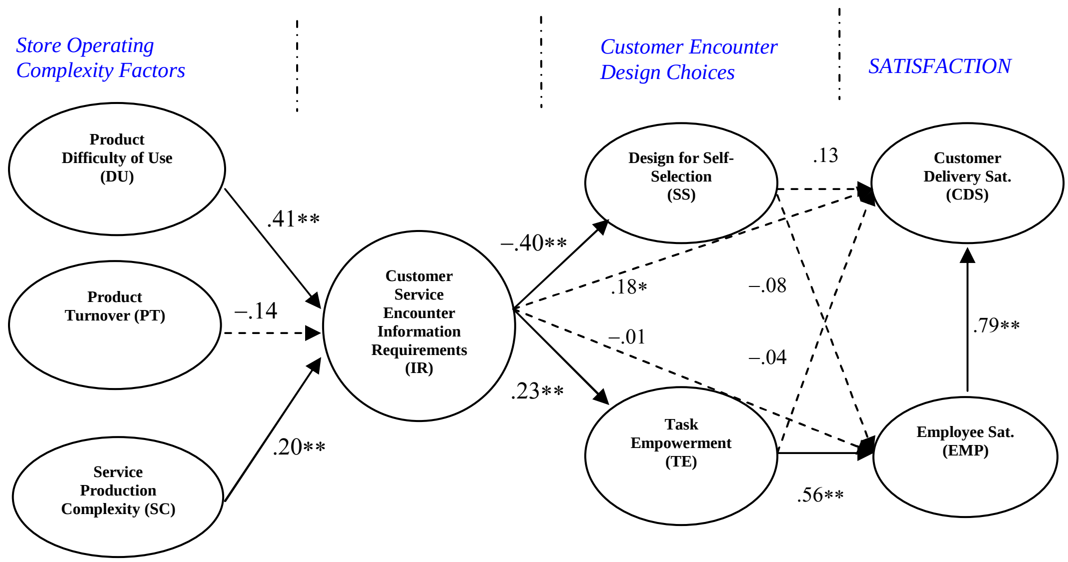
____

Thank You for Help !

7.3 Chapter 3 Additional Analysis

Table 7.3.1

Diagram of the Mediation (Control) Model (n=175) – Model 2
– For Analyzing Total (T.E.), Direct (D.E.), and Indirect (I.E.) Effects
(Standardized Maximum Likelihood Parameter Estimates for multi-item latent constructs)



* $p < 0.10$, ** $p < 0.05$

7.4 Chapter 4 Additional Analysis

7.4.1 Panel Data Analysis Diagnostics and Alternative Model Testing

A.1 Tests for Serial Dependence (Autocorrelation of Errors) in the Dependent Variable

Serial dependence of the dependent variable can be tested by using any of a wide range of tests (e.g. Baltagi, 2003, (pp.81-102) discusses many of these tests including the popular Lagrange multiplier (LM) and Likelihood ratio (LR) tests). We use an easy (and robust) test for serial correlation recommended by Drukker (2003), who discusses Wooldridge's (2002) method for testing serial autocorrelation by "using the residuals from a regression in first differences" of the specified model (p.169). Drukker's (2003) simulation analysis finds that Wooldridge's (2002) test for serial correlation removes individual effects by taking the first differences of the model, and then it compares the correlation of the differenced error term to the lagged differenced error term. Wooldridge's reports that, if the error terms of the dependent variable "are not serially correlated," then the "coefficient on the lagged residuals" should be equal to -.5 (Drukker, 2003, p.169). Like the Durbin-Watson test statistic and the Breusch-Godfrey LM test statistic, this method tests for autocorrelation in the model under the null hypothesis of no autocorrelation. The f-test is executed in STATA as follows:

. xtserial *variablename*

Wooldridge test for autocorrelation in panel data
H0: no first order autocorrelation

Dependent Variable	**F (df) =**	**Prob > F =**
ROA	309.13 (df=219)	.000
ROS	244.59 (df=219)	.000

A.2 Collinearity Diagnostics

Collinearity is assessed using the "collin" procedure in STATA following the procedures discussed in Plummer (2007, p.83) and Baum (2006, p.85). The table statistics are explained as follows: R-squared (R-Sq) is the independent variable regressed on the other independent variables, the "tolerance" value equals one minus the reported r-squared, the variance inflation factor (VIF) equals the reciprocal of the tolerance, and the model condition index is the square root of the ratio of the largest to smallest eigenvalue in the model matrix. A condition index >30 or a VIF > 10 are often used as cutoffs.

