An Empirical Examination of the Decision to Invest in Fulfillment Capabilities: A Study of Internet Retailers

Taylor Randall
David Eccles School of Business
University of Utah
Salt Lake City, UT 84112
acttr@business.utah.edu

Serguei Netessine
The Wharton School
University of Pennsylvania
Philadelphia, PA 19104
netessin@wharton.upenn.edu

Nils Rudi
INSEAD
Boulevard de Constance 77305
Fontainebleau, France
nils.rudi@insead.edu

Forthcoming in *Management Science*

July 2004, Revised February 2005, July 2005, and October 2005

We would like to thank Karl Ulrich, Bill Moore, Ryan Sundquist, Noah Springer, and Chetan Salian; workshop participants at the University of Utah, the University of Texas-Austin, Molde College, Harvard University, and Stanford University; the OM roundtable at Northwestern University; and participants at the 2002 POMS and M&SOM conferences for help and comments. Feedback from two referees, the associate editor and the departmental editor helped strengthen our analysis. Financial support from Wharton E-business Initiative is gratefully acknowledged.

An Empirical Examination of the Decision to Invest in Fulfillment Capabilities: A Study of Internet Retailers

Abstract: Internet technology has allowed for a higher degree of decoupling between the information-intensive sales process and the physical process of inventory management than its brick-and-mortar counterpart. As a result, some Internet retailers choose to outsource inventory and back-end operations in order to focus on the sales/marketing aspects of e-commerce. Nonetheless, many retailers keep fulfillment capabilities in-house. In this paper we identify and empirically test factors that persuade firms to integrate inventory and fulfillment capabilities with virtual storefronts. Based on the extant literature and previous research in e-commerce, we formulate nine theoretical predictions. We then use data from a sample of over 50 public Internet retailers to test whether empirical data are consistent with these hypotheses. Finally, given the strategic importance and financial magnitude of the inventory investment decision, we analyze the effect of this decision on the economic success of Internet retailers during the period of study.

We find that there are many circumstances in which it is prudent to own fulfillment capabilities and inventory. Empirical data are consistent with hypotheses that this tendency is higher for older firms selling small, high-margin products, offering lower levels of product variety and facing lower demand uncertainty. We also discover that firms making inventory ownership decisions that are consistent with an empirical benchmark derived from environmental and strategic factors are less likely to go bankrupt than those making inconsistent inventory choices.

1. Introduction

The early Internet popular press proposed that e-commerce technology would allow the decoupling of the information-intensive sales process from the physical delivery of products, thus permitting consumers to browse, at no cost, endless stocks of goods for the precise product and price they desired. The accompanying retail corollary to the consumer proposition suggested that retailers need not hold inventory; rather, a retailer should provide only a virtual storefront for customers, leaving the burdensome task of inventory management to third parties who would *drop-ship*[1] orders directly to consumers. Together these practices promised to revolutionize retailing (see Evans and Wurster [2000] and Ghosh [1998]).

However, the widespread adoption of drop-shipping fulfillment strategies and their subsequent success or failure are not readily apparent. Surveys report that only between 23 and 33 percent of Internet retailers rely on drop-shipping as their primary method of order fulfillment [3, 4, 5]. Indeed, most companies maintain the practice of keeping fulfillment capabilities and inventories in-house, the practice to which we refer throughout this paper as, variously, the traditional approach, the traditional channel, and inventory ownership. Furthermore, anecdotal evidence of retailers using a drop-shipping strategy suggests only mixed success. For example, the drop-shipping retailer Value America declared bankruptcy in late 2000, blaming in part its inability to deliver products to customers in a timely manner [1]. In contrast, CD retailer Spun.com has thrived by leveraging the inventory of its distributor, Alliance Entertainment [2]. Interestingly, a cursory examination of Internet retailers who have chosen the traditional channel by investing in inventory yields equally mixed results. Unable to justify the expenses associated with maintaining inventory and warehouses, grocery retailer

[1] Drop-shipping refers to an arrangement whereby the retailer forwards customers' orders to the wholesaler, distributor or manufacturer, who fills customer orders directly from its own inventory. Throughout this paper, we will refer to firms using this type of arrangement as using the drop-shipping approach or the drop-shipping channel.

WebVan.com declared bankruptcy in 2001. In contrast, Amazon.com invested heavily in fulfillment capabilities and at the time of this writing reported profitability.

Recent analytical work identifies and analyzes factors that lead Internet retailers to appropriately adopt drop-shipping or traditional inventory strategies (see Netessine and Rudi [2004a, 2004b] and Singh et al. [2003]). Detailed accounts of drop-shipping operations in e-commerce are well documented, too (see Johnson [2002a, 2002b] and Randall et al. [2002]), but do not test developed theories pertaining to the adoption of drop-shipping. Motivated by these studies as well as by unexplained and contradictory observations made in practice, this paper provides initial empirical evidence pertaining to the factors associated with the adoption of drop-shipping versus traditional fulfillment strategies in Internet retailing and examines the association between a firm's choice of fulfillment strategy and its economic performance.

From extant theory we derive nine hypotheses linking product variety, demand uncertainty, the number of retailers served by one wholesaler, the firm's mean revenues, relative gross margin, firm age, product size/weight, product obsolescence and the cost of capital with the decision to use a traditional or drop-shipping inventory structure. Empirical tests using data from Internet retailers are consistent with several of our hypotheses. Older firms delivering smaller, high-margin products, and operating with lower levels of variety and facing lower demand uncertainty, tend to use the traditional channel. Conversely, newer firms with larger, low-margin products and higher levels of variety with higher demand uncertainty tend to use the drop-shipping channel. Working from these results, we analyze how the inventory investment choice—the drop-shipping versus the traditional channel—affects the firm's performance. Using an empirically derived benchmark to identify outlier firms, we find statistically significant support for the argument that companies whose choice of channel is consistent with empirical benchmarks have a lower risk of bankruptcy over the time period in our study.

This paper contributes to the growing body of literature on electronic commerce by demonstrating the strategic importance of inventory and fulfillment capabilities (i.e., physical assets) in the e-commerce world. While issues of pricing, customer acquisition and distribution of information goods on the Internet have been addressed both theoretically and empirically, decisions related to fulfillment have received attention mostly from a modeling point of view. Johnson and Whang [2002] and Simchi-Levi et al. [2004] provide an overview of emerging research that includes theoretical papers, cases and a few empirical studies, none of which examine the fulfillment or inventory ownership aspects of e-commerce. The only exception we are aware of is the paper by Dinlersozy and Li [2003], which empirically investigates the shipping policies of Internet retailers without focusing on the ownership of inventory and fulfillment capabilities.

More narrowly, this paper contributes to current work on drop-shipping (see Scheel [1990], Netessine and Rudi [2004a, 2004b] and Singh et al. [2003]) by providing an empirical examination of when drop-shipping is a valuable and viable method of order fulfillment. More generally, our work contributes to the empirical literature linking a firm's performance with its operational strategy (see Hendricks and Singhal [2005] for an examination of the impact of supply chain disruptions on a company's financial performance, Lieberman and Dhawan [2005] for an explanation of heterogeneity in automotive manufacturers' performance and Roth and Jackson [1995] for a study of the impact of operations capabilities on a service firm's strategic behavior). In particular, this research provides empirical support to the literature in operations strategy claiming that favorable economic outcomes for firms are a function of the fit between a chosen strategy and the competitive environment (Randall and Ulrich [2001]).

