

AMA Marketing Strategy SIG Working Paper Series
07-003

EMBEDDEDNESS OF ORGANIZATIONAL CAPABILITIES *

RAJDEEP GREWAL †

The Smeal College of Business Administration
The Pennsylvania State University
407 Business Bldg.
University Park, PA 16802
Phone: 814-863-0728
Fax: 814-865-3015
Email: rug2@psu.edu

REBECCA J. SLOTEGRAAF

Kelley School of Business
Indiana University
1309 East Tenth Street
Bloomington, IN 47405
Phone: 812-855-1014
Fax: 812-855-6440
Email: rslotegr@indiana.edu

* The authors are listed in alphabetical order and contributed equally to the paper. This research benefited from the feedback of Steven Brown, Chris Moorman, Peter Dickson, Dhruv Grewal, Bob Lusch, Neil Morgan, Xing Pan, Ratti Ratneshwar, and seminar participants at the University of Missouri-Columbia and the University of Houston. This research was partly supported by a grant from The Center for Education and Research in Retailing, Kelley School of Business, Indiana University.

† Corresponding author.

EMBEDDEDNESS OF ORGANIZATIONAL CAPABILITIES

ABSTRACT

Managers must regularly make decisions on how to access and deploy their limited resources in order to build organizational capabilities for a sustainable competitive advantage. However, failure to recognize that organizational capabilities involve complex and intricately woven underlying processes may lead to an incomplete understanding of how capabilities affect competitive advantage. As a means of understanding this underlying complexity, we discuss how managerial decisions on resource acquisition and deployment influence capability embeddedness and argue that capability embeddedness has an incremental effect on firm performance beyond the effects from organizational resources and capabilities. To investigate these issues, we present a hierarchical composed error structure framework that relies on cross-sectional data (and allows for generalizations to panel data). We demonstrate the framework in the context of retailing, where we show that the embeddedness of organizational capabilities influences retailer performance above and beyond the tangible and intangible resources and capabilities that a retailer possesses. Our results illustrate that understanding how resources and capabilities influence performance at different hierarchical levels within a firm can aid managers to make better decisions on how they can embed certain capabilities within the structural and social relationships within the firm. Moreover, understanding whether the underlying objectives of the capabilities that are being built and cultivated have convergent or divergent goals is critical, as it can influence the extent to which the embedded capabilities enhances firm performance.

Subject Areas: Composed Error Models, Embeddedness, Organizational Capabilities, Resource-based Theory, Retail Management, and Stochastic Frontier Models.

INTRODUCTION

One of the fundamental strategic choices that managers face is how to deploy their limited resources not only to achieve a competitive advantage but also to make that advantage sustainable. Theoretically, the resource-based view of the firm (RBV) depicts resources to vary in value, inimitability, substitutability, and rarity (Barney, 1991), from which organizations can draw to generate competitive advantage (e.g., Penrose, 1959; Wernerfelt, 1984). However, it is more than the resources themselves, but the specific decisions involved in how resources are accessed, combined, and deployed that generate a firm's capabilities (Grant, 1991; Moran & Ghoshal, 1999). For the purpose of this article, we adopt the definition of organizational capabilities espoused by Grant, (1996, p. 377), that is, the "ability to perform repeatedly a productive task which relates either directly or indirectly to a firm's capacity for creating value through effecting the transformation of inputs into outputs." From this perspective, resources serve as the inputs, or "source of a firm's capabilities" (Grant, 1991, p. 119; see also, for example, Learned, Christensen, Andrews, & Guth, 1969; Teece, Pisano, & Schuen, 1997). Decisions regarding which capabilities to build or accumulate, and how this should be accomplished, are integral to understanding how capabilities can influence a firm's competitive advantage.

To enhance the sustainability of the advantage, managers can purposefully build capabilities by focusing on resources that are interconnected (e.g., Dierickx & Cool, 1989), deeply rooted within the intra-firm relationships and knowledge-base of the firm (Kogut & Zander, 1992), and span the firm's business functions and hierarchical levels (e.g., Grant, 1996; Zeitz, Mittal, & McCauly, 1999; Erdem & Swait, 2004). As a result, the capabilities become embedded within the organization (Day, 1994). With decision making shaped "by the formal system of rules and organizational hierarchies, and by the multilevel relational contexts within which action occurs" (Sutcliffe & McNamara, 2001, p. 486), managers who weave an organization's capabilities throughout different interconnected and hierarchical processes create capability embeddedness, which makes the capability more difficult for competitors to imitate; thereby enhancing the sustainability of a competitive advantage.

Therefore, through deliberate decisions over time, managers can embed specific capabilities into the fabric of an organization. For example, it is what Andersen Consulting deliberately created when it developed a knowledge management capability where information, insights, and experiences were synthesized into knowledge and shared throughout the organization to support complex decision making in a global and fast-paced environment (Slotegraaf, 1999). Moreover, their decision to dedicate valued human and physical resources for updating and managing this process further entrenches this capability within Andersen Consulting. Capability embeddedness is also what Wegmans Food Markets generated through structural, cultural, and relational decisions that created a strong customer relationship capability (*Fortune*, 2005). Among the numerous interconnected strategic choices available to Wegmans, it hires individuals with a passion for food and then offers top-notch training at all levels in the firm; it empowers store employees to use various means to heighten customer experience, and it provides online recipes that are easy for consumers to follow and links the ingredients to the store's vast product offerings. Each of these decisions is interrelated such that, for example, employee empowerment is more valuable from passionate and knowledgeable employees. In this way, Wegmans' decisions to utilize activities that are idiosyncratically tied to its social structure, highly interrelated, and selected with the objective to enhance the customer experience will embed a customer relationship capability in its social fabric. Do observe that while organizational capabilities involve routines and processes (Nelson & Winter, 1982) that make superior use of a firm's resources (Penrose, 1959), capability embeddedness is distinct in that it reflects a by-product that occurs as a result of the extent to which a capability is contextually entrenched within the structural and socio-cultural fabric of the firm. Thus, deliberate decisions over time, based on the different resources available to a firm, can create capability embeddedness.

As previously mentioned, an advantage of capability embeddedness is its creation of a barrier to imitation. In particular, the nested hierarchies and evolutionary interdependence of firm resources makes copying best practice imperfect if not impossible (Dickson, 2003). Moreover, various activities and processes are entrenched in the organization's shared understandings and meanings that have evolved over time (Dacin, Ventresca, & Beal, 1999). For example, it is what allows Dell to disclose their direct

business model yet retain barriers of replication. Similarly, it is how the nature and level of customer service at Nordstrom that generates its competitive advantage can be repeatedly revealed, yet remain inimitable by Nordstrom's competitors (Spector & McCarthy, 2000). However, capability embeddedness may also pose problems for firms. In particular, failure to recognize capability embeddedness can lead to internal ambiguity as to which factors are actually responsible for superior performance (Demsetz, 1973). The complex and deeply interrelated routines upon which organizational capabilities are built lead to causal ambiguity, or an incomplete understanding of the linkage between actions and outcomes (Lippman & Rumelt, 1982; Nelson & Winter, 1982; Granovetter, 1985; Reed & DeFillippi, 1990).

Though research in economics, management, and sociology have highlighted the value of understanding the role of embeddedness in competitive advantage and pursuit of economic rents in other contexts (Lippman & Rumelt, 1982; Reed & DeFillippi, 1990; Zukin & DiMaggio, 1990; Baum & Dutton, 1996; Uzzi & Gillespie, 2002), the empirical effects of capability embeddedness have remained largely unexplored. Moreover, given the contextualized nature of decision making and the role that firm resources play in shaping organizational context, it is important to understand how capability embeddedness influences competitive advantage so that managers can make better decisions.

Therefore, in this article, we describe capability embeddedness and empirically estimate its potential effect on firm performance. We propose that the underlying objectives of a firm's capabilities (e.g., enhancing customer satisfaction, reducing channel costs, etc.) play a role in the extent to which embeddedness generates economic rent. Methodologically, we utilize a hierarchical composed error structure framework to assess capability embeddedness, which presents a powerful and flexible alternative to prior work that has relied on case studies (e.g., Uzzi, 1996), indirect measures such as duration of a relationship (e.g., Uzzi & Gillespie, 2002), or visual representations to assess social network embeddedness (Grewal, Lilien, & Mallapragada, 2006). Importantly, the model enables us to disentangle and empirically assess the embeddedness associated with organizational capabilities. We then demonstrate the model in the context of retailing, where we examine both store management and merchandise management capability embeddedness and show the contributions that

embeddedness makes to retailer performance separate from that attributable to the retailer's tangible and intangible resources and capabilities. Our results illustrate that understanding how resources and capabilities influence performance at different hierarchical levels within a firm can aid managers to make better decisions on how they can embed certain capabilities within the structural and social relationships within the firm. In our retail context, we also show that when two capabilities have opposing objectives (i.e., maximization versus minimization), firms garner higher economic returns if they concentrate on one capability rather than both. More generally, the results show that it might not be in the firm's best interest to embed two or more capabilities with divergent goals. Therefore, understanding whether the underlying objectives of the capabilities that are being built and cultivated have convergent or divergent goals is also critical, as it can influence the extent to which the capabilities enhance performance.

CONCEPTUAL FRAMEWORK

Capability Embeddedness

Broadly speaking, *embeddedness* reflects the assimilation or incorporation of something into its surrounding environment. Conceptions of embeddedness often refer to the contingent nature of action and decision making with respect to social structure, organizational culture, and competition for resources (e.g., Zukin & DiMaggio, 1990; Dacin et al., 1999; Morgan, Zou, Vorhies, & Katsikeas, 2003). For example, many organizational researchers have examined the social aspects of embeddedness with respect to the pattern of ongoing interpersonal and inter-firm exchanges (e.g., Granovetter, 1985; Baum, Calabrese, & Silverman, 2000; Grewal et al., 2006). Firms are said to be embedded in social networks when the ties between firms involve fine-grained information exchange of tacit and proprietary knowledge, trust as a coordination device that promotes knowledge transfer, and problem-solving routines that are difficult to codify without the loss of information (e.g., Uzzi, 1997).

Drawing from this literature on embeddedness in sociology (Granovetter, 1985; Zukin & DiMaggio, 1990) and management (Baum & Dutton, 1996; Dacin et al., 1999), we define *capability embeddedness* as an unobservable that reflects the extent to which a capability is contextually entrenched

within the structural, social, and cultural aspects of the firm. Thus, greater reliance on tacit and intangible resources and capabilities that are richly connected and are dispersed and cooperatively shared across individuals, departments, and other areas within the firm will create a greater level of capability embeddedness. It is important to understand that, since managers make deliberate decisions over time that are contextualized in the organization, capability embeddedness is unobservable yet is distinct and varies across firms and capabilities.

Capability embeddedness is created by the combination of resources across functions and hierarchical levels within the firm (Nelson & Winter, 1982; Day, 1994; Grant, 1996; Zeitz et al., 1999). An evolutionary economics perspective indicates that every process and procedure in a firm is embedded in a set of other processes (Nelson & Winter, 1982). From a hierarchical perspective, at the foundation are a firm's specialized knowledge and resources, which are combined to generate lower-order capabilities; these, in turn, are combined to generate higher-order capabilities. For example, a firm's specialized knowledge and resources can be combined to generate an engineering capability; this, in turn, is combined with other lower-order capabilities to generate an operations capability, which in turn is combined with other broad functional capabilities (e.g., research and development capabilities, marketing capabilities) to generate a new product development capability (Grant, 1996). The nesting of a firm's resources and capabilities at multiple levels embeds the capability within the firm and builds from the firm's core resource strengths (Grant, 1991; Dickson, 2003).

There are also constitutive aspects that create embeddedness (Dacin et al., 1999). First, the underlying resources used to form a capability are often interconnected (Dierickx & Cool, 1989). For example, a firm's capability for fast product improvements requires the combination of strong technological resources and strong marketing resources (Moorman & Slotegraaf, 1999). An interdependence between resources illustrates not only a complex, interconnected web of critical resources necessary to generate specific capabilities but also increases the consequential extent to which capabilities become embedded into the context of the firm. Furthermore, the resources used to develop a capability are often tacit and idiosyncratic. For example, a firm's knowledge is a foundational resource

that is often tacit and based on firm-specific routines and relationships (Kogut & Zander, 1992; Day, 1994; Johnson, Sohi, & Grewal, 2004). Utilization of such resources embeds the capability into the firm.