STATA: 'collin independent variables'

Variable	VIF	SQRT VIF	Tolerance	R-Sq	Order	Condition Index
SLinc	1.20	1.09	0.83	.16	1	2.5
SLdec	1.43	1.20	0.69	.30	2	2.9
SKinc	1.21	1.10	0.82	.17	3	3.4
SKdec	1.41	1.19	0.70	.29	4	4.7
Log'S"	1.22	1.10	0.82	.17	5	5.4
RG	1.77	1.33	0.56	.43	6	8.4
NG	1.52	1.23	0.65	.34	7	13.4
I	1.69	1.30	0.59	.40	8	19.1
SM	1.63	1.28	0.61	.39	9	25.8
SG	1.05	1.02	0.95	.04	10	28.6
E	1.12	1.06	0.89	.10	11	58.6

*****Final Iteration[1]

Variable	VIF	SQRT VIF	Tolerance	R-Sq	Order	Condition Index
SLinc	1.19	1.09	0.84	.16	1	2.1
SLdec	1.43	1.20	0.69	.30	2	2.6
SKinc	1.21	1.10	0.82	.17	3	3.0
SKdec	1.41	1.19	0.71	.29	4	4.1
Log'S'	1.17	1.08	0.85	.15	5	4.7
RG	1.72	1.31	0.58	.41	6	7.5
NG	1.52	1.23	0.65	.34	7	11.7
I	1.18	1.09	0.84	.15	8	20.1
E	1.08	1.04	0.92	.07	9	29.4

[1]Removal of IVs for SM and SG were shown to exhibit collinearity, so we respecified the model without these most problematic variables and it showed acceptable properties. The sensitivity analysis revealed that including any of industry segment variable had no impact on the design responsiveness coefficients of interest.

A.3 Panel-level Heteroscedasticity Diagnostics

Greene (2003, pp.230-232) reports several methods to test for normality of errors in panel data, including the Likelihood ratio (LR), Lagrange multiplier (LM), and the Wald test (p.230). The Wald test is a particularly easy and robust procedure to run in STATA. The standardized Wald test statistic (Greene, 2003) tests the null hypothesis of homoscedasticity of errors by comparing the maximum likelihood results of two covariance matrices of data (e.g. homoscedastic versus heteroscedastic error structures would be compared). A rejection of the null hypothesis of homoscedasticity, suggests that the data is heteroscedastic and that robust estimation of errors (and related Hansen test statistics) is needed to adjust for scalar differences in the data structure. We run a series of linear models in STATA, followed by the 'xttest3' postestimation:

Modified Wald Statistic[1]
STATA postestimation command: 'xttest3'

Cross-sectional time-series generalized least squares regression:
xi: xtgls ROA SLinc SLdec SKinc SKdec logS xRG NG xI xE i.fyear

Modified Wald test for groupwise heteroscedasticity
in cross-sectional time-series FGLS regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (226) = 1.6e+05
Prob>chi2 = 0.0000

Fixed-effects (within) regression:
xtreg ROA Slinc Sldec Skinc Skdec 207ogs xRG NG xI xE, fe

Modified Wald test for groupwise heteroscedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (226) = 4.0e+32
Prob>chi2 = 0.0000

[1] Both models show strong evidence of heteroscedasticity across panels as p<.01 (Baum, 2006, p.222)

A.4 Dependent Variable Stationarity* Diagnostics

STATA: xtfisher *dependentvariable*, drift lags(1)

Fisher Test for panel unit root using an augmented Dickey-Fuller test (1 lags)
Ho: unit root is non-stationary[1]

Dependent Variable	X^2	Prob > X^2
ROA	905.92(df=344)	.000
ROS	881.96(df=344)	.000

[1]Null (Ho) of non-stationarity is rejected in all cases.