The rest of the paper is organized as follows. In Section 2, we derive the nine hypotheses. In Section 3, we describe our data. Section 4 reports the results of tests of the hypotheses. In Section 5, we examine whether the decision to invest in fulfillment capabilities is associated with a firm's performance. We discuss the implications of our results and the limitations of our study in Section 6.

2. Development of Hypotheses

In this section we hypothesize about nine factors that mitigate economic trade-offs and influence the decision to couple the ownership of fulfillment capabilities with an Internet storefront. These factors are: the variety of products offered, demand uncertainty, the number of retailers in the channel, the firm's mean revenues, relative gross margin, firm age, product size/weight, product obsolescence and the cost of capital. Predictions for the varying influences of these factors upon the inventory fulfillment strategy are obtained using results from the operations literature as well as results from Netessine and Rudi [2004b] and Singh et al. [2003].

In the following pages, we assume a decision path where the Internet retailer starts by selecting the market opportunity. For example, Amazon chooses to become an online book retailer, Amazon.com. Having made this choice, the retailer finds itself in a position to make tactical decisions whereby the product gross margin, product characteristics, demand uncertainty and supplier base are relatively constrained, given the retailer's decision about which market opportunity to pursue. Thereafter, the retailer makes the operational decision to use a particular distribution channel structure while choosing the amount of variety to offer to consumers.

2.1 Product Variety

Research in marketing and operations has long recognized that offering a wider variety of products increases a firm's demand (see Ramdas [2003]). At the same time, additional operational costs associated with higher product variety and driven by demand uncertainty are also well documented (see Randall and Ulrich [2001] and van Ryzin and Mahajan [1999]). In the drop-shipping channel, the higher cost of product variety is mitigated by the effect of risk pooling (see Eppen [1979] for cornerstone work on risk pooling): since the wholesaler is stocking inventory for multiple retailers, demand uncertainty is reduced due to imperfect demand correlation among products. In practice, wholesalers serve many retailers (sometimes thousands of them), so we expect the drop-shipping channel to benefit from economies of scale. Therefore, the mismatch between demand and supply due to product variety will be lower in the drop-shipping channel and it will thus be cost-effective to carry a larger variety of products. In particular, Singh et al. [2003] demonstrate that, due to this effect, the wholesaler under drop-shipping typically chooses to offer a larger product variety than does the retailer in the traditional channel, which leads to our first hypothesis:

***Hypothesis 1**. Inventory ownership will be negatively associated with product variety.*

2.2 Demand Uncertainty

The traditional operations management literature provides ample evidence that higher demand variability leads to higher supply chain costs due to the increasing mismatch between demand and supply (see Cachon and Terwiesch [2004] and Ramdas [2003]). Starting with the seminal work of Eppen [1979], research on risk pooling has demonstrated that a strategy of pooling inventory into one location mitigates this harmful effect. A variety of strategies related to risk pooling have been proposed in the operations literature, including component commonality and variety postponement (Cachon and Terwiesch [2004]), but the concept underlying all of these strategies is risk pooling. Similarly, in the drop-shipping supply chain, the wholesaler is able to mitigate the detrimental effects of demand variability due to the benefits of risk pooling: instead of stocking inventory at thousands of retail locations, inventory is stocked in one—the wholesaler's—location, which allows pooling of demand and reduction in overall variability. Hence, in line with other research on inventory management, we predict the following:

Hypothesis 2. *Inventory ownership will be negatively associated with demand uncertainty.*

2.3 Number of Retailers in the Channel

The benefits of risk pooling in the drop-shipping channel mitigate both the cost of product variety and the cost of demand uncertainty. However, the extent of these benefits depends on the number of retailers that each wholesaler serves: the higher the number, the lower the effective uncertainty that the wholesaler ultimately faces.[2] In the traditional channel, on the other hand, inventory pooling poses no benefits for retailers. Hence, with all else being equal, we expect that a larger number of retailers in the channel should make the drop-shipping arrangement more attractive to retailers, as has been demonstrated formally by Netessine and Rudi [2004b]. Another justification for this hypothesis comes from theory examining the benefits of operational pooling. For example, the wholesaler serving more retailers should be able to capitalize on the economies of scale to reduce the cost of order processing, picking and packing. These savings would ultimately be passed on to the retailers, making drop-shipping more attractive.

In practice, a retailer often buys the same product from multiple wholesalers. Since our goal is to measure the extent of the benefits of risk pooling, the relevant variable to consider is the ratio of retailers to wholesalers, which leads to the following hypothesis:

Hypothesis 3. *Inventory ownership will be negatively associated with the ratio of the number of retailers to the wholesalers.*

---

[2] Throughout this paper we assume that the wholesaler is the one who drop-ships products at retailers' request. In practice, products can be drop-shipped by manufacturers and even by other retailers. We believe this is a reasonable simplification, since, as our interactions with executives indicate, a majority of products are drop-shipped by the wholesalers.

2.4 Firm's Mean Revenues

We offer two basic arguments for our hypothesis that firm revenues will be positively associated with inventory ownership. First, a firm's revenues capture the size of a firm. Larger firms can leverage economies of scale to reduce the costs of order processing, picking and packing, and hence inventory ownership becomes more attractive. Reports from Internet retailers indicate that the fixed investment in inventory and warehousing capabilities can range from $8 million (Spun.com—CD retailing) to $1 billion (Webvan.com—grocery retailing). Back-end software systems are expensive as well: Amazon.com reports that these costs have historically accounted for 10-15% of the cost of goods sold (see Ghemawat and Baird [1998]). We believe that total fixed costs are much higher if the Internet retailer decides to own inventory and warehouses, a finding independently confirmed by many executives with whom we communicated as well as by numerous trade publications citing the huge investment costs incurred by retailers utilizing traditional supply chains.

Second, in order to invest in fulfillment capabilities, a firm needs to acquire capital. From the early years of the Internet until recently, financial analysts used large revenues to justify market valuations of Internet retailers. For example, multiples of sales were used instead of multiples of earnings (see Davis [2002] and citations therein). Hence, companies with large revenues were rewarded with favorable market valuations, allowing them to acquire cash to invest further in infrastructure. This reasoning suggests that larger firms (in terms of their having larger revenue streams) will be more willing to take on fixed-cost investments because they acquire cash from capital markets more readily, while smaller firms will choose to drop-ship to avoid large outlays of cash.

Hypothesis 4. *Inventory ownership will be positively associated with a firm's revenues.*

2.5 Relative Gross Margin

We hypothesize that a retail firm operating in an industry characterized by high relative gross margins is more likely to internally accumulate the cash necessary to recoup fixed investments than a firm operating in an industry with smaller margins. As both Netessine and Rudi [2004b] and Singh et al. [2003] demonstrate, a higher gross margin for products directly translates into higher profitability which in practice leads to a better cash flow. Hence, we expect that companies enjoying higher gross margins are more favorably positioned to recoup fixed costs of investing into fulfillment capabilities than companies that have to rely on low gross margins.