As shown in Figure 1, firms combine various resources to form capabilities, which in turn can be combined to develop higher-order capabilities and impact overall firm performance. We expect the embeddedness of a firm's capabilities to impact performance in addition to the impact from the firm's resources and capabilities themselves. Although embeddedness might not be valuable in all situations (Postrel, 2002), we expect it to generate economic rents. In particular, we suggest that capability embeddedness creates an isolating mechanism (Rumelt, 1984), which protects firms from imitation and preserves their rent streams. This causal ambiguity surrounding the link between actions and outcomes (Lippman & Rumelt, 1982) prevents rivals from understanding a firm's formula for success, thereby creating barriers to imitation. As a result, the distinct embeddedness associated with a capability is likely to influence performance in addition to the effects from the capability itself, and it is therefore valuable to parcel out effects due to embeddedness.

[Insert Figure 1 about here]

Paradox of Embeddedness

While firms are endowed with a set of resources that can be combined in multiple ways to create various capabilities, their resources are not boundless and they may, therefore, concentrate on a select set of capabilities. Consequently, one question is whether it is possible to obtain high embeddedness across a set of capabilities. Beyond resource constraints, the underlying objectives of a set of capabilities can influence the embeddedness obtained across the set of capabilities. For example, the objective of one capability might be minimization, such as the minimization of costs or employee turnover, whereas the objective of another capability might be maximization, such as the maximization of customer satisfaction or revenue (Rust, Moorman, & Dickson, 2002). While the former would be examined with a cost frontier and the latter with a production frontier (Kumbhakar & Lovell, 2000), such a dual focus might not be always feasible or sustainable. Consequently, a tension may be created when firms pursue capabilities that are founded on divergent objectives under conditions of resource constraints.

The second question is whether it is valuable for a firm to have high levels of embeddedness across a set of different capabilities. When a firm builds capabilities, it can choose to focus its resources or spread them across multiple areas. It is a question of whether returns to capability embeddedness are higher if a firm concentrates its efforts toward building one capability or multiple capabilities. Given the long-held view that capabilities, in general, enhance performance (e.g., Grant, 1991; Day, 1994), one might expect that a firm should seek to generate high embeddedness across multiple capabilities. However, it is possible that integration of capabilities with a high degree of embeddedness can have detrimental effects on performance. For example, when two capabilities have divergent objectives, attempting to excel at both might reduce performance (e.g., the notion of a generalist as opposed to a specialist) (Miles & Snow, 1978). This logic suggests that competitive advantage could be weaker when attempting to embed capabilities that are not complementary. It also reinforces the distinction between embeddedness and allocative efficiency, since efficiency in multiple tasks should always increase performance, but embeddedness of multiple capabilities need not always lead to increased performance.

In the next section, we offer a general framework for assessing capability embeddedness. We then apply our framework in the retail industry to provide some initial insight into the potential effects of embeddedness on firm performance and whether a paradox of embeddedness occurs in this industry.

General Framework for Assessing Capability Embeddedness

Given the hierarchy of organizational resources and capabilities (as shown in Figure 1) and the multiple levels of influence that structure decision making within firms (Sutcliffe & McNamara, 2001), firm performance may also be viewed in a hierarchical fashion. For example, performance of a consumer packaged goods firm is affected by its performance in category management, relationship management, and brand management. Similarly, a retail firm's performance is driven by its store management and merchandise management performance. While the imperative lower-order capabilities are likely to vary by industry, it is possible to identify and measure a firm's success at these lower-order capabilities and build a multi-level hierarchical model of firm performance. We formalize this hierarchical model for two-levels; nonetheless, generalization to more than two levels is a simple algebraic extension of this

model.

Specifically, for capability g for firm f , we denote performance as:

$$PER_{gf} = \beta_g X_{gf} + v_{gf} + \delta_g \zeta_{gf}, \quad (1)$$

where PER_{gf} refers to performance of firm f on capability g , X_{gf} is the matrix of variables (including the constant term) likely to influence PER_{gf} , β_g is the vector of coefficients, v_{gf} is the standard normal error term, ζ_{gf} is the asymmetric error term that it is always positive, and δ_g is a qualitative variable that specifies the type of frontier. We define $\delta_g = 1$ when the objective of capability g is to minimize (similar to cost frontiers, such that the data has a right skew) and $\delta_g = -1$ when the objective of capability g is to maximize (similar to production frontiers, such that the data has a left skew).

However, unlike traditional stochastic frontier analysis that is based on theoretical input-output economic efficiency analysis and uses a multiplicative functional form (which leads to the popular log-linear model), we use an additive form for several reasons. First, our work is motivated from economic sociology where an additive form is considered appropriate (e.g. Smelser & Swedberg, 1994; Lin, Cook, & Burt, 2001). Second, it allows for inclusion of intangible resources that are often overlooked in traditional production function analysis and for which the measures tend to be perceptual in nature and limited in range. Third, an additive form retains the ability to estimate the embeddedness of capabilities, as we have the symmetric error term to capture random perturbations and an asymmetric error for embeddedness.

Also observe that the error term in Equation 1 has two components (v_{gf} and ζ_{gf}) and is referred to as a composed error model or stochastic frontier model (Aigner, Lovell, & Schmidt, 1977; Meeusen & van den Broeck, 1977). Consistent with standard procedures for composed error models (Kumbhakar & Lovell, 2000), we assume that $v_{gf} \sim \text{iid } N(0, \sigma_v^2)$. Further, since the literature suggests using a simple form for ζ_{gf} , i.e., the exponential distribution (Ritter & Simar, 1997), we assume that $\zeta_{gf} \sim \text{iid exponential}$. We do, however, test for the sensitivity of our results to this exponential form by also examining the

normal and gamma forms. Among the two error terms in the model, ν_{gf} represents the random error and ζ_{gf} represents the asymmetric error for capability g of firm f . Given $E(\nu_{gf}) = 0$, we can write the asymmetric error component as:

$$E(\delta_g \zeta_{gf}) = E(PER_{gf} - \beta_g X_{gf}), \quad (2)$$

where $E(\cdot)$ denotes expectation, and $\delta_g \zeta_{gf}$ represents the difference between attained performance (PER_{gf}) and the performance the firm could have attained ($\beta_g X_{gf}$). When the objective is to maximize ($\delta_g = -1$), we expect $PER_{gf} \leq \beta_g X_{gf}$, whereby $-\zeta_{gf}$ represents the degree to which the firm is able to attain its maximum possible output. Similar reasoning follows for minimization objectives ($\delta_g = 1$), where we expect $PER_{gf} \geq \beta_g X_{gf}$, whereby costs are higher than those that could have been ideally achieved. Thus, ζ_{gf} represents the extent to which a firm succeeds in its maximization or minimization objectives (note that when $PER_{gf} = \beta_g X_{gf}$ the firm is operating at maximum efficiency for capability g).

Our assertion is that ζ_{gf} captures the embeddedness from capability g for firm f . The logic behind this assertion stems from the literature on frontier economics (e.g., Kumbhakar & Lovell, 2000). First, it is critical to note that we are not equating capability embeddedness with error, and that random error is captured by the symmetric error component (ν_{gf}). The asymmetric component offers a means of capturing capability embeddedness because it allows for the combination of various lower-level resources and capabilities (including interconnected and tacit resources) to develop the capability, allows for distinct capability objectives (maximization or minimization objectives captured by δ_g), and retains the nested context of embeddedness.

Furthermore, building on studies in economics that have used frontier regression models to assess technical (in)efficiency (e.g., Kamakura, Lenartowicz, & Ratchford, 1996; Dutta, Narasimhan, & Rajiv, 1999), we offer a broader perspective of ζ_{gf} . In particular, while our model is statistically similar to

these frontier models, there are three critical differences. First, our model specification incorporates intangible resources and capabilities (rather than focusing solely on tangible resource inputs) to delineate embeddedness. Second, our multi-level hierarchical framework suggests that the efficiency of capabilities at different hierarchical levels reflects information about embeddedness of the higher-order capability. Third, in our model ζ_{gf} captures more than technical or allocative efficiency, since the formation of capabilities depends on more than an efficient utilization of resources but also reliance on tacit resources that are interconnected and cooperatively shared across the firm. In sum, we purport that given explicit measurement of a firm's hierarchical performance as well as measurement of its intangible skills and capabilities, ζ_{gf} contains information on the embeddedness of a capability. Nomological validity for this measure of embeddedness is examined from the directional skew evident in Kernel density plots of performance indicators and the resultant effects of capability embeddedness on firm performance. As an aside, given that efficiency in multiple tasks should increase (not decrease) performance, results lend support to our argument that ζ_{gf} does more than simply capture efficiency, by showing a negative effect of ζ_{gf} on performance. We expand on this in greater detail in the results section later in the manuscript.

Model specification

Consistent with the literature on frontier economics, we estimate the embeddedness of each lower-order capability g for firm f as: $EMD_{gf} = \delta_g \exp(-\zeta_{gf})$ (Jondrow, Lovell, Materov, & Schmidt, 1982; Kumbhakar & Lovell, 2000). In other words, we must first estimate ζ_{gf} and once embeddedness has been computed for each of the lower-order capabilities, the embeddedness for these lower-order capabilities can be used as explanatory variables in the model of higher-order performance. Although many methods have been proposed to estimate ζ_{gf} (Aigner et al., 1977; Jondrow et al., 1982; Kumbhakar & Lovell, 2000), we use the method proposed by Jondrow et al., (1982) that relies on the conditional distribution of ζ_{gf} given μ_{gf} , where $\mu_{gf} = \nu_{gf} - \zeta_{gf}$. This method has been shown to be

robust across diverse conditions (e.g., Kumbhakar & Lovell, 2000). Therefore, in a two-level model, higher-order performance can be firm performance ($FPER$), which one could specify as:

$$FPER_f = \beta X_f + \sum_{g=1}^G \gamma_g \exp(\zeta_g) + \nu_f - \zeta_f, \quad (3)$$

where X is the matrix of explanatory variables including the constant term, β is a vector of coefficients for the explanatory variables, and γ_g represents the coefficient for the influence of the embeddedness of the g^{th} capability out of G total capabilities. Note that in this equation, we specify firm performance as a maximization objective (i.e., maximize profits, revenues, etc.), with $\delta = 1$. This equation also allows for complementarities between capability embeddedness ($\exp(\zeta_g)$) and firm resources (relevant X_f variables) as well as among the embeddedness of different capabilities (i.e., among $\exp(\zeta_g)$). We expand on this in our empirical application of the proposed framework.

APPLICATION OF THE MODEL: A FIELD STUDY

To apply our model in a specific setting, a context in which research has identified specific resources and capabilities needed for firm performance is important for model identification. In addition, a context entrenched in both cost frontiers and production frontiers (i.e., $\delta_g = \pm 1$ across all g 's) provides the richest possible setting. We therefore tested our model within the retail industry, because research points to specific resources that are valuable across a broad array of retail organizations and retailing scholars have demonstrated that store management capabilities (SMC) and merchandising management capabilities (MMC) are valuable in developing a competitive advantage within the retail environment (Levy & Weitz, 2001; Dunne, Lusch, & Griffith, 2002). Though it is an empirical question (which we test), there is reason to believe that SMC and MMC have divergent objectives. Specifically, in the case of store management, the focus on issues such as productivity of store employees, satisfying customer needs, and store sales (Dunne et al., 2002; Zahay & Griffin, 2004) largely emphasizes maximizing productivity, customer satisfaction, and store performance. In contrast, in the case of merchandise management, the emphasis on inventory management (i.e., reducing inventory costs), buying center management, and cost

management associated with purchasing and handling merchandise (Donnellan, 1996; Levy & Weitz, 2001) appear to center around the minimization of inventory, purchasing, and material costs. Note that in support of this perspective, results empirically establish that overall store management performance is a maximization issue and overall merchandise management performance is a minimization issue. We do recognize, however, that components of store management may focus on minimization (e.g., labor costs) and components of merchandise management may focus on maximization (e.g., gross margin return on inventory investment); narrowing the sub-processes to lower levels would enable finer specification of cost and production frontiers (e.g., customer service as a production frontier; inventory management as a cost frontier) and would require a simple algebraic extension of our model to one with more levels.

We utilize the literature in retailing to propose the hierarchical model depicted in Figure 2. In addition, we control for number of stores, number of employees, and type of retail firm within our model estimation.

[Insert Figure 2 about here]

The Embeddedness of Store Management Capabilities

Store management involves multiple activities, including overall store image and facilities presentation, sales planning, goal setting and budget control, customer service, and personnel administration and development. Thus, for firms to develop a capability in store management they must possess (i) a superior climate for customer service, (ii) an emphasis on in-store atmospherics and store design, and (iii) strong skills in store management (see Figure 2; Zeithaml, Berry, & Parasuraman, 1996; Homburg, Hoyer, & Fassnacht, 2002).

