Manufacturing & Service Operations Management

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

Impact of Variety and Distribution System Characteristics on Inventory Levels at U.S. Retailers

Sampath Rajagopalan,

MANUFACTURING & SERVICE OPERATIONS MANAGEMENT
Vol. 15, No. 2, Spring 2013, pp. 191–204
ISSN 1523-4614 (print) | ISSN 1526-5498 (online)
http://dx.doi.org/10.1287/msom.1120.0407

Impact of Variety and Distribution System Characteristics on Inventory Levels at U.S. Retailers

Sampath Rajagopalan
Marshall School of Business, University of Southern California, Los Angeles, California 90089, raj@marshall.usc.edu

Over the past six decades, numerous analytical models have been developed to determine optimal inventory levels. These models predict that inventories carried by a retailer should be a function of the product variety carried by the retailer, distribution system characteristics, economies of scale, etc. A few recent empirical studies have explored the impact of some of these factors on aggregate inventories at U.S. retailers. Building on these works, this study empirically explores the role of key factors such as product variety, number of stores, and number of warehouses in explaining inventory levels at U.S. retailers using data obtained from both primary and secondary sources. We find that variety as measured by the number of stock-keeping units carried and number of stores is associated with higher inventories, whereas scale economies are associated with lower inventories. We do not find the number of warehouses to be significant in explaining inventory levels. Increased demand fluctuations are also associated with higher inventories, although the effects are less robust. The significant variables together with retailer segment identifiers explain a substantial fraction of the variance in inventory levels and can be potentially useful to managers in benchmarking their inventory levels.

Key words: retailing; empirical research; econometric analysis; supply chain management; inventory
History: Received: December 9, 2009; accepted: May 31, 2012. Published online in *Articles in Advance* October 24, 2012.

1. Introduction

There has been an explosion of variety at retail stores in the past few decades. According to the Food Marketing Institute, the number of items offered per store increased from approximately 14,000 in 1980 to over 30,000 by 2004 (Ellickson 2006). Inventory theory (Zipkin 2000, §5.2) suggests that this increase in variety should result in higher inventory levels expressed in days of supply (DOS) (inventory dollars divided by cost of goods sold (COGS) per day). But there appears to be little empirical evidence on the impact of variety on inventories at retailers. Similarly, theory suggests that a retail chain having more stores will have higher inventories, but this inventory growth may be mitigated by having more warehouses supply the stores and exploiting risk pooling benefits. Again, there appears to be little empirical evidence on how the number of stores and warehouses in a retail chain actually impacts inventory levels. This study builds upon prior literature that has explored the role of various factors in explaining inventories at the firm level by investigating factors such as product variety and distribution system characteristics. In particular, we focus on the U.S. retail sector because inventories represent their largest asset (approximately 50% of total assets; Luttrell 2007). Also, the U.S. retail sector is an important sector, and U.S. retail inventories constitute approximately 36% of total U.S. inventories.

Inventory theory recommends the optimal inventory levels to carry based on stylized models that consider a few factors. In reality, managers have to consider several factors, many of which cannot be incorporated in one inventory model because of analytical intractability. For example, a retail manager deciding order quantities may have to consider joint replenishment of multiple items with uncertain demands at different stores and may have to take into account quantity discounts, storage constraints, truckload considerations, etc. Considering all these complex interactions, it is not clear to what extent the factors considered in typical inventory models impact inventory levels at the aggregate firm level. For example, if a firm follows a simple policy of holding n days of inventory of each item, then the variety of items stocked may not impact inventory expressed as DOS. The focus of this work is to explore whether the relationships between inventories and factors such as variety, number of stores, number of warehouses, etc., predicted by inventory theory are observed in reality.

Identifying the factors that are significant in explaining inventory levels carried by U.S. retailers can also help senior retail managers better understand their inventory performance at the aggregate level. It can provide benchmarks for evaluating inventory performance and assessing the sensitivity of inventory level to changes in the various factors. In motivating an analysis of aggregate inventory performance, Zipkin (2000, p. 112) stated that "senior managers and even investors pay close attention to aggregate performance measures." We restrict our study to U.S. retailers because it allows us to explore the impact of fundamental factors such as variety, number of stores, etc., on inventories and provides a sharper study of the factors identified in the inventory literature.