Hypothesis 5. *Inventory ownership will be positively associated with the relative gross margin.*

2.6 Firm Age

Stigler [1951] suggests generally that ownership is influenced by the stage of industry development. Specifically, he asserts that at early stages of the product life cycle, firms will choose to be vertically integrated, because low levels of product demand cannot sustain specialized firms. The lack of specialized firms leads to a scarcity of both capabilities and options for firms to outsource inventory and inventory fulfillment capabilities. In the case of electronic retailing, we argue that firms who entered at early stages of the industry integrated vertically because potential fulfillment partners did not exist or, in the case of many wholesalers, had not developed drop-shipping capabilities. As third-party alternatives become more available, we would expect firms to divest themselves of inventory and warehouses. However, because of committed investments in warehouses and inventory and documented stickiness of supply chain investments (Randall [2001] and Fine [1999]), we believe early electronic retailers will continue to maintain an integrated structure. Furthermore, our observation suggests that some Internet retailers operated in some other form (e.g., through catalog sales) long before the advent of the Internet. These companies had to invest in their own fulfillment capabilities because, at that point, communication with wholesalers in real time was too costly (see Scheel [1990]).

Hypothesis 6. *Inventory ownership will be positively associated with firm age.*

2.7 Product Size/Weight, Product Obsolescence, and Cost of Capital

Some products naturally lend themselves to distribution through drop-shipping, whereas others can be stocked effectively internally. For example, large and heavy products incur significant shipping and handling costs every time they are transported, thus reducing the gross margin. Since the drop-shipping channel avoids the extra cost of shipping the product from the wholesaler to the retailer, it is economical to distribute large and heavy products through the drop-shipping channel. In addition, large and heavy products are expensive to hold in inventory, since they occupy a lot of warehouse space and require more handling. Notice that holding costs are incurred by the retailer in the traditional channel and by the wholesaler in the drop-shipping channel. Hence, for products characterized by large size and weight, retailers should prefer the drop-shipping channel.

Hypothesis 7. *Inventory ownership will be negatively associated with product size/weight.*

The second part of this line of argument concerns product obsolescence. A retailer of groceries or flowers may have products that become obsolete daily. Naturally, holding such products in inventory is costly when demand is uncertain. In contrast, jewelry may actually appreciate in value over time. Obsolescence is equivalent to incurring a holding cost for a product and hence, similar to Hypothesis 7, a higher rate of obsolescence should translate into a higher likelihood of the retailer's adopting the drop-shipping channel.

Hypothesis 8. *Inventory ownership will be negatively associated with product's rate of obsolescence.*

Finally, carrying inventory means incurring the opportunity cost of capital, because money invested in inventories has other potential uses (see Cachon and Terwiesch [2004] for discussions). Hence, a company that is able to borrow capital cheaply is more likely to invest in inventory and fulfillment capabilities, as reflected in our last hypothesis:

Hypothesis 9. *Inventory ownership will be negatively associated with a firm's cost of capital.*

3. Research Design, Sample Description, and Definition of Variables

3.1 Research Design and Sample Description

To test our hypotheses about a firm's choice of supply chain, we use a cross-sectional sample from a population of publicly traded Internet retailers operating between the start of Internet retailing (approximately 1994) and 2001. The advantage of a cross-sectional sample as opposed to a longitudinal study is that we expect to see more variation in decisions across companies than changes within companies across time. The cross-sectional design also eases data gathering requirements, as companies often do not maintain accurate records pertaining to our variables of interest. The cross-sectional design does present some difficulties for the gathering of data for bankrupt companies. For these companies, data were gathered in late 2001 and early 2002, but respondents were asked to provide data on the last year of viable operation.

Our sample is limited to the public domain in order to gather the financial information necessary to test our expectations about economic outcomes. Public companies tend to be larger, more tightly monitored, and better capitalized than nonpublic companies. By combining several sources of data containing lists of all publicly traded Internet companies, we identified a list of potential sample firms. Sources include: EDGAR, the Securities and Exchange Commission site listing all publicly traded companies; BizRate.com, an e-commerce site that rates Internet retailers; *Industry Standard*, an Internet magazine that publishes lists of publicly traded Internet companies; and Yahoo Finance, an Internet site that provides financial fundamentals for all publicly traded companies. From these sources, we identified 187 publicly traded Internet companies, 62 of which qualified under our criteria as Internet retailers. To qualify as such, one of a firm's primary means of obtaining revenue had to be the sale of physical goods (accounting for over 33% of all revenues). Almost all Internet firms either had no connection with physical goods or were clearly in retailing, so changing this threshold to some other number would not have impacted our sample. Companies delivering digitized goods, which were previously predominantly delivered physically, were excluded (i.e., ticket companies and music companies now delivering electronic tickets and MP3 files). We conducted interviews, examined Web sites and examined public financial records to complete our questionnaire. Of the 62 companies, 54 responded favorably to the questionnaire, resulting in 53 usable surveys and giving us an overall usable response rate of 85.4%. Depending upon assumptions about market size in Internet retailing, we believe these 53 companies account for 50-70% of all retailing revenue on the Web (which was around $40B in 2002, according to the U.S. Census Bureau). When available, financial data were obtained from COMPUSTAT tapes; otherwise, financial data were obtained from annual report information and 10-K filings to the Securities and Exchange Commission.

3.2 Definition of Variables

In this section, we describe the variables used as constructs in our analyses. Table 1 reports descriptive statistics on each of the variables, including mean, standard deviation, and 10^{th}, 50^{th} and 90^{th} percentiles.

The Dependent Variable:

Inventory Ownership: We classify a firm as having integrated inventory and Web interface using an indicator variable. Inventory ownership takes a value of 1 if over 50% of a firm's sales come from its own inventory and 0 otherwise. Sixty-four percent (64%) of the firms in the sample rely primarily on owning inventory, while 36% rely primarily on drop-shipping. These results are similar to results reported by PriceWaterhouse Coopers [3], who reported that in 2000, 30.6% of all Internet retailers (both publicly traded and private) relied primarily on drop-shipping to fulfill their orders. In practice, firms sometimes both own inventory and use drop-shipping arrangements such that some portion of sales is filled from firm-owned inventory and the remaining portion is filled from outside inventories. The choice to use a dichotomous variable instead of a continuous variable such as "percent of sales from owned inventory" was made necessary when, during pilot testing of the survey, we found that respondents would not or could not provide estimates of the percentage of sales filled from their own inventory. While less precise than continuous variables, a dichotomous variable has been commonly used to represent firm investments in supply chain assets in the vertical integration literature (see, for example, Anderson and Schmittlein [1984]). Long [1997] suggests that using a dichotomous variable to represent an unmeasured continuous variable is neither uncommon nor inappropriate. To provide some validity for the use of a dichotomous variable, we examined the average days of inventory (Average Inventory/Cost of Goods Sold) for firms during our time period. For those classified as drop-shipping, the median number of days in inventory was 0, with 70% of all firms reporting no inventory. For those classified as owning inventory, the median number of days in inventory was 85, with 100% of all firms reporting some level of inventory. However, the direct use of days of inventory as an independent variable is problematic because, for many of our hypotheses, the association between days of inventory and the inventory ownership variable is not monotonic. Using demand uncertainty as an example, we see that as demand uncertainty increases, theory suggests that days in inventory would also increase (Cachon and Terwiesch [2004]). However, as demand uncertainty hits extremes, we expect to see firms choose to drop-ship, at which point the value of the days-of-inventory variable becomes 0.