Retailers with superior store management skills are better able to manage and train store employees for enhanced productivity, and have a better understanding of consumers so they can offer stronger customer service (Levy & Weitz, 2001). Firms with these skills are likely to recruit and train employees to foster a superior climate for customer service. In an age when retailers offer similar assortments, prices, and hours of operations, the predominant way for retailers to gain differentiation is through strong customer service (Homburg et al., 2002). Indeed, fostering a climate for customer service is imperative

for retailers (Vargo & Lusch, 2004). Thus, a firm's store management capability is driven by its ability to offer superior customer service as well as by the interconnectedness between the firm's customer service and store management skills.

In addition to these intangibles, the tangible elements of the store itself are also important (Kotler, 1973; Baker, Grewal, & Parasuraman, 1994). The physical surroundings within the retail store create an image that influences customer perceptions (Bitner, 1992). The store's atmospheric design, which reflects the structural and architectural presentation of the retail environment, enhances perceptions of quality and is highly related to store patronage intentions (Baker, Parasuraman, Grewal, & Voss, 2002). Further, strong store management skills should enable firms to better understand and implement better atmospheric designs so that the interconnectedness between strong store management skills and store design garners greater returns.

We therefore specify store management performance as the first lower-order goal from Equation 1, and, assuming the goal of store management is maximization and effectiveness (which we empirically test), we specify the following production frontier:

$$SP_f = \beta_{s0} + \beta_{s1}(SM_f) + \beta_{s2}(CS_f) + \beta_{s3}(SD_f) + \beta_{s4}(SM_f)(CS_f) + \beta_{s4}(SM_f)(SD_f) + v_{sf} - \zeta_{sf}, \quad (4)$$

where SP_f refers to store management performance of firm f ; SM_f refers to store management skills at firm f ; CS_f denotes climate for customer service at firm f ; SD_f refers to store design at firm f ; v_{sf} is the random error for store management performance (thus the subscript s) for firm f and ζ_{sf} the asymmetric error (i.e., store management capability embeddedness) for firm f . We expect the β_{s1} - β_{s4} coefficients to be positive.

In addition, we predict that:

H1: Store management capability embeddedness will influence firm performance.

H2: Store management capability embeddedness follows a production frontier.

The Embeddedness of Merchandise Management Capabilities

Merchandise management involves numerous activities associated with procuring merchandise from vendors and ensuring that the merchandise is available in stores. While the degree of merchandise assortment, quality, prices, and promotions reflects how retail firms choose to compete, there are essential

intangible skills that firms must develop in order to establish superior merchandise management capabilities. Typically, these include (i) strong merchandise management skills, (ii) buying expertise, and (iii) effective vendor relationships (see Figure 2; Donnellan, 1996; Levy & Weitz, 2001; Dunne et al., 2002).

Strong merchandise management skills reflect commitment to developing and updating the merchandise infrastructure, which focuses on minimizing merchandising costs to enhance merchandise management performance (Levy & Weitz, 2001). Regarding buyer expertise, a firm's buyers are ultimately responsible for merchandise selection, planning, and distribution (Keaveney, 1992), and because experts are better able to recognize and process complex information (Alba & Hutchinson, 1987), buyer expertise is crucial to a firm's merchandise management performance. Furthermore, firms with strong merchandise management skills have a good understanding of merchandise assortment, and should, therefore, be better able to leverage their buying expertise. As a result, the interconnectedness between buyer expertise and merchandise management skills is likely to enhance merchandise management performance.

Relationships with vendors are another important resource for retail firms, as they often enable efficient inventory control and stronger merchandise management performance (e.g., Ganesan, 1994; Levy & Weitz, 2001; Mishra & Raghunathan, 2004). Retailers with strong skills in merchandise management are also better able to extract economic knowledge and specialized value from their vendor relationships (e.g., Dunne et al., 2002). Thus, the interconnectedness between merchandise management skills and vendor relationships is likely to be valuable for merchandise management performance.

We therefore specify merchandise management performance as the second lower-order goal from Equation 1, and, assuming the goal of merchandise management is efficiency and cost minimization (which we empirically test), we specify the following cost frontier:

$$MP_f = \beta_{m0} + \beta_{m1}(MS_f) + \beta_{m2}(BE_f) + \beta_{m3}(VR_f) + \beta_{m4}(MS_f)(BE_f) + \beta_{m5}(MS_f)(VR_f) + v_{mf} + \zeta_{mf}, \quad (5)$$

where MP_f refers to merchandise management performance of firm f , MS_f refers to merchandise management skills at firm f , BE_f denotes buyer expertise of firm f , VR_f refers to strength of vendor

relationships of firm f ; v_{mf} is the random error for merchandise management performance (thus the subscript m) for firm f , and ζ_{mf} the asymmetric error (i.e., merchandise management capability embeddedness) for firm f . We expect the β_{m1} - β_{m4} coefficients to be positive. In addition, we propose the following hypotheses:

H3: Merchandise management capability embeddedness will influence firm performance.

H4: Merchandise management capability embeddedness follows a cost frontier.

The Effect of Capability Embeddedness on Retail Firm Performance

As previously indicated, for retail firms to garner greater economic returns, they must exhibit strong capabilities in store management and merchandising management (e.g., Levy & Weitz, 2001; Dunne et al., 2002). However, if the underlying objectives of these two capabilities differ, as predicted, then will a retail firm achieve higher returns from focusing on one of these capabilities rather than on both? In particular, firms that do not specialize in one or the other capability are likely to find that they must deal with a wider range of issues that magnify problems in coordinating behavior (Haunschild & Rhee, 2004). In addition, spreading resources across multiple areas may create tradeoffs where, for example, a focus on minimizing costs might limit the service provided to customers (Berman & Evans, 2007). The deliberate decisions of managers to embed a capability within the firm might also be more successful when it can be focused toward specific goals. Thus, while we expect store management capabilities and merchandise management capabilities to enhance retailer performance, we expect retailers to attain even greater economic returns when they focus on one of these capabilities rather than on both.

H5: The interaction between store management capability embeddedness and merchandise management capability embeddedness will have a negative effect on firm performance.

METHODOLOGY

Data Collection

To fully depict the hierarchical nature of firm performance and allow for varying strategic approaches across divisions, we focused on the strategic business unit (SBU). Furthermore, we elected to attain stronger variance in the skills and processes across SBUs, so we relied on a diverse population of retail

SBUs. In particular, we elicited a list of top volume retail SBUs and their executive contacts from The Center for Education and Research in Retailing, which included larger SBUs, and supplemented this list with a purchased list of smaller retail firms. We also contacted the firms on this latter list to verify their retail nature. Overall, our sampling frame included 591 SBUs of retail organizations within the United States. A survey was mailed to the Vice President of Marketing, Chief Operating Officer (COO), or Chief Executive Officer (CEO) at the SBU based on the contact information provided in the sampling frame, and we verified this person's specific knowledge about the SBU's abilities across its stores to confirm that he or she could serve as the key informant. The survey was also pre-tested to assess measure validity.

Among the 591 SBUs, approximately 9% of the surveys were undeliverable (e.g., respondents recently left the firm and had not yet been replaced, or the company was closing). Overall, a total of 110 surveys (105 usable) were returned, yielding a response rate of 21%, surpassing the 10-20% average range for top management survey responses (Menon, Bharadwaj, & Howell, 1996). A post-hoc examination of early versus late responders also suggests that there is no systematic distortion in responses, offering some evidence to lessen concerns over nonresponse bias. Of the final sample, 35% were department or apparel retail firms, 24% food and drug retail firms, 8% hardware or home improvement firms, 6% electronics retail firms, and 27% other or specialty retail firms. In addition, the size of the SBU varied, from a minimum of 1 store to a maximum of 6,000 stores. We therefore incorporated the type of retail firm, number of employees, and number of stores into our model to control for any extraneous effects on overall firm performance.

Measures

Measures for store management included overall store management skills, climate for customer service, and atmospheric store design. First, *store management skills* comprised a six-item measure that incorporates skills related to the multiple facets of store management responsibilities (Appendix A). For example, highly qualified employees fall under the rubric of store management, so emphasis on recruiting and training employees is one critical element. All six items were adapted from the responsibilities

outlined by Levy and Weitz (2001). Second, *climate for customer service* comprised a seven-item measure that focuses on the extent to which a firm supports the delivery of quality service to customers. This measure was based on the service climate scale of Schneider, White, & Paul, (1998), which is shown to influence customer perceptions of service quality. Third, *atmospheric store design* comprised a four-item measure adapted from Baker et al. (2002). Specifically, we included the organization of merchandise, attractiveness of facilities, color scheme, and general ambience as key elements of store design.

Measures for merchandise management included overall merchandise management skills, buyer expertise, and effectiveness in managing relationships with vendors. First, *merchandise management skills* comprised a six-item measure that incorporates skills related to the multiple facets of merchandise management responsibilities (Appendix A), which were adapted from the responsibilities outlined by Donnellan (1996) and Levy and Weitz (2001). Second, *buyer expertise* comprised a nine-item measure (Appendix A) related to the knowledge and skills specific to buyers, such as tailoring merchandise to customer needs and procuring merchandise most efficiently (Donnellan 1996). Third, *vendor relationships* comprised an eight-item measure that incorporated effectiveness in managing vendor relationships (from Johnson et al., 2004) and retailer reputation (from Ganesan, 1994).

In measuring performance, we focus on overall firm performance as well as the two lower-order process goals of store management performance and merchandise management performance. *Firm performance* comprised a four-item measure rating the firm's performance relative to specific standards including major competitor performance, growth rate objectives, ROI objectives, and market share objectives. Both *store management performance* and *merchandise management performance* comprised seven-item measures (Appendix A), each of which contained specific lower-order performance goals adapted from Levy and Weitz (2001).

With multi-item measures, we also account for measurement error and use factor scores to compute an aggregate score for each construct before proceeding to estimate the composed error structure models. For more detail on our approach, see Appendix B.

Measure Validation

We took a three-step approach to assess the quality of our measures. First, given a sample size of 105, we estimated a confirmatory factor analysis model for each construct in order to maintain a healthy ratio of sample size to number of parameters. With the asymptotic covariance matrix as the input matrix, the overall model fit statistics and the range of factor loadings established the unidimensionality for each construct. Specifically, the Goodness of Fit Index ranged from .94 to .99; the Comparative Fit Index ranged from .92 to .99, and the factor loadings ranged from .43 to .99. Second, to assess discriminant validity, we estimated confirmatory factor analytic models for every combination of the latent construct (${}^{\circ}C_2 = 45$) and statistically compared the ϕ^2 value to 1 (Anderson & Gerbing, 1988). None of the ϕ^2 values statistically equaled 1, thus establishing discriminant validity. Third, to assess internal consistency we calculated the composite scale reliabilities (Bagozzi & Yi, 1988) and average variance extracted (Fornell & Larcker, 1981) for the latent constructs. As shown in Appendix A, the composite scale reliabilities (ρ_c) ranged from .86 to .98 and average variance extracted (τ_a) ranged from .52 to .86, demonstrating good internal consistency. The bivariate correlation coefficients and descriptive statistics for the factor scores of latent variables are shown in Table 1. Together, the average variance extracted and bivariate correlation seem to mitigate potential multicollinearity concerns in the presence of measurement error (Grewal, Cote, & Baumgartner, 2004).

[Insert Table 1 about here]

Common Method Bias

Since we use a single survey to collect the data, we took four steps to alleviate common method concerns (e.g., Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). First, the design of the questionnaire consisted of four subsections, with one section each for store management variables, merchandise management variables, performance variables, and descriptive firm information. Thus, the explanatory and outcome variables were separated into distinct sections. We also used different response formats. For example, the items for store management skills were anchored with strongly disagree and strongly agree; the items for customer service were anchored with much lower and much higher, and the items for in-store

atmospherics were anchored by very dissatisfied and very satisfied. Second, all of the hypothesized models (i.e., for store management performance, merchandise management performance, and firm performance) included interaction effects. It is widely accepted that respondents have difficulty rationalizing interaction effects while responding to survey questions, as these effects can be plentiful and difficult to ascertain from the survey instrument. Third, we used the Harmon's single factor test to assess common method bias. Using exploratory factor analysis, we estimated a model comprised of all items for all nine latent constructs (Appendix A). Results show that 12 eigenvalues exceed 1 (ranging from 19.15 to 1.03) and account for 76% variance in the items, and that the number of extracted factors exceeds the number of latent constructs with no cross-loading between constructs. Finally, we collected return on assets (ROA) data as an objective performance measure. Although we were only able to locate data for 41 SBUs in our sample, we found that ROA correlates positively ($\rho = .42, p < .01$) with our performance measure, thereby lending credibility to the performance measure and alleviating common method concerns (Podsakoff et al., 2003).