Table A.5:
Alternative Model Specification Using Difference GMM estimator, DV=ROS[1] & ROAF

Dependent Variable	ROS	ROAF
Model (column)	1	2
time lag t-1	0.33 **	0.12
	[2.45]	[1.55]
Firm		
SLinc - Increasing store labor responsiveness	-0.01	0.14
	[0.16]	[1.07]
SLdec - Decreasing store labor responsiveness	0.27 **	0.36
	[1.99]	[1.47]
SKinc - Increasing store capital responsiveness	-0.07 *	-0.16 *
	[1.65]	[1.66]
SKdec - Decreasing store capital responsiveness	-0.14 *	-0.11
	[1.74]	[0.69]
Sales (logS)	0.08	-0.08
	[1.45]	[0.69]
Revenue Growth (RG)	0.15 **	0.34 **
	[2.91]	[2.26]
Store Growth (NG)	0.00	-0.21 *
	[0.20]	[1.86]
Relative Inventory (I)	-0.14	-0.93 *
	[0.94]	[1.86]
Segment		
Competitive Intensity (E)	-0.00	0.10
	[0.20]	[0.06]
Time		
Time dummies (included)	Yes	Yes
Constant		
Observations	1555	1340
Number of Firms	218	207
Hansen Test (p-value)	.308	.308
Arellano-Bond AR(1)	-2.7 **	-3.3 **
Arellano-Bond AR(2)	0.5	1.1
F Test	4.1 **	5.7 **

Difference GMM estimates (Stata, xtabond2..nolevelseq); the lag of dependent variable is endogenous; all the independent variables entered as exogenous; absolute value of t statistics are in brackets; robust standard errors
One-tailed tests: * Significant at 10%; ** Significant at 5%

[1]Sensitivity analysis revealed for the ROS DV that reported coefficient patterns were similar (albeit weaker) to those observed for an ROA DV.

Table A.6:
Alternative Model Specification Using System GMM estimator, DV=ROS[1] & ROAF

Dependent Variable	ROS	ROAF
Model (column)	1	2
time lag t-1	0.60 **	0.64 **
	[4.90]	[4.47]
Firm		
SLinc - Increasing store labor responsiveness	0.01	0.14
	[0.25]	[1.08]
SLdec - Decreasing store labor responsiveness	0.23 **	0.38
	[1.96]	[1.52]
SKinc - Increasing store capital responsiveness	-0.11 **	-0.12
	[1.97]	[1.51]
SKdec - Decreasing store capital responsiveness	-0.14 **	0.15
	[2.41]	[0.80]
Sales (logS)	0.00	0.02
	[0.35]	[0.96]
Revenue Growth (RG)	0.15 **	0.32 **
	[4.50]	[2.24]
Store Growth (NG)	0.01	-0.22 **
	[0.41]	[2.37]
Relative Inventory (I)	-0.06	-0.11
	[1.51]	[1.06]
Segment		
Competitive Intensity (E)	-0.03	0.02
	[0.02]	[0.49]
Time		
Time dummies (included)	Yes	Yes
Constant		
Observations	1784	1562
Number of Firms	226	220
Sargan / Hansen Test (p-value)	.334	.838
Arellano-Bond AR(1)	-4.5 **	-4.3 **
Arellano-Bond AR(2)	0.67	1.1
F Test	19.6 **	21.1 **

System GMM estimates (Stata, xtabond2); the lag of dependent variable is endogenous; all the independent variables entered as exogenous; absolute value of t statistics are in brackets; robust standard errors;
One-tailed tests: * Significant at 10%; ** Significant at 5%

[1]Sensitivity analysis for the ROS DV revealed that reported coefficient patterns were similar to those observed for an ROA DV.