The Independent Variables:

We measure some of the independent variables (namely, firm age, firm revenues, product variety, product size/weight, product obsolescence and cost of capital) using firm-specific data obtained either through public records or through questionnaires. The remaining variables (namely, demand uncertainty, the number of retailers in the channel, and relative gross margin) are measured for the firm's industry. Thus, these variables might reflect some industry-level effects. We measure relative gross margin and demand uncertainty at the industry level to avoid potential endogeneity problems with the inventory investment decision. The number of retailers is an industry-level measure by nature. Unless otherwise noted, we estimated variables at the industry level by taking an average in the primary industry of activity as defined by the company using a six-digit North American Industry Classification System (NAICS) code. Firms in our sample fall into 16 different NAICS industry classifications. For demand uncertainty and relative gross margin, data were gathered for a ten-year period prior to 1995 for all firms in the industry using COMPUSTAT. This time period was selected because it immediately preceded the launch of Internet operations by companies in our sample and hence represented data that these companies could reasonably use to make their decisions.

Product Variety: We use the number of brands offered by a retailer as a proxy for product variety. Ideally, we would measure the number of products carried or SKUs (stock-keeping units). However, many companies could not provide such a measure. To check the validity of our measure, we examined a subsample of Internet retailers where we could verify the brands and products carried. We note a strong positive and significant correlation between the two measures (r=0.56, p<0.01). This is consistent with studies of other industries in which alternative measures of variety are correlated with the number of end products (see, for example, Randall et al. [1998]). The average number of brands offered by firms in our sample is 812. We noted several firms with unusually high levels of product variety. We tested our results for robustness by trimming or windsorizing large outlier firms. We report no difference between these results and those reported in the tables.

Demand Uncertainty: We measure demand uncertainty using the coefficient of variation of demand. This coefficient of variation is calculated using annual inflation-adjusted, industry-level data for the ten years prior to the period of study. MacMillan et al. [1986] use a similar statistical measure of uncertainty. We use the coefficient of variation rather than the standard deviation in order to adjust the scale of demand uncertainty to the size of the industry. The average coefficient of variation of demand is 0.21. We also examined several other measures of demand uncertainty calculated using quarterly and annual data that were both raw and price-adjusted. These measures yielded coefficients that were below conventional significance cutoffs with respect to the demand uncertainty measures.

Number of Retailers in the Channel: For our empirical specification, we calculate the ratio of retailers to wholesalers at the industry level and use it as a proxy for the number of retailers that each wholesaler serves. Data on both retailers and wholesalers come from the 1990 U.S. Census of retailers and wholesalers. We calculate the ratio of retailers to wholesalers by collecting the number of retailers and wholesalers in the primary SIC code for each company. The average retailer-to-wholesaler ratio is 9.06. In the analysis, we find no statistically significant association between inventory ownership and the ratio of retailers to wholesalers. Netessine and Rudi [2004b] suggest that this association is not linear, but increases in the square root of the number of retailers. Subsequent results are presented using this measure, which is statistically significant in some tests. We also calculate a retailer-to-wholesaler ratio using a blend of the retailer wholesaler ratios for all SIC codes used by the company, but results do not differ from results using the ratio from the primary SIC code.

Firm's Mean Revenues: We use sales to measure revenues. The average firm among the 53 respondents has $315 million in sales. Due to the skewed nature of this measure, we perform subsequent analyses using the natural logarithm of firm sales. We verified that all retailers in our sample consistently recognized revenues based on gross revenue figures.

Relative Gross Margin: We measure relative gross margin at the industry level as described above. The average as well as median industry margin is 29%.

Firm Age: We measure firm age in quarters. We use quarters (rather than years) to provide some variance in age due to the short history of Internet retailing. The average firm age is 35 quarters or about 9 years old.

Product Size/Weight: We measured product size/weight by asking company personnel to place the majority of their product sales on the following scale: 1 = small (CDs, books), 2 = small to medium (personal computers), 3 = medium (furniture), and 4 = large (automobiles). Average product size/weight is 1.75 on this scale.

Product Obsolescence: We measured obsolescence rate by asking company personnel to rate on average how frequently their products become obsolete on the following scale: 1 = daily, 2 = weekly, 3 = monthly, 4 = annually, and 5 = never. The mean response rate is 3.0, indicating that most companies report that their products go obsolete on a monthly basis.

Cost of Capital: We calculate the weighted average cost of capital (WACC) as the average interest rate on long-term debt plus the average return on equity, each weighted by the proportion of debt and equity to the total company valuation (Brealey and Myers [1991], page 408). The average cost of capital for firms in our sample is 0.11.

Table 2 provides Pearson correlation coefficients for the independent variables. We report no problems with colinearity or multi-colinearity.

4. Results of Tests of the Hypotheses

We provide evidence supporting our hypotheses using two types of tests: a univariate test comparing means between companies owning and not owning inventory, and a multivariate logistic regression analysis. Table 3 shows the test of mean differences between firms that own inventory and those that drop-ship. We report significant differences between firms in the sample for product variety, relative gross margin, firm age, and product size/weight. Firms that own inventory tend to sell fewer brands (247 brands vs. 1822 brands), participate in industries with higher gross margins (31% vs. 26%), be older (40 quarters vs. 27 quarters), and sell smaller products (1.53 vs. 2.15). With these univariate tests, we report no significant difference between groups for demand uncertainty, number of retailers, firm sales, product obsolescence, and the weighted average cost of capital.

Table 4 presents results from a logistic regression model in which ownership of inventory is the dependent variable. Our assumed decision environment and theory associated with our hypothesis that larger product variety is negatively associated with inventory ownership suggests that the product variety offered by a firm is not exogenous to the decision to hold inventory (see Novak and Eppinger [2001] for similar arguments when examining the effect of complexity on vertical integration in the auto industry). In such circumstances, Kennedy [1998] recommends an instrumental variable approach to remove bias from the parameter estimates. We use an instrument similar to that used in Bayus and Putsis [1999], where brands are considered to be a function of brands offered by competitors, firm market share, expected market growth, whether the firm markets its own brand or not, and the average price of products offered. The predicted value resulting from this regression serves as our instrument. The resulting R-squared value of the regression to form the instrumental variable was 0.66 and the number of brands offered by the competition is the variable significantly correlated with firm-level variety.

The model in Table 4 has a statistically significant likelihood ratio and a maximum rescaled R-squared value of 0.69. In support of hypotheses 1, 5, 6, and 7 and consistent with univariate tests, we report a statistically significant negative association between inventory ownership and product variety and product size/weight and a statistically significant positive association between inventory ownership and relative gross margin and firm age. Differing from univariate tests and supporting hypotheses 2 and 3, we report a statistically significant negative association between inventory ownership and demand uncertainty and the number of retailers. Similar to univariate tests, we report no association between inventory ownership and firm sales, inventory ownership and obsolescence, and inventory ownership and WACC. Rerunning these models using firm market share in place of firm demand yields no significant results for the market share variable. Overall, we find full or partial support for 6 of 9 hypotheses.

In the second column of Table 4, we calculate the standardized factor change in the odds of holding inventory (Long [1997]), calculated as follows: standardized factor change = exp(coefficient estimate x standard deviation of independent variable)-1 x 100. This allows for some comparison of the magnitude of the effects each variable has on the odds of holding inventory. For example, a standard deviation change in the relative gross margin increases the odds of owning inventory by 236.6%. Using this measure to compare effects, it appears that standard deviation changes in relative gross margin and firm age have the strongest positive influence on the odds of owning inventory, while product variety and the number of retailers have the strongest negative influence on the odds of owning inventory. Examination of regression diagnostics, including Pearson residuals and deviance residuals, showed no influential data points.