Estimation Procedure

As the literature recommends simple models (Ritter & Simar, 1997), we use the normal-exponential model for estimation. Specifically, the following distributional assumptions apply:

- $\nu_f \sim iid \ N(0, \sigma_\nu^2)$.
- $\zeta_f \sim iid$ exponential with parameter λ ; i.e., the probability density function is given as:

$$f(\zeta) = \lambda e^{-\theta\lambda}.$$
- ν_f and ζ_f are distributed independent of each other and the regressors.

Thus, the joint densities of ν_f and ζ_f are the product of their individual densities and the shape of the joint distribution depends on the standard deviation parameters σ_ν and σ_ζ . For an individual firm the log-likelihood can be specified as:

$$\log(L_f) = -\log(\lambda) - \frac{\lambda^2 \sigma_\nu^2}{2} - \lambda \varepsilon_f - \log \Phi\left[-\left(\frac{\varepsilon_f}{\sigma_\nu} + \lambda \sigma_\nu\right)\right], \quad (8)$$

where $\Phi(\cdot)$ is the standard normal probability density function. Thus, for a sample size of F , the log-likelihood would be:

$$\log(L) = \sum_{f=1}^F \log(L_f) \quad (9)$$

We maximized this sample log-likelihood to obtain parameter estimates.

RESULTS

The Kernel density plots for the three performance variables (firm performance, store management performance, and merchandise management performance) are illustrated in Figure 3. Along with the numerical values for skewness (-.106, -.472, and .081 respectively for the three performance variables), these plots lend support to our assertions that production frontier models should be used for retail firm performance (Panel A of Figure 3) and store management performance (Panel B of Figure 3) while a cost frontier model would be more appropriate for merchandise management performance (Panel C of Figure 3). Overall, these findings lend support to H2 and H4 for store management and merchandise management respectively. Thus, for subsequent analysis we used the production frontier model for firm performance and store management performance and a cost frontier model for merchandise management performance.

[Insert Figure 3 about here]

Store Management

In Table 2, we present results from three production function normal-exponential models (SM1, SM2, SM3) for store management performance as the dependent measure. In terms of the explanatory variables, the first model (SM1) includes only the control variables (number of stores, number of employees, and firm type dummy variables); the second model (SM2) includes the main effects of store management skills, climate for customer service, and atmospheric store design, and the final model (SM3) adds the anticipated interaction terms specified in equation 4. Likelihood ratio tests reveal that SM1 is outperformed by SM2 ($\chi^2_3 = 32.10$, $p < .01$) and SM3 ($\chi^2_5 = 32.66$, $p < .01$), but SM3 does not outperform the parsimonious model SM2 ($\chi^2_2 = .56$, $p > .75$). In addition, store management capability

embeddedness assessed from this normal exponential model correlated highly with that produced from the normal-half normal ($\rho = .987, p < .01$) and normal-gamma models ($\rho = .998, p < .01$). Finally, multicollinearity does not appear to be an issue, since statistical significance of coefficients across the three models does not change.

Results for the optimal model (i.e., SM2) show a negative main effect for number of stores ($b = -.041, p < .10$), a positive main effect for number of employees ($b = .533, p < .01$), and a positive interaction between the two variables ($b = .231, p < .01$; we mean-centered the independent variables prior to computing the interaction). These results suggest that retailers with more stores and employees had higher store management performance. We also find that store management skills ($b = .408, p < .01$) and store atmospherics ($b = .184, p < .05$) have positive effects on store management performance, but climate for customer service does not ($b = .032, p > .10$). The Kernel density plot of store management capability embeddedness shows a long left tail (which suggests that a few firms have very low levels store management capability embeddedness), and truncation on the right (which suggests limits to the embeddedness of this capability; see Panel A, Figure 4). To assess the sensitivity of the store management capability embeddedness measure to missing variables, we estimated the normal-exponential composed error model for two of the three lower-order resources and capabilities (store management skills, climate for customer service, and atmospheric store design). Correlations among the embeddedness measure for these three models and the model with all three explanatory variables ranged from .97 to .99, suggesting that our measure of store management capability embeddedness is robust toward missing variables.

[Insert Table 2 and Figure 4 about here]

Merchandise Management

In Table 3, we present results from three cost function normal-exponential models (MM1, MM2, MM3) for merchandise management performance as the dependent measure. Similar to the models for store management, the first model (MM1) includes only the control variables (number of stores, number of employees, and firm type dummy variables); the second model (MM2) incorporates the main effects from

merchandise management skills, buyer expertise, and vendor relationship management, and the final model (MM3) adds the interaction terms specified in equation 5. Likelihood ratio tests reveal that MM1 is outperformed by MM2 ($\chi^2_3 = 77.12$, $p < .01$) and MM3 ($\chi^2_5 = 82.16$, $p < .01$), and MM3 marginally outperforms the parsimonious model MM2 ($\chi^2_2 = 5.48$, $p < .07$). Further, merchandise management capability embeddedness assessed from the normal-exponential model correlates strongly with that from the normal-half normal ($\rho = .958$, $p < .01$) and the normal-gamma models ($\rho = .989$, $p < .01$), thereby increasing confidence in the measurement of merchandise management capability embeddedness. Finally, multicollinearity does not seem to be an issue, as the statistical significance of coefficients across the three models does not change.

Results for the optimal model (i.e., MM3) show that the number of stores decreases merchandise management performance ($b = -.061$, $p < .10$), but number of employees does not (see Table 3). Results further show that merchandise management skills ($b = .627$, $p < .01$) and buyer expertise ($b = .296$, $p < .01$) positively influence merchandise management performance, while vendor relationship management does not ($b = .084$, $p > .10$). We also find a positive interaction effect between merchandise management skills and buyer expertise ($b = .144$, $p < .05$), which is consistent with our assertions that the positive effect of buyer expertise on merchandise management performance increases as merchandise management skills increase. Finally, the Kernel density plot shown in Panel B of Figure 4 shows a marked tail on the right-hand side suggesting that few firms have high merchandise management capability embeddedness. To assess the sensitivity of the merchandise management capability embeddedness measure to missing variables, we estimated the normal-exponential composed error model for two of the three lower-order resources or capabilities (merchandise management skills, vendor relationship management, and buyer expertise). Correlations among the embeddedness measure for these three models and the model with all three explanatory variables ranged from .94 to .99, suggesting that our measure of merchandise management capability embeddedness is indeed robust towards missing variables.

[Insert Table 3 about here]

Firm Performance

The results for five normal-exponential production function models (FP1-FP5) for firm performance as the dependent measure are shown in Table 4. The first model (FP1) includes control variables and main effects for store and merchandise management; the second model (FP2) adds the anticipated store management interaction terms and merchandise management interaction terms; the third model (FP3) adds the main effects for store management capability embeddedness (SMCE) and merchandise management capability embeddedness (MMCE); the fourth model (FP4) adds the interaction between SMCE and MMCE, and the final model (FP5) adds the interactions between SMCE and store management resources as well as MMCE and merchandise management resources. A series of likelihood ratio tests showed that model FP5 outperformed FP1 ($\chi^2_{13} = 31.26$, $p < .01$), FP2 ($\chi^2_9 = 25.52$, $p < .01$), and FP3 ($\chi^2_7 = 14.98$, $p < .05$), but was statistically equivalent to the parsimonious FP4 model ($\chi^2_6 = 7.86$, $p > .24$). Another series of likelihood ratio tests showed that FP4 outperformed FP1 ($\chi^2_7 = 23.40$, $p < .01$), FP2 ($\chi^2_3 = 17.66$, $p < .01$), and FP3 ($\chi^2_1 = 7.12$, $p < .01$) models. Thus, we use the results from FP4 to test our theoretical conjectures.

[Insert Table 4 about here]

Results show that retail firms with more stores tend to have higher performance ($b = .094$, $p < .01$) and, in our sample, department stores have lower performance than food and drug stores ($b = -.400$, $p < .10$). We also find that climate for customer service ($b = .402$, $p < .01$), atmospheric store design ($b = .206$, $p < .10$), and buyer expertise ($b = .173$, $p < .10$) all positively influence retailer performance, whereas store management skills, merchandise management skills, and vendor relationship management do not have statistically significant effects.

Importantly, results show that capability embeddedness impacts retailer performance beyond that from the tangible and intangible resources that a retailer possesses. Since the interaction term between SMCE and MMCE is statistically significant, we discuss the results from the main effects model (FP3) and the interaction effect model (FP4). Results from the main effects model (FP3) show that *SMCE* ($b =$

.320, $p < .05$) and *MMCE* ($b = .445$, $p < .01$) positively influence retailer performance, thus supporting H1 and H3, respectively. However, in the interaction effect model (FP4), the main effect of *SMCE* is not statistically significant, whereas the main effect of *MMCE* is positive and statistically significant ($b = 1.046$, $p < .01$) and the interaction term between the two capability embeddedness measures is negative and statistically significant ($b = -1.770$, $p < .05$). This negative interaction term supports H5. To better understand this interaction effect, we plot it in Figure 5. It appears that the highest level of retailer performance ensues when the retailer has lower levels of store management capability embeddedness and higher levels of merchandise management capabilities embeddedness. We expand on this in the discussion section.

[Insert Figure 5 about here]

DISCUSSION

Numerous scholars have touted the importance of organizational capabilities to a firm's competitive advantage. An element left unexplored, however, is the recognition that the complex and intricately-woven underlying processes by which a firm's capabilities are formed embeds the capability into the firm, and this embeddedness may itself drive competitive advantage. Our research asserts that there is distinctive value in discerning the embeddedness of organizational capabilities to understand how embeddedness influences competitive advantage and to guide managers toward making better decisions. In this section, we discuss implications of our research for theory and practice.

Theoretical Implications

Reinforcing the idea that naturally occurring hierarchical layers be used to study firms (Nelson & Winter, 1982; Grant, 1996; Dickson, 2003), our results empirically illustrate the importance of examining a firm's resources and capabilities at different hierarchical levels. For example, our results show that lower-order resources, such as atmospheric store design, can influence lower-order store management performance as well as overall retailer performance, whereas other lower-order resources, such as climate for customer service, only influence the higher-order goal of retailer performance.

Furthermore, through deliberate decisions over time, managers who combine interconnected

resources that span multiple functions and hierarchical levels are able to embed the resultant capability into the socio-cultural and structural system of the firm. In this research, we find that this embeddedness itself plays a significant role in explaining a firm's competitive advantage. Though others have emphasized the importance of unobservable factors on firm performance (Jacobson, 1990), our model provides a means of capturing not only the effects of intangible resources and capabilities but also the embeddedness that underlies the formation of capabilities.

Our results also point to the importance of the underlying objectives of capabilities. Specifically, firms often possess a limited set of resources, thus two essential issues are (i) whether it is possible to obtain high embeddedness across a set of different marketing capabilities, and (ii) whether it is even valuable to do so. In our retail application, the correlation between store management capability embeddedness and merchandise management capability embeddedness is positive ($\rho = .22, p < .05$), suggesting that firms with high store management capability embeddedness also have high merchandise management capability embeddedness (and vice versa). To offer a more detailed perspective, we carried out a latent class cluster analysis to examine whether there were groups of firms for which the correlation coefficient between the two capability embeddedness terms is negative. Results indicate that a four-cluster solution was optimal (based on Consistent Akaike Information Criterion), and the correlation coefficients were .28, .18, -.06, and .34 for clusters one through four, respectively (consisting of 63, 17, 14, and 11 SBUs, respectively). These results suggest that most SBUs (87% of our sample) possessed high store management and merchandise management capability embeddedness. However, for a few SBUs, embeddedness of one capability (e.g., store management) provides no information about the embeddedness of the other (e.g., merchandise management).