Table A.7: Alternative Model Specification Using System GMM estimator for ROAF

Dependent Variable	ROAF	ROAF
Model (column)	1	2
time lag t-1	0.82 **	0.64 **
	[4.90]	[4.47]
Firm		
SLinc - Increasing store labor responsiveness	0.00	0.14
	[0.03]	[1.08]
SLdec - Decreasing store labor responsiveness	0.01	0.38
	[0.17]	[1.52]
SKinc - Increasing store capital responsiveness	-0.00	-0.12
	[1.18]	[1.51]
SKdec - Decreasing store capital responsiveness	0.08	0.15
	[1.33]	[0.80]
Sales (logS)	-0.00	0.02
	[0.18]	[0.96]
Revenue Growth (RG)	0.02	0.32 **
	[4.50]	[2.24]
Store Growth (NG)	-0.01	-0.22 **
	[0.93]	[2.37]
Relative Inventory (I)	-0.07 **	-0.11
	[2.21]	[1.06]
Segment		
Competitive Intensity (E)	0.00	0.02
	[0.63]	[0.49]
Time		
Time dummies (included)	Yes	Yes
Constant	.01	-.18
Observations	1562	1562
Number of Firms	220	220
Hansen Test (p-value)	1.00	.838
Arellano-Bond AR(1)	-4.6 **	-4.3 **
Arellano-Bond AR(2)	-0.46	1.1
F Test	93.1 **	21.1 **

System GMM estimates (Stata, xtabond2); the lag of dependent variable is endogenous; model treats IVs as follows: Column 1 = (I, logS - endogenous; NG, RG – predetermined); Column 2 = (all IVs exogenous); absolute value of t statistics are in brackets; robust standard errors;
One-tailed tests: * Significant at 10%; ** Significant at 5%

[1]Sensitivity analysis for the ROS DV revealed that reported coefficient patterns were similar to those observed for an ROA DV.

Table A.8: Forward ACSI[1] - Scores Analysis using System GMM Estimation

Dependent Variable	ACSIF2
Model (column)	1
time lag t-1	0.76 **
	[12.15]
Firm	
SLinc - Increasing store labor responsiveness	-15.8 **
	[2.05]
SLdec - Decreasing store labor responsiveness	-15.1 **
	[2.81]
SKinc - Increasing store capital responsiveness	3.08 **
	[3.10]
SKdec - Decreasing store capital responsiveness	10.6 **
	[2.37]
Sales (logS)	-0.83
	[1.09]
Revenue Growth (RG)	2.0
	[1.48]
Store Growth (NG)	-0.51
	[1.46]
Relative Inventory (I)	-1.8
	[0.55]
Segment	
Competitive Intensity (E)	-0.1
	[0.21]
Constant	21.2 **
	[2.41]
Time	
Time dummies (included)	Yes
Constant	
Observations	141
Number of Firms	24
F-test	179 **

System GMM estimates (Stata, xtabond2); the lag of dependent variable is endogenous; absolute value of t statistics are in brackets; robust standard errors;
model treats IVs as follows: (I, logS - endogenous; NG, RG – predetermined);
One-tailed tests: * Significant at 10%; ** Significant at 5%

[1]The acsiF2 (1-year forward customer satisfaction score) dependent variable was calculated using only a subset of firms. Furthermore, our analysis of acsi score data (See Appendix 7.3.3) revealed that any specification of the System model yielded similar results for the responsiveness coefficients.