5. Implications of Inventory Choices on Economic Performance

In this section, we examine the implications of inventory choices on economic performance. We explore two alternative views of how a firm's inventory decision affects its economic performance. The first view hypothesizes that one inventory choice is dominant. In other words, either drop-shipping or the traditional channel will lead to better firm performance. The second view is a contingent view hypothesizing that successful performance is a function of whether or not the firm chooses the inventory structure most appropriate to its particular competitive situation. Like much recent literature in operations strategy, this hypothesis assumes that high performance comes from the alignment or fit of complementary assets (Milgrom and Roberts [1990], Bozarth and Edwards [1997], Nath and Sudharshan [1994], and Randall and Ulrich [2001]).

When testing the contingent view, that performance is associated with how well the inventory investment decision fits a particular firm, Donaldson [2001] identifies several key methodological issues relevant to our situation. First, a performance measure should be reliable and measured after decisions determining fit are made. Following this suggestion, we use firm bankruptcy as our measure of firm economic performance. Bankruptcy substantially lags behind the decision to invest in inventory capabilities.[3] Furthermore, we believe it to be the most reliable measure of performance, given that in our sample of Internet firms we observe profitability measures to be highly volatile. Bankruptcy takes a value of 1 if the company declared bankruptcy during the period between 1995 and

[3] In our sample, we noted few cases in which firms had shifted substantially from the initial decision to hold inventory or drop-ship. In other words, a firm would choose an inventory strategy and in general maintain the strategy through our period of study. One noted exception to this rule was Amazon.com (Ghemawat and Baird [1998]). Early in the time period it changed its strategy from drop-shipping to inventory ownership.

2001 and 0 otherwise. Bankruptcies were regularly reported in the Internet magazine *Industry Standard* and on industry Web sites. Ten out of 53 firms, or 19%, declared bankruptcy during the study period.

Second, the measure of fit should be reliable. We use a common and reliable method that determines fit empirically (see Pennings [1987] and Ittner et al. [2003] as examples). Fit, or more appropriately misfit, is determined by the residual from the logistic regression reported in Table 4 and is defined as follows:

$$\text{MISFIT} = \begin{cases} 1 - \text{predicted probability if the firms owns its inventory,} \\ \text{predicted probability otherwise.} \end{cases}$$

We also square our MISFIT measure, resulting in MISFIT^2. By squaring the measure, we exaggerate the distance of those firms making more inappropriate decisions from those making the optimal decision prescribed by our model. We expect our measures of MISFIT to be *positively* associated with bankruptcy. An underlying assumption with empirically derived fit models is that the predictive model of fit reported in Table 4 is a reasonable benchmark by which to judge fit. This raises a question as to whether bankrupt firms should be included in the initial regression model that determines fit. One might argue that bankrupt firms have clearly not made appropriate choices and should not be included in the regression model that determines fit. However, firms may make appropriate inventory choices but still go bankrupt due to other decisions. In this case, they should be included in the regression model that determines fit. We take both views into consideration when calculating our MISFIT variables. We also note that the analysis using surviving firms resulted in separation. The implications of separation are that the estimates may not be reliable. Allison [1999] suggests that the reason for this separation may be model over specification. In our case this problem is caused by the obsolescence and WACC variables which are not statistically significant. In keeping with Allison [1999], we removed these variables from the model that used only surviving firms. We also calculated the misfit measure using the estimates from the separated estimation procedure. We report no differences when using either method of determining MISFIT in the surviving firm sample.

Third, other factors associated with firm performance should be included as control variables. In our model, we control for several factors commonly associated with bankruptcy, including market share, Altman's Z-score (a measure of financial distress), order of entry into the industry, and the age of the CEO. Market share is defined as the firm's market share at the end of the study or at the time of bankruptcy. We expect larger firms to go bankrupt at a lower rate than smaller firms.

Although researchers have not arrived at a conclusive measure of financial distress (Mossman et al. [1998]), we use a commonly cited measure, Altman's Z-score, which was developed to predict corporate bankruptcy using a weighted combination of several financial ratios (Altman [1993]). For nonmanufacturing firms, Altman's Z-score (Z) is calculated as

$$Z = 6.56\left(\text{Working Capital}/\text{Total Assets}\right) + 3.26\left(\text{Retained Earnings}/\text{Total Assets}\right) + 6.72\left(\text{Earnings Before Income Taxes}/\text{Total Assets}\right) + 1.05\left(\text{Market Value of Equity}/\text{Book Value of Debt}\right).$$

Altman's Z-score has proven effective in predicting bankruptcy when measured a year in advance of the event (see Altman [1993]). Consistent with these findings, we measure Altman's Z-score the year before a firm declares bankruptcy or a year before the end of the study period. Firms are categorized as being high-risk, medium-risk or low-risk based on two cutoffs. These cutoffs are 1.1 and 2.6 for nonmanufacturing firms (White et al. [2003]). We calculate an indicator variable equal to 1 for firms with Z-scores less than 1.1. We expect bankruptcy to be *positively* associated with the Z-score indicator.

We measure order of market entry as the rank of entry into the industry. Studies in population ecology find a positive relation between the order of market entry and bankruptcy, with firms entering the industry later going bankrupt more quickly (Carrol and Hannan [1989]). Finally, we measure CEO age in years. Joos et al. [2003] and references therein argue that the market sorting process should result "in younger CEOs (less effort and risk averse, with longer horizons) being hired by firms requiring more effort (startups and high growth firms), riskier firms, and firms with large portfolios of growth options." We believe that this description of firms that should hire younger CEOs is consistent with the description of the Internet retailers we study. Anecdotal evidence from the industry suggests that given the new technology involved in Internet firms and the considerable uncertainty associated with these businesses, experience will play less of a role in success; indeed, experience serves as an obstacle. Hence, we expect CEO age to be positively associated with firms' rate of bankruptcy. Like Joos et al. [2003], we do not want to suggest that boards of directors hire CEOs based on age. Rather, qualitative traits of CEOs (effort and risk aversion, expected horizon and human capital) happen to be correlated with age. Although we have attempted to control for the predominant variables associated with bankruptcy, at this point we recognize that there may be other correlated but omitted variables associated with bankruptcy.

To analyze the bankruptcy of companies in our sample, we use a common survival analysis technique known as the Cox proportional hazards model (Cox [1972]). Like most survival analysis techniques, the Cox model accommodates right censoring of the data (Allison [1995] and Kiefer [1998]). The Cox model estimates a partial likelihood ratio that assumes that the hazard rate between observations is proportional over time even though the underlying hazard rate for all observations varies with time. Practically, this assumption means that time-dependent variables that do not vary across observations are eliminated from the estimation procedure as long as the time of origin is selected carefully. For example, macroeconomic factors that vary by time but not by observation would be eliminated from the estimation procedure. We use calendar time, as opposed to firm time, as the point of origin and adjust for firms that have late entry into the data set. We choose calendar time because of the macroeconomic influences that accompany the Internet era. This allows us to interpret the proportional hazards as the proportional hazards between observations at a given point in calendar history. It also legitimizes the elimination of the macroeconomic variables from the estimation procedure. We use the exact method to handle tied data. Consistent with Shumway [2001], when firms leave the group of well-performing companies for some reason other than bankruptcy (e.g., merger), we consider them censored or no longer observed. The general hazard function estimated, $h_i(t)$, for the ith observation at time t is represented by:

$$h_i(t) = \lambda_0(t)\exp\begin{pmatrix} \beta_1(\text{measure of MISFIT}_\text{i}) + \beta_2(\text{Market Share}_\text{i}) + \beta_3(\text{Altman's Z}_\text{i}) \\ + \beta_4(\text{Entry Order}_\text{i}) + \beta_5(\text{CEO Age}_\text{i}) \end{pmatrix}.$$

Here t is the time to bankruptcy and $\lambda_0(t)$ is the baseline hazard rate, which cancels in the partial likelihood estimation procedure.