It is critical to note, however, that the interaction between store management capability embeddedness and merchandise management capability embeddedness negatively influences retailer performance (Figure 5). In other words, although firms may have high levels of store management and merchandise management capability embeddedness, such high levels might not be in their best interest. In fact in our research context, firms with high merchandise management capability embeddedness and

low store management capability embeddedness perform the best (see Figure 5). Therefore, in this research context, deliberate decisions focused on building store management or merchandise management capabilities might require specialized knowledge that makes it more economical (Demsetz, 1973; Postrel, 2002) to focus on embedding one capability rather than both. Since firms possess a limited pool of resources, one of the critical decisions that managers must make is how to most effectively and efficiently build specific capabilities. We do not contend that store management and merchandise management capabilities are not valuable for retailer performance. Rather, it is the embeddedness associated with these capabilities, driven by managers' deliberate decisions in building and cultivating capabilities with different underlying objectives, which indicate that retailers might attain even higher performance when they focus on embedding one of the capabilities rather than both. It is also important to note that this finding lends support to our argument that ζ_{gf} does more than simply capture technical or allocative efficiency, since efficiency in multiple tasks should always increase performance but embeddedness of multiple capabilities might not always do so.

Finally, it is important to note that performance is usually modeled using standard *iid* assumptions (i.e., the error is independent and identically normal distributed with mean zero and constant variance). Given the significant effect of capability embeddedness on firm performance, future research that focuses on the effects of organizational capabilities on firm performance should consider composed error models in order to account for skewness that is likely to manifest due to embeddedness. Further, researchers could study capability embeddedness in other industries. For example, consider the banking industry, where multiple hierarchies are natural to the industry with multiple branches for each bank. In addition, the hierarchical nature of capabilities is prevalent in the consumer packaged goods industry, where performance can be measured for the advertising department, promotions department, distribution department, brand management department and so on.

Managerial Implications

While intangible resources can play a critical role in a firm's market performance and shareholder value (Srivastava, Shervani, & Fahey, 1998), the embeddedness of a firm's capabilities is also a key driver of

competitive advantage. For managers, the value of capability embeddedness lies in the barrier to imitation that embeddedness creates. In particular, as a firm combines its resources to form a capability, the capability becomes embedded in the organizational socio-cultural fabric and results in barriers to imitation. Thus, firms that want to impede competitors from imitating their best practices might want to consider nurturing the embeddedness of their capabilities. For example, firms that have developed a strong relationship capability could intertwine this capability with other capabilities, such as customer knowledge management. At the same time, however, firms should consider the underlying objectives of different capabilities, because it might not be valuable to pursue high embeddedness across a set of capabilities. A deeper understanding of embeddedness, the processing by which firms can consciously embed capabilities, and the effects of embeddedness on performance offers the opportunity for a firm to discern how to create barriers to imitation.

For retailers in particular, our results also point to important implications. First, we confirm extant research that tangible resources, such as number of stores and store design, as well as intangible resources and skills, such as climate for customer service and buyer expertise, can influence firm performance. Importantly, our results also illustrate the value of resource interconnectedness and how it can impact retailer performance at different hierarchical levels within the firm. In particular, understanding how resources and capabilities influence performance at different hierarchical levels can aid managers to make better decisions on how they can embed certain capabilities within the structural and social relationships within the firm. Moreover, our results illustrate that store management capability embeddedness and merchandise management capability embeddedness have strong (and robust) effects on retailer performance, yet that, due to the divergent objectives of each, it might not be in the retailer's best interest to combine the embeddedness of these capabilities. Therefore, it is important for retail managers to understand the underlying objectives of the capabilities they are building and cultivating to know whether these capabilities have convergent or divergent goals, as this could influence the extent to which the capabilities will foster improved performance.

While we demonstrate the model for retailing, it is generalizable to other contexts. Specifically,

this model can be extended to any context in which performance is obtained through hierarchical objectives. For example, a firm's resources and capabilities influence the success of new products at multiple levels, including concept development, implementation, and product launch. Similarly, salesperson performance influences SBU performance, which in turn plays a strong role in organizational performance. Given that organizational capabilities themselves also involve a hierarchy of organizational routines and processes, this suggests broad implications for this model. In various contexts, managers need to (i) view and think about capability embeddedness; (ii) consider the underlying objectives of a portfolio of capabilities, and (iii) understand the potential interactions, synergies or contradictions, and value across this portfolio of capabilities.

Limitations and Further Research

We argue for the importance of embeddedness, propose a method to assess it, and demonstrate the method in the context of retailing. While we expect the effects of capability embeddedness to be fairly robust, replications are needed to assess the strength of these effects. For example, the impact of embeddedness might vary depending on the type of capability in which the embeddedness lies. Clearly, the framework can be used to study the embeddedness of any firm capability and should prove useful in other business disciplines where capabilities in logistics management or information technology management may be of paramount interest. In addition to examining the economic consequences of embeddedness, further research could discern the role of capability embeddedness by investigating (i) additional consequences of embeddedness, (ii) sources of embeddedness, and (iii) how to embed capabilities to attain sustained economic rents. Endeavors in these areas will further unveil the underlying value of embeddedness in pursuit of a sustainable competitive advantage.

Our model application included three specific store management resources and capabilities and three merchandise management resources and capabilities, all argued to be critical to a competitive advantage for a retailer. While other tangible and intangible resources and capabilities may also influence retailer performance, our model accounts for these in two ways. First, the symmetric error component accounts for the resources that have yet to be identified in the literature. Second, our results show robust

effects of capability embeddedness across different combinations of these resources. However, further research is still needed to uncover additional, yet untapped, resources and capabilities critical to performance. Furthermore, our model included two lower-order goals that contained divergent objectives. Extending the model to additional hierarchical levels that contain multiple capabilities of convergent and divergent objectives would offer additional insight, which we expect to further highlight the value of embeddedness.

CONCLUSION

The criticality of organizational capabilities for generating economic rents is well researched in various business disciplines. However, the notion of capability embeddedness is not well understood and we believe that understanding the implications of organizational capabilities would remain incomplete if capability embeddedness is overlooked. Our theoretical arguments and methodological approach for assessing the role of capability embeddedness highlights the importance of capability objectives and the hierarchical nature of capabilities and performance. Overall, our fundamental framework is expected not only to aid managers to make better decisions on how they cultivate specific capabilities but also to spark interest and facilitate research in this domain across various business disciplines.

REFERENCES

- Acito, F., & Anderson, R. D. (1986). A simulation study of factor score indeterminacy. *Journal of Marketing Research*, 23(2), 111-118.
- Aigner, D. J., Lovell, C. A. K., & Schmidt, P. (1977). Formulation and estimation of stochastic production frontier models. *Journal of Econometrics*, 6(7), 21-37.
- Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, 13(4), 411-454.
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411-423.
- Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, 16(1), 74-94.
- Baker, J., Grewal, D., & Parasuraman, A. (1994). The influence of store environment on quality inferences and store image. *Journal of the Academy of Marketing Science*, 22(4), 328-339.
- Baker, J., Parasuraman, A., Grewal, D., & Voss, G. B. (2002). The influence of multiple store environment cues on perceived merchandise value and patronage intentions. *Journal of Marketing*, 66(2), 120-141.
- Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1), 99-120.
- Bartlett, M. S. (1937). The statistical conception of mental factors. *British Journal of Psychology*, 28, 97-104.
- Bartlett, M. S. (1938). Methods of estimating mental factors. *Nature*, 141, 609-610.
- Baum, J. A. C., & Dutton, J. E. (Eds.) (1996). *The embeddedness of strategy*. Greenwich, CT: JAI Press.
- Baum, J. A. C., Calabrese, T., & Silverman, B. S. (2000). Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal*, 21(3), 267-294.
- Berman, B., & Evans, J. R. (2007). *Retail management: A strategic approach (10th ed.)*. Upper Saddle River, NJ: Pearson Prentice Hall.
- Bitner, M. J. (1992). Servicescapes: The impact of physical surroundings on customers and employees. *Journal of Marketing*, 56(2), 57-71.
- Dacin, M. T., Ventresca, M. J., & Beal, B. D. (1999). The embeddedness of organizations: Dialogue & directions. *Journal of Management*, 25(3), 317-356.
- Day, G. S. (1994). The capabilities of market-driven organizations. *Journal of Marketing*, 58(4), 37-52.
- Demsetz, H. (1973). Industry structure, market rivalry, and public policy. *Journal of Law and Economics*, 16(2), 1-9.

- Dickson, P. R. (2003). The pigeon breeders' cup: A selection on selection theory of economic evolution. *Journal of Evolutionary Economics*, 13(3), 259-280.
- Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science*, 35(11), 1504-1511.
- Donnellan, J. (1996). *Merchandise buying and management*. New York, NY: Fairchild Publications.
- Dunne, P., Lusch, R. F., & Griffith, D. A. (2002). *Retailing*. Cincinnati, OH: South-Western College Publishing.
- Dutta, S., Narasimhan, O., & Rajiv, S. (1999). Success in high-technology markets: Is marketing capability critical? *Marketing Science*, 18(4), 547-568.
- Erdem, T., & Swait, J. (2004). Brand credibility, brand consideration, and choice. *Journal of Consumer Research*, 31(1), 191-198.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50.
- Fortune*. (2005). The Wegmans way. 151(2), 62-68.
- Ganesan, S. (1994). Determinants of long-term orientation in buyer-seller relationships. *Journal of Marketing*, 58(2), 1-9.
- Granovetter, M. (1985). Economic action and social structure: The problem of embeddedness. *American Sociological Review*, 15(3), 478-499.
- Grant, R. M. (1991). The resource-based theory of competitive advantage: Implications for strategy formulation. *California Management Review*, 33(3), 114-135.
- Grant, R. M. (1996). Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organization Science*, 7(4), 375-387.
- Grewal, R., Cote, J. A., & Baumgartner, H. (2004). Multicollinearity and measurement error in structural equation models: Implications for theory testing. *Marketing Science*, 23(4), 519-529.
- Grewal, R., Lilien, G. L., & Mallapragada, G. (2006). Location, location, location: How network embeddedness affects project success in open source systems. *Management Science*, 52(7), 1043-1056.
- Haunschild, P. R., & Rhee, M. (2004). The role of volition in organizational learning: The case of automotive product recalls. *Management Science*, 50(11), 1545-1560.
- Homburg, C., Hoyer, W. D., & Fassnacht, M. (2002). Service orientation of a retailer's business strategy: Dimensions, antecedents, and performance outcomes. *Journal of Marketing*, 66(4), 86-101.
- Jacobson, R. (1990). Unobservable effects and business performance. *Marketing Science*, 9(1), 74-85.
- Johnson, J. L., Sohi, R. S., & Grewal, R. (2004). The role of relational knowledge stores in interfirm partnering. *Journal of Marketing*, 68(3), 21-36.

Jondrow, J., Lovell, C. A. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2/3), 233-238.

Kamakura, W., Lenartowicz, T., & Ratchford, B. T. (1996). Productivity assessment of multiple retail outlets. *Journal of Retailing*, 72(4), 333-356.

Keaveney, S. M. (1992). An empirical investigation of dysfunctional organizational turnover among chain and non-chain retail store buyers. *Journal of Retailing*, 68(2), 145-173.

Kogut, B., & Zander, U. (1992). Knowledge of the firm, combinative capacities and the replication of technology. *Organization Science*, 3(4), 383-397.

Kotler, P. (1973). Atmospherics as a marketing tool. *Journal of Retailing*, 49(4), 48-54.

Kumbhakar, S. C., & Lovell, C. A. K. (2000). *Stochastic frontier analysis*. Cambridge, UK: Cambridge University Press.

Lastovicka, J. L., & Thamodaran, K. (1991). Common factor score estimates in multiple regression problems. *Journal of Marketing Research*, 28(1), 105-112.

Learned, E. P., Christensen, C., Andrews, K., & Guth, W. (1969). *Business policy: Text and cases*. Homewood, IL: Irwin.

Levy, M., & Weitz, B. A. (2001). *Retailing management (4th ed.)*. Boston, MA: McGraw-Hill Irwin.

Lin, N., Cook, K., & Burt, R. S. (Eds.) (2001). *Social capital: Theory and research*. New York, NY: Aldine de Gruyter.

Lippman, S., & Rumelt, R. P. (1982). Uncertain imitability: An analysis of interfirm differences in efficiency under competition. *Bell Journal of Economics*, 13(2), 418-438.

McDonald, R. P., & Burr, E. J. (1967). A comparison of four methods of constructing factor scores. *Psychometrika*, 32(4), 381-401.

Meeusen, W., & van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas productions with composed errors. *International Economic Review*, 18(2), 435-444.

Menon, A., Bharadwaj, S. G., & Howell, R. (1996). The quality and effectiveness of marketing strategy: Effects of functional and dysfunctional conflict in intraorganizational relationships. *Journal of the Academy of Marketing Science*, 24(4), 299-313.