There has been significant interest in empirical research focusing on inventory performance in the operations area over the past decade. Lieberman et al. (1999) explored the drivers of inventory levels in the automotive parts industry in the United States and Canada and identified significant technological and managerial factors. Rajagopalan and Malhotra (2001) explored inventory trends in U.S. manufacturing firms using aggregate industry-level data from 1961 to 1992. More recently, Chen et al. (2005) explored inventory trends over time and the impact of inventory on a firm's stock performance using firm-level data during the period 1981 to 2000.

Some studies have explored the impact of product variety on the operational performance of manufacturing firms. Kekre and Srinivasan (1990) found that an increase in variety did not result in higher product costs or poorer operational performance based on a large-scale study using the PIMS (Profit Impact of Market Strategy) database. On the other hand, Fisher and Ittner (1999) found that increased variety results in higher inventory and labor hours and more rework in the automotive industry. Randall and Ulrich (2001) explored the impact of variety on firm performance in the bicycle industry and found that supply chain structure, represented by scale and distance between supply sources and markets, plays an important facilitating role. Hwang and Weil (1998) found that adoption of information technologies can help reduce inventory levels significantly and counteract the impact of increased variety based on a study of firms in the apparel industry. Cachon et al. (2005) studied the impact of variety on inventory levels, sales, and profit margins of U.S. manufacturing firms and found that variety, as measured by trademark counts, results in increased finished goods inventories but has no impact on raw material and work-in-process inventories. We study many factors other than variety that impact inventories and focus on the retail sector.

Kesavan et al. (2010) showed that time-series methods for forecasting firm-level retail sales can be improved by incorporating cost of goods sold, inventory, and gross margin as three endogenous variables. Ren and Willems (2007) explored inventory policies and levels across the dealer network for a major industrial tractor manufacturer and found that economic, organizational, and behavioral factors jointly determine dealers' actual inventory policy choices and their preferred inventory levels. Iyer and Radhakrishnan (2009) explored the impact of product variety and other factors on inventory levels in the distribution system of a consumer product manufacturer. Cachon and Olivares (2010) explored the impact of several interesting factors driving inventory levels in the U.S. auto industry and found the number of dealers and the manufacturer's production flexibility to be the most significant factors. Olivares and Cachon (2009) explored the impact of competition on the inventory levels of dealers in the distribution network of General Motors by disentangling sales- and service-level effects and found that competition increases inventory levels. Matsa (2011a) found that increased competition can reduce stockout levels in supermarkets, implying that retailers carry higher inventories if competition is more intense.

In pioneering work on the behavior of inventories in the retail sector, Gaur et al. (2005) (hereafter referred to as GFR (2005)) studied the effects of the following variables on U.S. retailer inventory turns: gross margin, capital intensity, and "sales surprise," defined as the ratio of actual to forecasted sales. Using public financial data from 1987–2000, GFR (2005) also explored inventory trends over time. Their study found all three variables identified above to be significant. GFR (2005) suggested that future research should explore the impact of variables omitted in their study, such as product variety.

Roumiantsev and Netessine (2007), referred to as RN (2007) henceforth, explored whether factors suggested by classical inventory models were instrumental in explaining aggregate inventory levels during 1992–2002 at a cross-section of U.S. public firms that included manufacturers, distributors, and retailers. They found that greater uncertainty in demand and higher gross margins lead to higher inventories. Unlike their study, we restrict our study to U.S. retailers and explore the effect of factors such as variety, number of stores, etc., on inventories. Also, the narrower focus of our sample eliminates potential sources of unobserved heterogeneity. In more recent work, Gaur and Kesavan (2009) explored the effects of firm size and sales growth rate on inventory turnover in the U.S. retail sector and found both to be significant in explaining inventory levels, but they did not consider some key variables considered in our study.

The contribution of our paper is in exploring the impact of some major factors identified in the inventory literature that influence inventory levels, such as variety, distribution system characteristics, etc., among U.S. retailers. These factors are not considered in prior studies such as those by GFR (2005) and RN (2007). Second, we find that the main factors explain a substantial fraction of the variation in inventory levels across retailers, and so the results can be useful to managers in benchmarking inventory levels.