Table 5 shows results of the Cox proportional hazard models. The likelihood ratio tests indicate that all models are significant. R-squared values range from 15.84% to 30.10%. Each column shows an alternative measure for inventory ownership or MISFIT. In column I, we report no association between the indicator variable for inventory ownership and the hazard of bankruptcy, implying that the simple inventory choice variable is not associated with performance in our sample. In columns II and III, we show results of models using MISFIT measures derived from a predictive model including all firms. We report no significant association between MISFIT and the hazard of bankruptcy, but a positive and significant association between MISFIT^2 and the hazard of bankruptcy. In columns IV and V, we show the results of models using MISFIT measures derived from a predictive model using only surviving firms. Consistent with expectations, we report a positive significant association between MISFIT and MISFIT^2. It is interesting to note that the significance of results for our misfit measures is much stronger in the models in which only surviving firms are included in the predictive model. We also examine whether the hazard of bankruptcy and inventory ownership varies by time. Interaction variables by year were introduced into the model. In this analysis, we note no significant results. Specifically, our data includes five bankruptcies in 2000 (including two firms that owned inventories) and five bankruptcies in 2001 (including three firms that owned inventories).

With respect to our control variables, we note that in every case the Altman's Z-score is positive and significant, indicating that firms with low Z-scores have a higher rate of bankruptcy, which is consistent with the findings in the extant literature. In columns IV and V, the entry order variable is positive and significant, indicating higher bankruptcy rates for later entrants. We report no association between market share and the hazard of bankruptcy and between CEO age and the hazard of bankruptcy. To test robustness, we examined deviance residuals and found no influential observations.

We tested our Z-score cutoff for robustness. We note that firms with Z-scores above the recommended 2.6 had a statistically lower hazard of bankruptcy than firms below 2.6. An alternative approach to specifying a cutoff would be to use sample statistics such as the median or lower quartile. Results using a median cutoff yielded significant results in models IV and V. Results using a lower quartile cutoff yielded results similar to those in Table 5, with the exception that the p-value on the MISFIT coefficient in model III was significant at the p=0.11 level.

Finally, we note that several firms in our sample reported being on the verge of bankruptcy and were acquired days before a formal announcement of bankruptcy. These firms were coded as having declared bankruptcy. We tested our results for robustness with respect to this assumption by eliminating these firms from the analysis. We report no significant differences in columns I, II, III, and IV of Table 5 when these firms are removed from consideration. In column V our MISFIT measure is positive and significant, but the Z-score and entry order variables lose significance at conventional levels.

6. Discussion of Implications and Limitations

This empirical study examines the factors associated with the choice to own fulfillment capabilities or to drop-ship products by Internet retailers. There exist numerous empirical studies that analyze firms on the Internet from marketing and information system perspectives. To the best of our knowledge, our work is one of the first to empirically analyze operational issues of Internet companies, namely, choice of supply chain. We find that product variety, demand uncertainty, relative gross margin, firm age, the ratio of retailers to wholesalers, and product size/weight are all significant factors in the decision to own inventory. In the analysis, we do not see any association between firm sales and the decision to hold inventory. This result may be an artifact of our sample, because we chose publicly traded companies that tend to be larger than private companies, effectively excluding smaller retailers from the analysis. We also find no association between product obsolescence and inventory ownership or WACC and inventory ownership. This result may be attributed to imprecise measurement of these constructs.

We find support for the idea that firms making appropriate decisions consistent with our empirical benchmarks are less likely to go bankrupt than outlier firms. This finding emphasizes the strategic importance of thoroughly understanding the fulfillment decisions. We are cautious about forecasting the future of firms that we classify as outliers, but which have not yet gone bankrupt. Often a firm will be in a temporary state of misalignment, having put assets in place for the future. However, if a strategy fails, the decision is costly and the investment is difficult to reverse. For example, one of the companies we studied went bankrupt in the process of trying to change its inventory strategy to a strategy that our model predicted would be more aligned with market and strategy conditions. From a recent interview with founders of Spun.com (a private retailer that is not part of our sample), we found that the company is currently in transition from drop-shipping operations to inventory ownership.

A possible limitation of our study arises from the fact that we focus on two extreme versions of inventory ownership, namely, the firm either drop-ships or owns inventory exclusively. In practice companies may employ hybrid strategies (see Netessine and Rudi [2004b] for an extensive treatment of this issue). An example would be a situation in which the company owns the most popular products but drop-ships slow-moving items, or uses drop-shipping as a backup mechanism once the company runs out of inventory. Our use of a dichotomous variable has the potential to weaken statistical results. One other limitation of our study is that we are unable to measure the number of wholesalers *able* to drop-ship products (i.e., those that have invested in drop-shipping capabilities). It is possible that this number varies by industry and/or over time. Difficulty accounting for this effect is dictated by the lack of data.

Like many studies, our results are subject to an omitted-variable bias. At the same time, adding more variables will begin to limit our ability to test all potential hypotheses because of the small sample size. Thus, we tried to limit judiciously the number of the variables (Peduzzi et al. [1996]). One example of an additional variable to consider is the geographical spread of customers. A large wholesaler may have multiple warehouses and hence might be able to serve geographically widespread customers more cheaply. However, information on the geographical spread is hard to obtain. It is also possible that the competitor's channel choice has an effect, although we do not have a clear prediction of the direction of this effect. Longer lead times (similar to demand uncertainty) are likely to favor drop-shipping but are hard to measure, and, moreover, lead times will probably vary by product and by supplier. A decision to invest into fulfillment capabilities may be connected to the company's liquidity, cash flow, and earnings, and it may also be affected by contractual arrangements prevailing in the industry. Future research may uncover other drivers of Internet retailers' decision to invest into fulfillment capabilities.

Likewise, there are limitations to our model of predicting bankruptcy of Internet retailers, since variables other than choice of supply chain might be important. The bankruptcy literature is quite voluminous (see Shumway [2001] and Hillegeist et al. [2004] for review and references), and there is no common approach to predicting bankruptcy that is generally reliable and acceptable. Many if not most of these papers rely on Altman's Z-score to predict bankruptcy, which is the reason we include this variable as well. Future literature may examine the impact of variables such as quality of pre-IPO investors, the impact of a retailer's brand name, and the competitive landscape. While we acknowledge that these are important considerations, at the same time they are hard to measure reliably and hence are absent from the analysis in our paper and in papers of which we are aware. Finally, all bankruptcies in our study occurred in 2000 and 2001, and hence we cannot claim that our results are generalizable beyond this period.

Our study was performed at a high strategic level. Future empirical work may be performed to examine operational questions surrounding how to achieve effective vertical integration or disintegration in the Internet environment and the comparative performance of companies with different supply chain structures. Internet retailers typically must invest heavily in software that ties front-end store operation with back-end fulfillment. In the case of virtual inventories, such investment may be particularly important, since the front end of one company has to be aligned with fulfillment performed by another company.

References

[1] The American dream gone bad. *The Industry Standard*, August 28, 2000, pages 71-73.

[2] Cheap tricks. *Forbes*, February 21, 2000, page 116.

[3] The state of eRetailing 2000. The supplement to *ERetailing World*. March 2000. PriceWaterhouse Coopers.