Miles, R., & Snow, C. C. (1978). *Organizational strategy, structure, and process*. New York, NY: McGraw Hill.

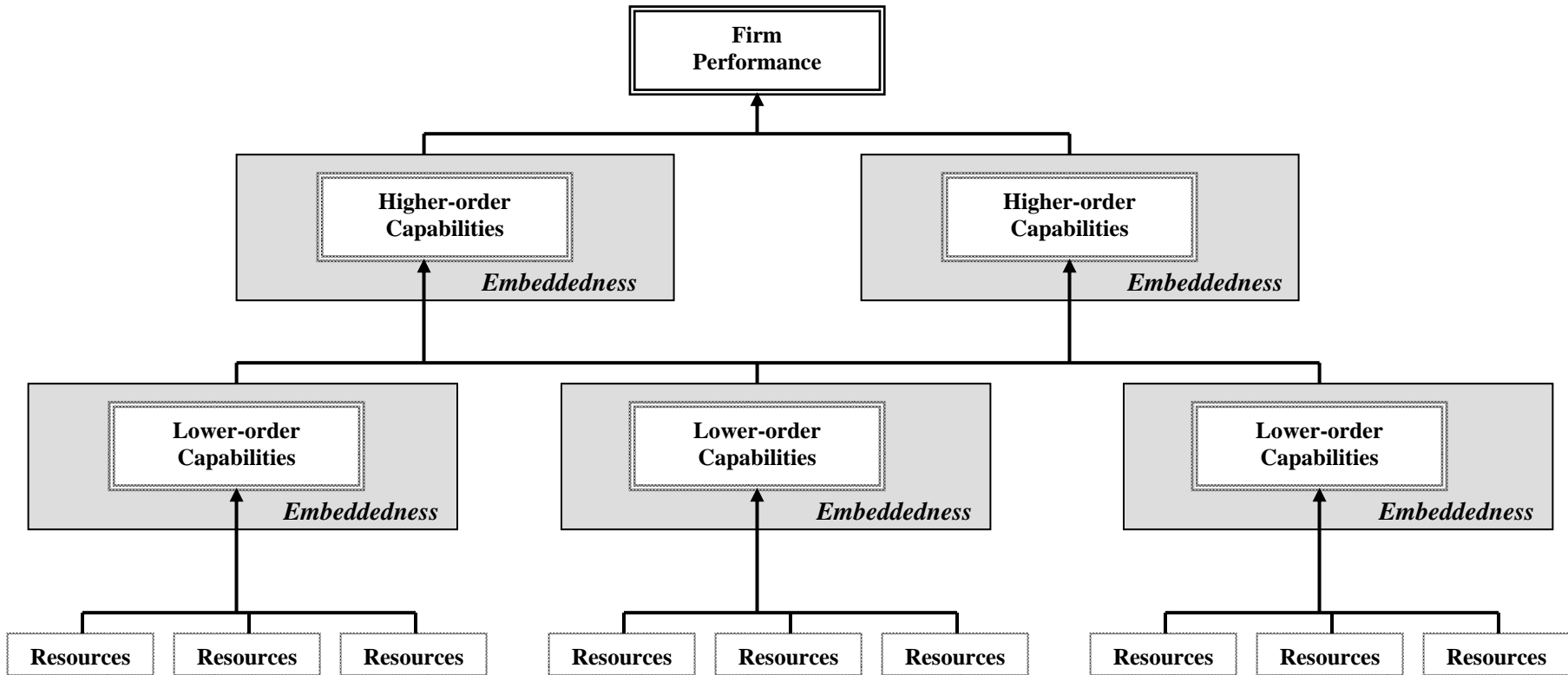
Mishra, B. K., & Raghunathan, S. (2004). Retailer- vs. Vendor-managed inventory and brand competition. *Management Science*, 50(4), 445-457.

Moorman, C., & Slotegraaf, R. J. (1999). The contingency value of complementary capabilities in product development. *Journal of Marketing Research*, 36(2), 239-257.

- Moran, P., & Ghoshal, S. (1999). Markets, firms, and the process of economic development. *Academy of Management Review*, 24(3), 390-412.
- Morgan, N. A., Zou, S., Vorhies, D. W., & Katsikeas, C. S. (2003). Experiential and informational knowledge, architectural marketing capabilities, and the adaptive performance of export ventures: A cross-national study. *Decision Sciences*, 34(2), 287-321.
- Nelson, R. R., & Winter, S. G. (1982). *An evolutionary theory of economic change*. Cambridge, MA: Harvard University Press.
- Penrose, E. T. (1959). *The theory of the growth of the firm*. New York, NY: John Wiley and Sons.
- Podasakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, 88(5), 879-903.
- Postrel, S. (2002). Islands of shared knowledge: Specialization and mutual understanding in problem-solving teams. *Organization Science*, 13(3), 303-321.
- Reed, R., & DeFillippi, R. J. (1990). Causal ambiguity, barriers to imitation, and sustainable competitive advantage. *Academy of Management Review*, 15(1), 88-102.
- Ritter, C., & Simar, L. (1997). Pitfalls of normal-gamma stochastic frontier models. *Journal of Productivity Analysis*, 8(2), 167-182.
- Rumelt, R. P. (1984). Towards a strategic theory of the firm. In R. B. Lamb (Ed.), *Competitive strategic management*. Englewood Cliffs, NJ: Prentice Hall.
- Rust, R. T., Moorman, C., & Dickson, P. R. (2002). Getting return on quality: Revenue expansion, cost reduction, or both. *Journal of Marketing*, 66(4), 7-24.
- Schneider, B., White, S. S., & Paul, M. C. (1998). Linking service climate and customer perceptions of service quality: Test of a causal model. *Journal of Applied Psychology*, 83(2), 150-163.
- Skrondal, A., & Laake, P. (2001). Regression among factor scores. *Psychometrika*, 66(4), 563-576.
- Slotegraaf, R. (1999). Market knowledge management. *Marketing Science Institute Conference Summary Report No. 99-102* Cambridge, MA.
- Smelser, N. J., & Swedberg, R. (Eds.) (1994). *Handbook of economic sociology*. Princeton, N.J.: Princeton University Press.
- Spector, R., & McCarthy, P. D. (2000). *The Nordstrom way: The inside story of America's #1 customer service company*. New York, NY: John Wiley & Sons.
- Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of Marketing*, 62(1), 2-18.
- Sutcliffe, K. M., & McNamara, G. (2001). Controlling decision-making practice in organizations. *Organization Science*, 12(4), 484-501.

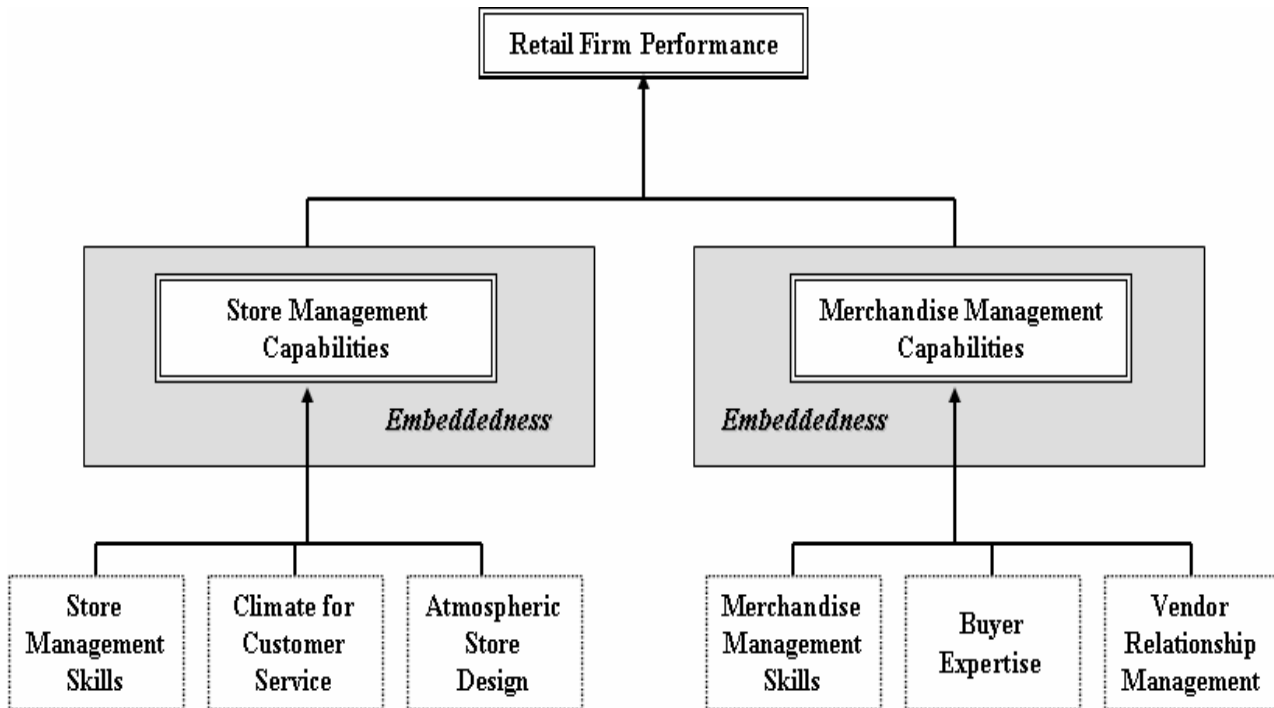
- Teece, D., Pisano, G., & Schuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, 18(7), 509-533.
- Thomson, G. H. (1934). The meaning of i in the estimate of g . *British Journal of Psychology*, 25, 92-99.
- Thurstone, L. L. (1935). *The vectors of mind*. Chicago, IL: University of Chicago Press.
- Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American Sociological Review*, 61(4), 674-698.
- Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly*, 42(1), 35-67.
- Uzzi, B., & Gillespie, J. J. (2002). Knowledge spillover in corporate financing networks: Embeddedness and the firm's debt. *Strategic Management Journal*, 23(7), 595-618.
- Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1), 1-17.
- Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, 5(2), 171-180.
- Zahay, D., & Griffin, A. (2004). Customer learning processes, strategy selection, and performance in business-to-business service firms. *Decision Sciences*, 35(2), 169-203.
- Zeithaml, V., Berry, L., & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing*, 60(2), 31-46.
- Zeitz, G., Mittal, V., & McCauly, B. (1999). Distinguishing adoption and entrenchment of management practices: A framework for analysis. *Organizational Studies*, 20(5), 741-776.
- Zukin, S., & DiMaggio, P. J. (Eds.) (1990). *Structures of capital: The social organization of the economy*. New York, NY: Cambridge University Press.

Figure 1: Embeddedness of organizational capabilities: A multi-hierarchy illustration.



Note: While the shaded region illustrates embeddedness that arises from the combination of resources and capabilities, the area of the region does not necessarily reflect the degree of embeddedness.

Figure 2: Embeddedness of marketing capabilities: A two-hierarchy application in a retail setting.



Note: The shaded region illustrates embeddedness that arises from the combination of resources and capabilities.