The motivating rationale and factors impacting inventory levels together with the hypotheses and measures used are explored in §2. Data sources are discussed in §3. Model estimation and related issues are provided in §4. The results of the estimation and their implications and limitations of the study are discussed in §5, and we conclude in §6.

2. Hypotheses and Measures

The inventory theory literature has identified numerous factors that influence inventory levels at a firm. Because firm-level inventories are an aggregation of item-level inventories, one would expect firm-level inventories to be influenced by these same factors, although the exact functional relationships predicted by inventory models may not hold at an aggregate level—see Zipkin (2000, §§5.2, 8.2, and 8.5) for such an analysis of aggregate inventories. In this study, we focus on the retail sector—key factors influencing inventory levels are similar across retailers, and several of them are observable, thus reducing unobserved heterogeneity.

2.1. Dependent Variable

The dependent variable in our study is *Inventory*, expressed as days of supply—the same term is used by Olivares and Cachon (2009). Days of supply is computed as follows:

$$DOS = 365 \times \mathit{Average\ Inventory}\ (\$)/(\mathit{COGS}),$$

where *Average Inventory* ($) is the average inventory over four quarters of the year, and *COGS* is the annual cost of goods sold, as reported in income statements.

2.2. Factors Impacting Inventory

Given the focus on inventory levels at *retailers*, our discussion will ignore some factors mentioned in the literature that impact inventory levels such as process complexity or setup time that are not relevant for a retailer. As discussed earlier, GFR (2005) explored three factors that explain inventory levels at U.S. retailers, Gaur and Kesavan (2009) explored the effects of firm size and sales growth rate among U.S. retailers, and RN (2007) explored the effects of several factors suggested by classical inventory models in explaining inventory levels among U.S. firms. We include many of the variables identified in these studies as control variables, but our study is different in two respects. First, we study the influence of factors such as variety and number of stores and warehouses not considered in these studies. Second, we use alternative measures for some of the variables included in these studies. The variables considered in the study and the use of proxy measures for some of the variables are discussed next. Data for the measures were obtained from public sources and a survey, and this is discussed in §3.

2.3. Variables Unique to This Study

2.3.1. Product Variety. There has been a substantial amount of literature in the inventory area exploring the impact of product variety on inventories (Zipkin 2000, §5.2). Inventory theory suggests that given the same total demand, higher variety will increase total inventory because both cycle and safety stocks will increase. As variety increases, there are more low-volume items. Based on standard inventory models, cycle stock, expressed as DOS, is higher for lower-volume items, and safety stock is likely to be higher because of higher demand variability for lower volume items. GFR (2005) and Cachon and Olivares (2010) provided similar arguments in their empirical studies, and so did Fisher and Ittner (1999). Furthermore, inventory increases with variety in practice because of minimum display requirements or minimum order quantities which imply higher DOS for lower-volume items. While greater variety may result in higher overall demand because the increased variety may attract more customers, we control for this effect by including total sales as another variable, so we measure the impact of changes in variety for the same total sales.

Increased variety often leads to more low-volume items being carried because most retailers typically stock the popular variants in each product line (e.g., every supermarket carries vanilla and chocolate ice cream), whereas they will carry only some of the less popular variants. Van Ryzin and Mahajan (1999) showed theoretically that stocking the popular variants is an optimal strategy, whereas Kök et al. (2008) described the assortment planning process at many retailers and suggested that items are stocked in decreasing order of popularity. Several industry articles (Softletter 1992, Berman 2010) suggest that this is indeed the case.

However, increased variety need not always increase DOS, as when a retailer adds a new product line that may have higher turns than their existing product lines. For example, Target stores started selling fresh produce in 2010, which has higher turns than existing items. When more product lines are added, inventories may increase or decline depending on the number of stock-keeping units (SKUs), minimum display or order quantities, the magnitude of the new product line's sales and inventories relative to existing sales and inventories, etc. The effect of changes in product lines on inventories is ambiguous.

Overall, based on the conventional wisdom in the academic literature, we hypothesize that *DOS increases with product variety*. We measure *variety* as the number of distinct SKUs carried by a retailer. Retailers typically have a good estimate of their SKU count due to the use of computerized systems for ordering and tracking inventories.