[4] Fulfillment Nets. 2000. *Commerce Infrastructure*, Vol. 4, Jupiter Communications.

[5] Online retailers will turn to drop-shippers as almost half lose money on shipping and handling. February 8, 2001. Press release, Jupiter Media Metrix.

Allison, P. 1995. *Survival analysis using the SAS system: a practical guide*. SAS Publishing.

Allison, P. 1999. *Logistic regression using the SAS system: Theory and Application.* SAS Institute, Inc., Cary, NC.

Altman, E. 1993. *Corporate financial distress and bankruptcy: A complete guide to predicting and avoiding distress and profiting from bankruptc*y. John Wiley & Sons, Canada.

Anderson, E. and D. C. Schmittlein. 1984. Integration of the sales force: An empirical investigation. *Rand Journal of Economics*, Vol. 15, 385-395.

Bayus, B.L. and W.P. Putsis. 1999. Product proliferation: An empirical analysis of product line determinants and market outcomes. *Marketing Science*, Vol. 18, 137-153.

Bozarth, C. and S. Edwards. 1997. The impact of market requirements focus and manufacturing characteristic focus on plant performance. *Journal of Operations Management*, Vol. 15, 161-180.

Brealey, R. and S. Myers. 1991. *Principles of Corporate Finance*. McGraw-Hill.

Cachon, G.P. and C. Terwiesch. 2004. *Matching supply with demand: An introduction to operations management.* McGraw-Hill, New York, NY.

Carrol, G. and M. Hannan. 1989. Density delay in the evolution of organizational populations: a model and five empirical tests. *Administrative Science Quarterly*, Vol. 34, 411-430.

Cox, D. 1972. Regression models and life tables. *Journal of the Royal Statistical Society*, Vol. 34, 187-220.

Davis, A. 2002. The value relevance of revenue for Internet firms: Does reporting grossed-up or barter revenue make a difference? *Journal of Accounting Research*, Vol. 40, 445-477.

Dinlersozy, E.M. and H. Li. 2003. Shipping news: An analysis of Internet retailers' shipping strategies. Working paper, University of Houston.

Donaldson, L. 2001. *The contingency theory of organizations.* Sage Publications, CA.

Eppen, G. 1979. Effects of centralization on expected costs in a multi-location newsboy problem. *Management Science,* Vol. 25, 498-501.

Evans, P. and T.S. Wurster. 2000. Getting real about virtual commerce. *Harvard Business Review* OnPoint product 4525.

Fine, C. 1999. *Clockspeed: Winning industry control in the age of temporary advantage*. Perseus Press.

Ghemawat, P. and B. Baird. 1998. Leadership online: Barnes & Noble vs. Amazon.com (A). Case study, Harvard Business School.

Ghosh, S. 1998. Making business sense of the Internet. *Harvard Business Review*, March-April, 126-135.

Hendricks, K.B. and V. Singhal. 2005. Association between supply chain glitches and operating performance. *Management Science,* Vol. 51, 695-711.

Hillegeist, S.A., E.K. Keating, D.P. Cram, and K.G. Lundstedt. 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies,* Vol. 9, 5–34.

Ittner, C., D. Larcker, and T. Randall. 2003. The implications of strategic performance measurement in financial services firms. *Accounting Organizations and Society*, October-November, 715-741.

Johnson, E.M. 2002a. Garden.com—at the end of the runway. Case study, Dartmouth College.

Johnson, E.M. 2002b. Chempoint and Yantra: Extraprise management in the specialty chemical industry. Case study, Dartmouth College.

Johnson, E.M. and S. Whang. 2002. E-business and supply chain management: An overview and framework. *Production and Operations Management,* Vol. 11, 413-423.

Joos, P., A.J. Leone and J.L. Zimmerman. 2003. Selecting CEOs: Matching the person to the job. Working paper, University of Rochester.

Kennedy, P. 1998. *A guide to econometrics*, 4th edition. MIT Press, Boston, MA.

Kiefer, N. 1998. Economic duration data and hazard functions. *Journal of Economic Literature,* June, 646-679.

Lieberman, M.B. and R. Dhawan. 2005. Assessing the resource base of U.S. and Japanese auto producers: A stochastic frontier production function approach. *Management Science,* Vol. 51, 1060-1075.

Long, J. S. 1997. *Regression models for categorical and limited dependent variables*. Sage Publications, CA.

MacMillan, I.C., D.C. Hambrick and J.M. Pennings. 1986. Uncertainty reduction and the threat of supplier retaliation—2 views of the backward integration decision. *Organizational Studies*, Vol. 7, 263-278.

Milgrom, P. and J. Roberts. 1990. The economics of modern manufacturing: Technology, strategy and organization. *American Economic Review*, Vol. 80, 511-528.

Mossman, C., G. Bell, G.L. Swartz and H. Turtle. 1998. An empirical comparison of bankruptcy models. *The Financial Review,* Vol. 33, 35-54.

Nath, D. and D. Sudharshan. 1994. Measuring strategy coherence through patterns of strategic choices. *Strategic Management Journal*, Vol. 15, 43-61.

Netessine S. and N. Rudi. 2004a. Supply chain structures on the Internet and the role of marketing-operations interaction. In *Handbook of supply chain analysis in the e-business era* by Simchi-Levi et al., editors. Kluwer Academic Publishers.

Netessine S. and N. Rudi. 2004b. Supply chain choice on the Internet. Working paper, University of Pennsylvania. Available at http://www.netessine.com.

Novak, S. and S. D. Eppinger. 2001. Sourcing by design: Product complexity and the supply chain. *Management Science,* Vol. 47, 189-204.

Peduzzi, P., J. Concato, E. Kemper, T. Holford, and A. Feinstein. 1996. A simulation study of the number of events per variable in logistic regression analysis, *Journal of Clinical Epidemiology* 99. 1373-1379.

Pennings, J.M. 1987. Structural contingency theory: A multivariate test. *Organization Studies,* Vol. 8, 223-240.

Ramdas, K. 2003. Managing product variety: An integrative review and research directions. *Production and Operations Management,* Vol. 12, 79-101.

Randall, T. 2001. The path-dependent effects of supply chain choice on the evolution of product line structure. Working paper, University of Utah.

Randall, T., S. Netessine and N. Rudi. 2002. Should you take the virtual fulfillment path? *Supply Chain Management Review,* November-December, 54-58.

Randall, T., K. Ulrich and D. Reibstein. 1998. Brand equity and vertical product line extent. *Marketing Science,* Vol. 17, 356-379.

Randall, T. and K. Ulrich. 2001. Product variety, supply chain structure, and firm performance: Analysis of the U.S. bicycle industry. *Management Science,* Vol. 47, 1588-1604.

Roth, A. and W.E. Jackson III. 1995. Strategic determinants of service quality and performance: Evidence from the banking industry. *Management Science,* Vol. 41, 1720-1733.

Scheel, N.T. 1990. *Drop-shipping as a marketing function*. Greenwood Publishing Group.

Simchi-Levi, D., S.D. Wu and Z.M. Shen. 2004. *Handbook of supply chain analysis in the e-business era.* Kluwer Academic Publishers.

Singh, P., H. Groenevelt, and N. Rudi. 2003. Product variety and supply chain structure. Working paper, University of Rochester.

Shumway, T. 2001. Forecasting bankruptcy more accurately: a simple hazard model. *Journal of Business,* Vol. 74, 101-124.