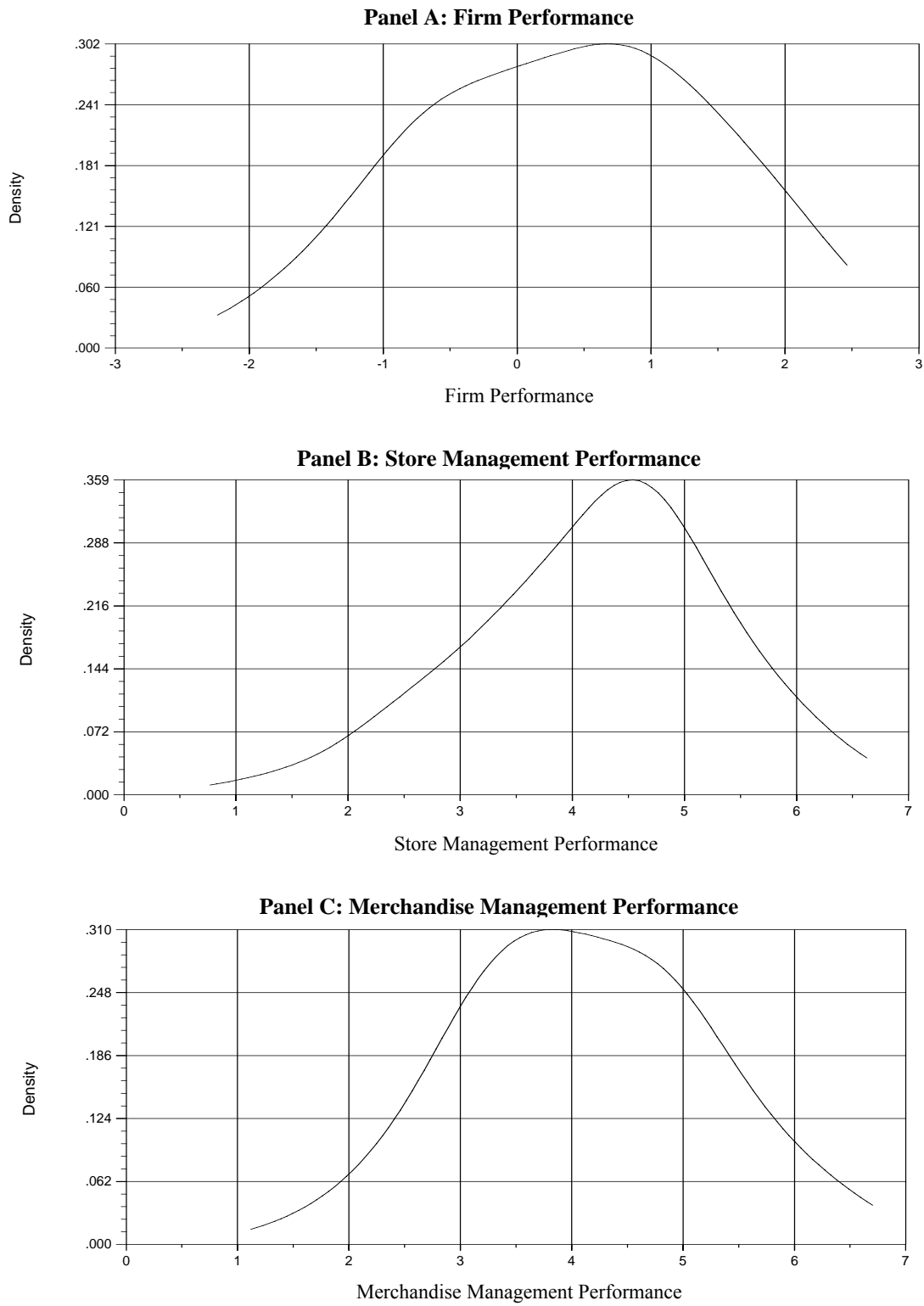
Figure 3: Kernel density estimation for performance variables.

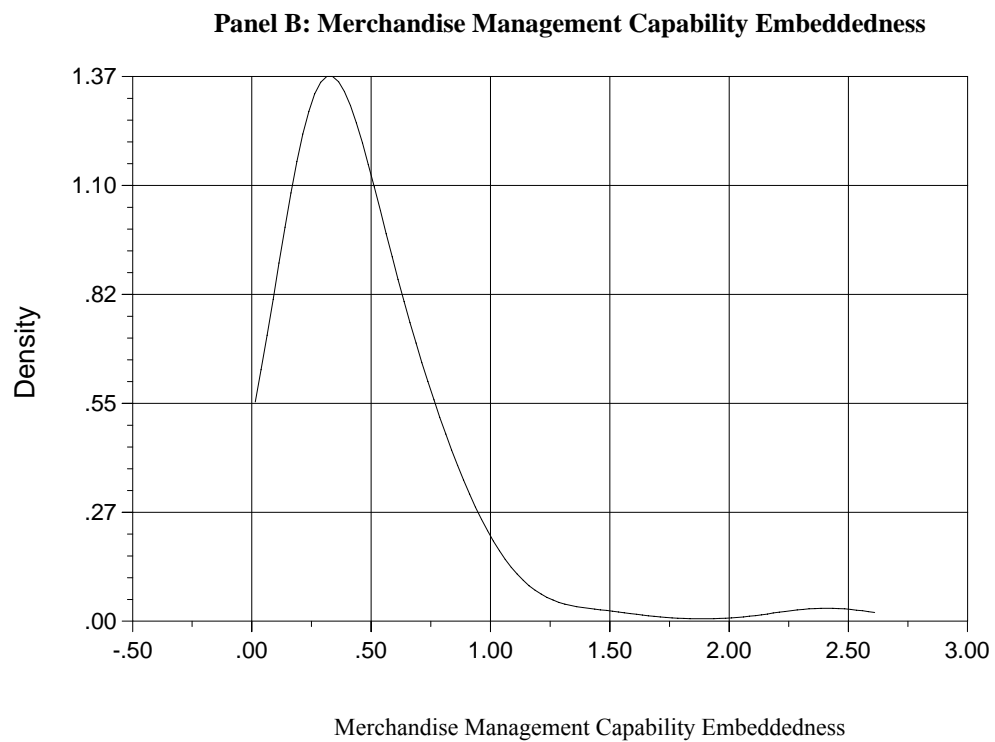
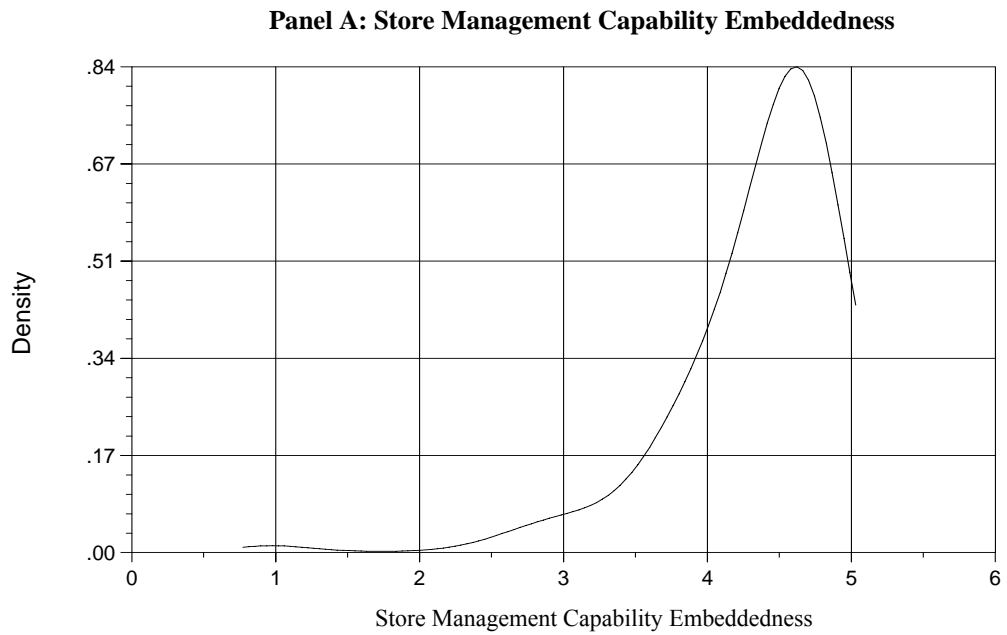
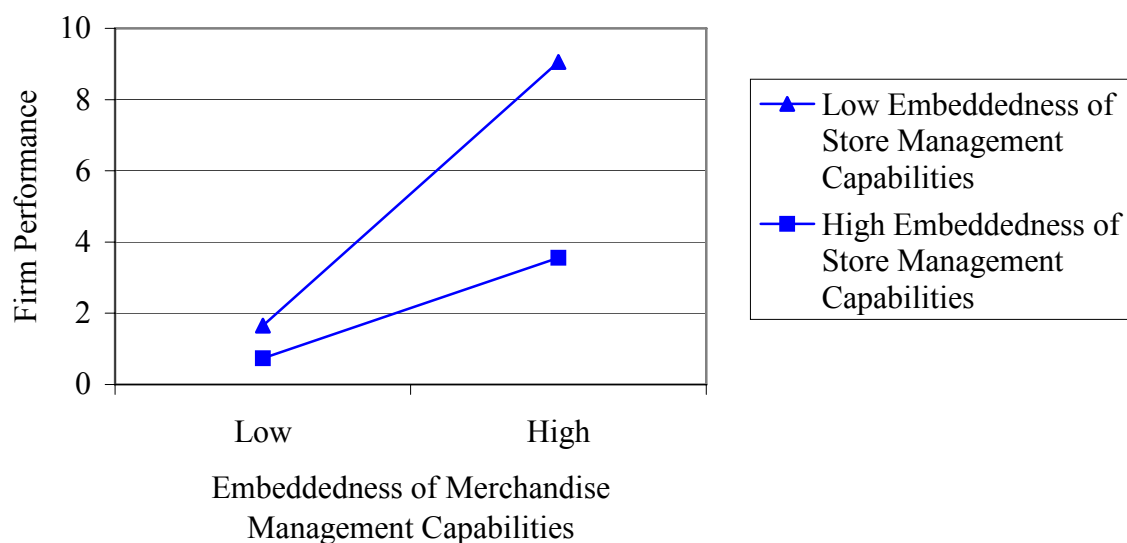
Figure 4: Kernel density estimation for capability embeddedness.

Figure 5: Interaction between the embeddedness of store and merchandise management capabilities.^a



NOTE: Low implies $\mu - 1.96\sigma$ and high is $\mu + 1.96\sigma$, where μ is the mean for embeddedness of the capability and σ is the standard deviation for the embeddedness of the capability.

^a It is important to observe that in economic terms the most valuable case of embeddedness of these two capabilities is when firms have low embeddedness of store management capabilities and high embeddedness of merchandise management capabilities. Consequently, this finding provides validity to using the asymmetric component of the composed error term to represent the embeddedness of capabilities, because if the term only captured technical (in)efficiency the best case scenario should be when both capabilities are efficient (i.e., high-high condition).

Table 1: Descriptive Statistics.

Variable Description	PER	SP	MP	SM	CS	SD	MS	BE	VR	NSTR
Firm Performance (PER)										
Store Management Performance (SP)	.47**									
Merchandise Management Performance (MP)	.56**	.66**								
Store Management Skills (SM)	.38**	.58**	.44**							
Climate for Customer Service (CS)	.45**	.51**	.39**	.66**						
Atmospheric Store Design (SD)	.41**	.50**	.51**	.63**	.58**					
Merchandise Management Skills (MS)	.34**	.51**	.63**	.58**	.29**	.40**				
Buyer Expertise (BE)	.45**	.50**	.64**	.46**	.45**	.55**	.60**			
Vendor Relationship Management (VR)	.36**	.35**	.46**	.33**	.40**	.37**	.36**	.49**		
Number of Stores (NSTR)	.03	-.12	-.13	.07	-.09	-.27**	.08	-.16	-.05	
Mean	.377	4.230	4.115	4.374	2.130	4.311	3.819	4.002	6.289	690.9
Standard Deviation	1.028	1.036	1.033	.909	.955	.967	.965	.947	.970	1223.6

** p < .01

* p < .05

Table 2: Assessing Store Management Capability Embeddedness. ^a

Variable Category	Variable Name	Model SM1	Model SM2	Model SM3
Control Variables	Constant	5.172 ^{***} (.174)	5.010 ^{***} (.221)	4.984 ^{***} (.182)
	Number of Stores (NSTR)	-.037 (.029)	-.041 [*] (.027)	-.039 [*] (.028)
	Number of Employees (NEMP)	1.483 ^{***} (.227)	.533 ^{**} (.274)	.556 ^{**} (.279)
	NEMP x NSTR	.246 ^{***} (.085)	.231 ^{***} (.065)	.229 ^{***} (.067)
	Specialty Stores ^b	-.420 ^{**} (.247)	-.247 (.196)	-.241 (.202)
	Department Stores ^b	-.534 ^{**} (.280)	-.338 [*] (.232)	-.339 [*] (.243)
	Other Retailing Organizations ^b	-.126 (.240)	.132 (.219)	.111 (.224)
Store Management Variables	Store Management Skills (SM)	---	.408 ^{***} (.164)	.389 ^{***} (.164)
	Climate for Customer Service (CS)	---	.032 (.102)	.059 (.118)
	Atmospheric Store Design (SD)	---	.184 ^{**} (.111)	.182 [*] (.113)
	SM x CS	---	---	.014 (.087)
	SM x SD	---	---	.042 (.090)
Variance Parameters for Compound Error	σ_v	1.595 ^{***} (.306)	1.591 ^{***} (.281)	1.581 ^{***} (.275)
	θ	.557 ^{***} (.091)	.410 ^{***} (.086)	.404 ^{***} (.082)
Overall Fit	Log-Likelihood Value	-126.06	-110.01	-109.73

^a We report one-tail tests. For each model we report the unstandardized coefficient with standard error in parentheses.