Table A.9: Distribution Statistics for Baseline Design Responsiveness Variables

Variable	*Mean*	*Std. Dev.*	*Obs*[1] *(Δt)*	*5%*	*25%*	*50%*	*75%*	*95%*
SL (labor)	-0.01	0.17	1793	-0.16	-0.06	-0.02	0.02	0.11
SK (capital)	0.03	0.27	1803	-0.17	-0.05	0.001	0.02	0.11

[1] The number of reported observations represents a loss of one degree of freedom to calculate the elasticity variable

7.4.2 Sensitivity Analysis

Summary of Sensitivity Analysis

While there are no established rules for conducting sensitivity analysis with panel data models, it is important to acknowledge how the findings react to inputting different variables or making certain assumptions when modeling the data (Plummer, 2007; Kennedy, 2003). We constructed a STATA "Do-file" and examined a series of alternative model specifications (A '.pdf' of the Log-file is available upon request) for each analytical approach and dependent variable (*ROA*, *ROAF*, *ROS*) used in the paper tables. First we examined a series of liner (non-dynamic) pooled and fixed-effect regression models. We find that these models generally confirm our findings on the negative performance impact of increasing store labor intensity responsiveness (*SLinc*) and also for both store capital intensity responsiveness measures (*SKinc* & *Skdec*). We also find that the firm-specific results are robust when controlling segment membership – e.g. the results hold up when segment effects are included (using the dummy variable code *i.Seg* and the xi: command in STATA).

In general, our findings related to the elasticity measure of store labor responsiveness (*SL*) are robust to different model specifications provided that firm-specific control variables for size (*logS*), sales growth (*RG*), store growth (*NG*) and inventory management (*I*) and store capital intensity responsiveness (*SKinc* & *SKdec*) are all included. As discussed in the text of the paper, the decision to include any or all of the segment control variables really has no bearing on any of the dynamic model results where ROA is the DV. This may be because the lagged dependent variable used in each equation term is incorporating much of the random error in the firm's segment. This finding was useful because it allowed us to remove any or all of these three variables to reduce model multicollinearity issues without affecting the model.

However, we do find that the results (particularly for increasing store labor and capital intensity responsiveness) become quite sensitive once we start instrumenting for any endogeneity and persistence bias in several firm-specific control variables, particularly those related to Size (logS) – for store labor intensity responsiveness - and revenue (*RG*) and store growth (*NG*) rates – for store capital intensity responsiveness. This is not particularly surprising given the role that each variable plays in firm staffing and capital planning models for populating stores in new locations, or in providing specific revenue support for revenue planning and capital management efforts. It is also clear that being overly responsive with capital intensity (*SKinc*) is not as robust, and does not have nearly the same negative performance effect as does under investing in store capital (*SKdec*) year to year. This finding may speak to both the importance to profits of a retail firm's ongoing investment in good store locations and the short-term significance of in-store capital investment in internal store systems.

Finally, we examined the alternative dependent variables (*ROS*) and (*ROAF*) to see if using different performance measures made a difference in interpreting the model findings and to find out if there were carryover affects on forward profits. The results for the *ROS* models largely mirror the findings using *ROA*, except that the findings for both store labor and capital responsiveness (*SLinc, SLdec, SKinc*, *SKdec*) are weaker ($p<.10$ or greater) in the ROS models. As reported in the paper text, for forward ROA (*ROAF*), we see no significant ($p<.05$) results for any of our design responsiveness measures.

7.4.3 ACSI Analysis Sensitivity

Summary Forward ACSI Analysis (STATA "Log-file" available upon request)

Since the University of Michigan ACSI data uses a different database (as well as a calendar versus fiscal year reporting schedule), and is available for a much smaller sub-sample of firms in our study, we conducted a separate sensitivity analysis to understand the impact that our specified model variables was having on forward customer satisfaction. Across all linear and difference models negative responsiveness variables (*SLdec, SKdec*) had negative and positive coefficients respectively, with the negative effect of *SLdec* on forward customer satisfaction scores (*acsiF2*) being about four times that of the positive affect of *SKdec*.

It is also interesting to note from our analysis while the acsi dependent variable is highly persistent, particularly after controlling for other firm-specific characteristics in the dynamic model. Given this fact and that the store subsample used is somewhat small, we primarily relied on system GMM for our findings. When using our fully instrumented model in the last series of tests, we discovered that our both our increasing and decreasing store labor intensity responsiveness measures were negatively associated with forward customer satisfaction scores. However, given that the number of variables used is large relative to the number of observations (Hansen test = 1.0), these results should be viewed with caution.