Stigler, G. J. 1951. The division of labor is limited by the extent of the market. *Journal of Political Economy*, Vol. 59, 185-193.

van Ryzin, G. and S. Mahajan. 1999. Retail inventories and consumer choice. In *Quantitative models for supply chain management,* S. Tayur, R. Ganeshan and M. Magazine, editors, Kluwer Academic Publishers.

White, G., C.S. Ashwinpaul, and D. Fried. 2003. *The Analysis and Use of Financial Statements.* John Wiley and Sons.

Table 1: Descriptive Statistics (N=53)

Panel A: Variables for Inventory Ownership Model			Percentiles		
	Mean	Std. Dev.	10^{th}	50th	90th
Product Variety (Brands)	812.45	2290.91	1	200	1000
Product Variety (Brands – Instrumented)	807.87	1856.29	25	490	901
Demand Uncertainty (Industry Coefficient of Demand Variation)	0.21	0.04	0.18	0.22	0.23
# of Retailers (Retailer Wholesaler Ratio)	9.06	7.46	1.78	7.78	17.02
Firm Sales (in millions of dollars)	315.51	865.82	0.02	20.08	812.41
Relative Gross Margin	0.29	0.08	0.19	0.29	0.39
Firm Age	35.53	21.85	11.00	27.00	79.00
Product Size/Weight	1.75	0.89	1.00	1.00	3.00
Product Obsolescence	3.00	0.85	2.00	3.00	4.00
Weighted Average Cost of Capital (WACC)	0.11	0.02	0.07	0.11	0.13

Panel B: Variables for Bankruptcy Model	Mean for All Firms	Mean Values by Survival	
		Surviving=43	Bankrupt=10
Own Inventory	34 firms	28 firms	6 firms
Market Share	0.01	0.02	0.003
Altman's Z-score	5.24	7.24	-3.34
Entry order	26.94	25.18	34.50
CEO Age	44.39	44.04	45.90
MISFIT calculated using all firms	0.20	0.03	0.0001
MISFIT calculated using surviving firms	0.15	0.03	0.65

Brands: Number of brands carried by the company.

Industry Coefficient of Demand Variation: standard deviation of industry sales over 10 years/industry sales since 1985.

Retailer Wholesaler Ratio: Retailers/Wholesalers.

Firm Sales: Sales at time of initial public offering.

Relative Gross Margin: Average gross margin for a firm's industry over 10 years prior to the firm's entry into the market.

Firm Age: Age of firm measured in quarters.

Product Size/Weight: 1 to 4 scale, 1 = small (CDs, books), 2 = small to medium (personal computers), 3 = medium (furniture), 4 = large (automobiles).

Product Obsolescence: 1 to 5 scale, 1 = daily, 2 = weekly, 3 = monthly, 4 = annually, 5 = never.

Weighted Average Cost of Capital (WACC): Cost of equity based on firm-level beta, plus cost of debt.

Market Share: Market share of firm the year before exit or end of study period.

Altman's Z-score: Measure of bankruptcy risk calculated at year before exit or end of study period.

Entry order: Sequential number indicating the quantity of firms in the marketplace after entry.

CEO Age: Age of CEO at the beginning of study period.

MISFIT: Absolute value of deviation of actual inventory choice, minus the predicted inventory choice.

Table 2: Correlation Among Independent Variables (N=53)									
	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Product Variety (Brands)	1.00								
2. Demand Uncertainty (Industry Coefficient of Demand Variation)	-0.16	1.00							
3. Square Root # of Retailers (Retailer/Wholesaler Ratio)	0.11	-0.06	1.00						
4. Ln (Firm Sales)	-0.17	0.19	-0.21	1.00					
5. Relative Gross Margin	-0.13	0.18	0.33**	-0.01	1.00				
6. Firm Age	-0.14	0.18	-0.18	0.35***	-0.04	1.00			
7. Product Size/Weight	0.31**	-0.03	-0.30**	0.21	-0.37***	0.21	1.00		
8. Product Obsolescence	0.21	0.14	-0.01	0.01	0.22	-0.15	0.05	1.00	
9. WACC	0.06	0.01	0.25*	-0.06	0.08	-0.17	0.01	0.30**	1.00

***,**,* p-value significant at p<.01, .05 and .10 respectively.

Table 3: Tests of Mean Differences for Firms Owning Inventory and Drop-Shipping (N=53)				
	Own Inventory (N=34)	Drop-Ship (N=19)	Difference	P-value for test of mean difference
Product Variety (Brands)	247.79	1822.89	(1635.10)	0.01
Demand Uncertainty (Industry Coefficient of Demand Variation)	0.21	0.21	0.00	0.98
Square Root # of Retailers (Retailer/Wholesaler Ratio)	2.83	2.76	-0.07	0.83
Ln (Firm Sales)	2.44	1.14	1.10	0.36
Relative Gross Margin	0.31	0.26	0.05	0.01
Firm Age	40.16	27.25	12.91	0.04
Product Size/Weight	1.53	2.15	-0.62	0.01
Product Obsolescence	2.91	3.15	-0.24	0.32
WACC	0.11	0.11	0.00	0.99

Table 4: Logistic Regression Model of Inventory Ownership
(N=53, Wald Chi-Square Statistics in brackets)

	Coefficient	Standardized Change
Intercept	15.59*	-
	[3.46]	
Product Variety (Brands Instrumental Variable)	-0.01***	-99.9%
	[6.45]	
Demand Uncertainty (Industry Coefficient of Demand Variation)	-69.03**	-93.7%
	[4.15]	
Square Root # of Retailers (Square Root of Retailer/Wholesaler Ratio)	-1.04**	-99.9%
	[3.99]	
Firm Sales	-0.01	-
	[0.01]	
Relative Gross Margin	15.17*	236. 6%
	[3.23]	
Firm Age	0.07**	361.6%
	[3.81]	
Product Size/Weight	-1.56**	-75.05%
	[5.00]	
Product Obsolescence	-0.19	-
	[0.11]	
WACC	32.88	-
	[1.19]	
Max Rescaled R-Squared	0.69	
Likelihood Ratio Test	36.95***	

Table 5: Association between Bankruptcy and Alignment of Inventory Choice
(N=53, Wald Chi-Square Statistics in brackets)

Dependent Variable: Bankruptcy		All Firms in Predictive Model		Surviving Firms in Predictive Model	
	Model I	Model II	Model III	Model IV	Model V
Own Inventory	0.55	-	-	-	-
	[0.66]				
MISFIT	-	1.66	-	4.47***	-
		[1.87]		[11.59]	
MISFIT^2	-	-	2.46*	-	4.23***
			[3.19]		[12.10]
Market Share	-41.67	-26.08	-28.02	-3.95	-9.95
	[1.06]	[0.43]	[0.49]	[0.02]	[0.07]
Altman’s Z-Score	1.28*	1.15*	1.09*	1.65**	1.73**
	[3.62]	[3.11]	[2.97]	[3.72]	[3.99]
Entry Order	0.03	0.03	0.03	0.10*	0.10**
	[1.37]	[1.22]	[1.40]	[3.65]	[3.76]
CEO Age	0.03	0.03	0.04	0.04	0.05
	[0.87]	[0.90]	[1.60]	[1.47]	[1.88]
R-squared	15.84%	17.55%	19.08%	30.10%	29.94%
Likelihood Ratio Test	9.14*	10.23*	11.22**	30.10***	29.94***

***,**,* significant at p<.01, p<.05, and p<.10