^b We created three dummy variables for the four types of retail firms. We treated food and drug stores as the base and dummy coded the other three types (specialty stores, department stores, and other retail firms such as restaurants, etc.).

*** $p < .01$

** $p < .05$

* $p < .10$

Table 3: Assessing Merchandise Management Capability Embeddedness. ^a

Variable Category	Variable Name	Model MM1	Model MM2	Model MM3
Control Variables	Constant	4.153* (2.702)	3.774*** (.238)	3.591*** (.223)
	Number of Stores (NSTR)	-.046 (.041)	-.050* (.034)	-.061** (.032)
	Number of Employees (NEMP)	.687** (.312)	-.077 (.249)	-.097 (.231)
	NEMP x NSTR	.208** (.115)	.003 (.091)	-.014 (.084)
	Specialty Stores ^b	-.326 (.267)	-.047 (.249)	-.001 (.234)
	Department Stores ^b	-.184 (.383)	-.096 (.270)	-.042 (.254)
	Other Retailing Organizations ^b	-.010 (.346)	.259 (.304)	.293 (.296)
Merchandise Management Variables	Merchandise Management Skills (MS)	---	.600*** (.097)	.627*** (.096)
	Buyer Expertise (BE)	---	.278*** (.110)	.296*** (.124)
	Vendor Relationship Management (VR)	---	.111* (.085)	.084 (.086)
	MS x BE	---	---	.144** (.083)
	MS x VR	---	---	.046 (.093)
Variance Parameters for Compound Error	σ_v	6.798 (125.147)	2.522*** (.648)	2.207*** (.581)
	θ	.961 (.411)	.553*** (.083)	.498*** (.086)
Overall Fit	Log-Likelihood Value	-146.05	-107.49	-104.75

^a We report one-tail tests. For each model we report the unstandardized coefficient with standard error in parentheses.

^b We created three dummy variables for the four types of retail firms. We treated food and drug stores as the base and dummy coded the other three types (specialty stores, department stores, and other retail firms such as restaurants, etc.).

*** p < .01

** p < .05

* p < .10

Table 4: Firm Performance Consequences. ^a

Variable Category	Variable Name	Model FP1	Model FP2	Model FP3	Model FP4	Model FP5
Control Variables	Constant	1.116*** (.255)	.908*** (.268)	.738*** (.256)	.764*** (.244)	-.742*** (.222)
	Number of Stores (NSTR)	.100*** (.029)	.103*** (.040)	.090** (.040)	.094*** (.039)	.096*** (.038)
	Number of Employees (NEMP)	.185 (.378)	-.164 (.393)	-.235 (.384)	-.225 (.398)	-.189 (.365)
	NEMP x NSTR	.004 (.098)	-.018 (.101)	.005 (.098)	.045 (.099)	.012 (.093)
	Specialty Stores ^b	-.163 (.268)	-.122 (.278)	-.059 (.286)	-.022 (.398)	.050 (.268)
	Department Stores ^b	-.466** (.281)	-.400* (.283)	-.350 (.279)	-.400* (.276)	-.332 (.267)
	Other Retailing Organizations ^b	.401 (.344)	.376 (.366)	.478 (.377)	.389 (.361)	.403 (.361)
Store Management Variables	Store Management Skills (SM)	-.128 (.195)	-.164 (.203)	-.024 (.202)	-.103 (.206)	-.124 (.198)
	Climate for Customer Service (CS)	.310*** (.134)	.359** (.165)	.328** (.161)	.402*** (.163)	.421*** (.179)
	Atmospheric Store Design (SD)	.248* (.162)	.280** (.165)	.236* (.162)	.206* (.150)	.233** (.135)
	SM x CS	---	.019 (.128)	-.031 (.139)	-.007 (.122)	-.039 (.108)
	SM x SD	---	.098 (.167)	.186 (.190)	.196 (.171)	.211* (.132)
	Merchandise Management Variables	Merchandise Management Skills (MS)	.111 (.157)	.084 (.165)	.082 (.168)	.109 (.170)
Buyer Expertise (BE)		.171* (.120)	.210* (.147)	.158 (.141)	.173* (.132)	.202* (.143)
Vendor Relationship Management (VR)		.090 (.100)	.066 (.132)	.042 (.129)	.082 (.115)	.075 (.118)
MS x BE		---	.107 (.103)	.087 (.098)	.106 (.094)	.151* (.097)
MS x VR		---	-.012 (.102)	.010 (.141)	.002 (.138)	-.066 (.136)

Capability Embeddedness	Store Management Capability Embeddedness (SMCE)	---	---	.320** (.182)	.083 (.189)	.220 (.203)
	SMCE x SM	---	---	---	---	-.254 (.391)
	SMCE x CS	---	---	---	---	-.079 (.419)
	SMCE x SD	---	---	---	---	.077 (.244)
	Merchandise Management Capability Embeddedness (MMCE)	---	---	.445** (.230)	1.046*** (.396)	1.533*** (.531)
	MMCE x MS	---	---	---	---	.359 (.356)
	MMCE x BE	---	---	---	---	-.115 (.611)
	MMCE x VR	---	---	---	---	-.213 (.421)
	SMCE x MMCE	---	---	---	-1.770** (.890)	-1.989** (1.094)
Variance parameters for Compound Error	σ_v	.533*** (.122)	.547*** (.125)	.538*** (.118)	.517*** (.104)	.454*** (.096)
	θ	1.533*** (.454)	1.677*** (.617)	1.854*** (.735)	1.899*** (.670)	1.766*** (.476)
Overall Fit	Log-Likelihood Value	-124.98	-122.11	-116.84	-113.28	-109.35

^a We report one-tail tests. For each model we report the unstandardized coefficient with standard error in parentheses.

^b We created three dummy variables for the four types of retail firms. We treated food and drug stores as the base and dummy coded the other three types (specialty stores, department stores, and other retail firms such as restaurants, etc.).

*** $p < .01$

** $p < .05$

* $p < .10$

APPENDIX A: MEASURES USED IN ANALYSIS

STORE MANAGEMENT

Store Management Skills (7-point level of agreement; $\rho_c = .86$; $\tau_a = .52$)

We have a very intensive program for recruiting and training store employees.

We are very dedicated to managing our stores' atmospherics.

We have excellent processes in place for in-store space planning.

We often review the design of our stores to determine whether changes are needed.

Detecting and preventing shoplifting is one of our highest priorities.

We emphasize controlling store management costs (e.g., labor, overhead)

Climate for Customer Service

(7-point scale, relative to main competitors; Schneider et al., 1998; $\rho_c = .92$; $\tau_a = .64$)

The job knowledge and skills of employees in your business to deliver superior quality work and service

The efforts to measure and track the quality of the work and service in your business

The recognition and rewards that employees receive for the delivery of superior work and service

The overall quality of service provided by your business

The leadership shown by management in your business in supporting the service quality effort

The effectiveness of your communication efforts to both employees and customers

The tools, technology, and other resources provided to employees to support the delivery of superior quality work and service

Atmospheric Store Design

(7-point level of satisfaction, relative to main competitors; adapted from Baker et al., 2002; formative construct)

Merchandise organization

Attractiveness of facilities

Color scheme

Ambience in general

MERCHANDISE MANAGEMENT

Merchandise Management Skills (7-point level of agreement; $\rho_c = .95$; $\tau_a = .76$)

We have strong assortment planning processes.

We have extensively invested in building our merchandise management infrastructure.

We have a good understanding of planning merchandising budgets.

We have strong capability to buy merchandise from vendors.

We have a state-of-the-art merchandise management infrastructure.

We regularly update our merchandise management assets.

Buyer Expertise (7-point level of agreement; $\rho_c = .93$; $\tau_a = .62$)

Our buyers visit domestic wholesale markets for product offerings much more often than do our competitors.

Our buyers have very frequent interaction with producers' sales agents.

Our buyers always work with store-line merchandisers to plan assortments on a store-by-store basis.

Our buyers have very frequent interaction with the store line.

Our buyers react to local trends by making adjustments, where needed, for either slow-sellers or those that demonstrate growth potential.

Our buyers have access to computer-based inventory management systems.

We utilize automatic order replenishment systems.

Our buyers are able to get the best merchandise, at the best price, and at the best delivery.

Our buyers are excellent at tailoring merchandise assortments to individual markets.

Vendor Relationships

(7-point level of agreement; first four items: Johnson et al., 2004; last four items: Ganesan, 1994; $\rho_c = .98$; $\tau_a = .86$)

For the most part, our supplier relationships are very effective.
 Across the board, our supplier relationships operate well for us.
 Our supplier relationships do everything we need them to do and more.
 In general, we find our supplier relationships to be very productive and efficient.
 We have a reputation for being honest.
 We have a reputation for being concerned about our suppliers.
 We have a bad reputation in the market. (reverse scaled)
 Most suppliers would like to deal with us.

PERFORMANCE MEASURES

Firm Performance *(7-point scale; much lower to much higher over the past year; $\rho_c = .96$; $\tau_a = .85$)*

Compared to our major competitors, our overall performance has been ...
 Compared to our growth rate objectives, our overall performance has been ...
 Compared to our ROI objectives, our overall performance has been ...
 Compared to our market share objectives, our overall performance has been ...

Store Management Performance *(7-point level of agreement; $\rho_c = .95$; $\tau_a = .74$)*

The productivity of our store operations has been satisfactory.
 We are satisfied with our efforts at managing our store employees.
 We are satisfied with our in-store management of merchandise.
 Our performance in managing special in-store events (e.g., sales events) is excellent.
 We are satisfied with the efforts of our store managers in displaying merchandise and maintaining visual standards.
 Overall, we are satisfied with the costs associated with managing our stores.
 Overall, our store management performance has been much higher than our objectives.

Merchandise Management Performance *(7-point level of agreement; $\rho_c = .98$; $\tau_a = .86$)*

The productivity of our inventory management operations has been satisfactory.
 We are satisfied with our efforts at managing employees who work in our merchandise management operations.
 We are satisfied with our merchandising decisions.
 Our assortment planning operations are very efficient.
 Buying operations in our firm are some of the best in the industry.
 Overall, we are satisfied with the costs associated with managing merchandise.
 Overall, our merchandise management performance has been much higher than our objectives.

NOTES: ρ_c – composite scale reliability (Bagozzi & Yi, 1988); τ_a – average variance extracted (Fornell & Larcker, 1981)

APPENDIX B: ACCOUNTING FOR MEASUREMENT ERROR

Given our multi-item measures, we account for measurement errors by using factor scores to compute an aggregate score for each construct before proceeding to estimate the composed error structure models. However, the indeterminacy of factor scores makes it difficult to select the appropriate method to calculate the scores (e.g., Acito & Anderson, 1986; Lastovicka & Thamodaran, 1991). One recommended approach is blockwise factor scores, which we use, where multiple factor scores are utilized in tandem to obtain the factor scores that most closely approximate the measurement error corrected covariance matrix among latent constructs (McDonald & Burr, 1967; Skrondal & Laake, 2001). In a recent study of blockwise factor scoring, Skrondal and Laake (2001) recommend the use of regression factor scores for explanatory latent variables and Bartlett factor scores for response (dependent) latent variables. For the explanatory latent variables, the regression factor scores can be calculated as (Thomson, 1934; Thurstone, 1935):

$$A_{\xi} = [\Phi \Lambda_x' (\Lambda_x \Phi \Lambda_x')^{-1} X']' \quad (6)$$

where, ξ represents the explanatory latent variables, A_{ξ} is the ($n * k$) matrix of factor scores for the explanatory latent variables such that n is the sample size and k is the number of explanatory latent variables, Φ ($k * k$) is the covariance matrix of ξ , Λ_x is the matrix of factor loadings ($q * k$) such that q is the number of items used to measure the k explanatory latent variables, and X is the ($n * q$) data matrix of items for the explanatory variables. For the dependent variables, the Bartlett factor scores can be calculated as (Bartlett, 1937, , 1938):

$$A_{\eta} = (\Lambda_y' \Theta_{\varepsilon}^{-1} \Lambda_y)^{-1} \Lambda_y' \Theta_{\varepsilon}^{-1} Y' \quad (7)$$

where, η represents the dependent latent variables, A_{η} is the ($n * j$) matrix of factor scores for the dependent latent variables such that n is the sample size and j is the number of dependent latent variables, Λ_y is the matrix of factor loadings ($p * j$) such that p is the number of items used to measure the j dependent latent variables, Θ_{ε} is the ($p * p$) covariance matrix of errors of measurement for items used to measure the dependent latent variables, Y is the ($n * p$) data matrix for the items of the dependent variables.