2.3.2. Distribution System Characteristics. Two key aspects of a retailer's distribution system that may impact inventory levels are the number of stores and warehouses (or distribution centers). Inventory theory (Zipkin 2000) suggests that centralizing the location of inventories will result in lower inventory levels for a given service level due to risk pooling. In a distribution system for a retailer, inventory may be held at both warehouses and at the stores that are replenished by the warehouses (some items may be shipped directly to stores and not stored at warehouses). For a given total sales, which is one of the variables included in our estimation, inventories will be higher if there are more stores because sales gets fragmented and risk pooling benefits are lost (see Cachon and Olivares 2010 for similar reasoning). Hence we hypothesize that *DOS* will *increase* with *an increase in number of stores*.

The impact of warehouses on inventories is more complex and not monotonic (Teo and Shu 2004). Consider a retailer that has no warehouse and keeps its entire inventory at the stores; the retailer will have to hold high inventories at the stores to achieve high service levels. If this retailer stocks some inventory at a warehouse that replenishes the stores periodically so as to exploit risk pooling benefits, then the reduction in inventories at the stores may be greater than the inventory carried at the warehouse, and total system inventories will decline (Vidyarthi et al. 2007). Total inventories may also go down due to lower cycle stocks at the stores because the warehouse can replenish the stores more frequently than, say, an outside supplier. However, as the retailer keeps adding more warehouses, the inventory reduction at the stores will be more than offset by inventory increases at the warehouses, and so at some point total system inventories will start increasing. Thus, for a given total sales and number of stores, one would typically expect inventories to decline and then increase as the number of warehouses is increased. Thus, we hypothesize that the relationship between *DOS* and *number of warehouses* is U-shaped.

2.4. Control Variables

Profit Margin. In classic inventory models, inventory levels increase with the profit margin or desired service level of an item. Service levels are not easily observable, and profit margin is a key driving force behind service levels. GFR (2005) identified profit margin as an important factor influencing inventory levels and used *Gross Margin* as an independent variable in their study. So, we include *Gross Margin* as a variable in the model, and it is measured as

$$\textit{Gross Margin}\ (\%) = 100 \times (1 - \textit{COGS}/\textit{Sales}).$$

Scale Economies. Standard inventory models predict that the order quantity should increase as the square root of demand, and so the average cycle stock expressed in DOS should decline with demand volume. RN (2007) provided a similar rationale for inventories decreasing with company size, and Gaur and Kesavan (2009) hypothesized that inventory turns will increase with *Sales*. So, a retailer's S*ales* is one of the variables included in the study.

Demand Variation. Inventory theory suggests that demand variation increases inventory levels, whether due to known factors such as seasonality or unknown ones, typically characterized as demand uncertainty. GFR (2005) explored the effects of demand forecast errors (which arise due to uncertainty in demand) on inventory levels using a measure called *Sales Surprise*, which is the ratio of the actual sales divided by the sales forecast, where sales forecasts are estimated using trend-adjusted exponential smoothing. In our study, we differentiate between the effects of known and unknown fluctuations, i.e., seasonality and demand uncertainty, respectively. RN (2007) has provided a rationale for the impact of demand uncertainty on inventories, so we only provide a rationale for considering the effect of known fluctuations or seasonality.

One might argue that demand fluctuations due to seasonality may not have an impact on DOS because retailers can adjust their inventories as a function of seasonal fluctuations, keeping DOS constant. But there are reasons why greater seasonal fluctuations may result in higher DOS. First, if demand is concentrated over a very short time period (e.g., Christmas), then it is difficult or expensive to replenish inventories during the short sales period. Second, retailers with greater seasonality may carry higher inventories due to supplier capacity constraints, costs of changing production, etc. Thus, we hypothesize that *greater seasonality in demand will be associated with higher DOS*.

We focus on measures of aggregate firm-level variation because individual item variations are not observable. We consider *Sales Surprise*, the measure of forecast error identified by GFR (2005). We consider two alternative measures for *Demand Uncertainty* as follows. (1) Demand can be decomposed into the following components: level term, trend, seasonality and noise, where the "noise" term is the measure of demand uncertainty. Using quarterly sales data over 1995 to 2004 (or fewer years depending on the availability of data for a firm), we estimate a regression model for each retailer with an intercept term, a trend component, and dummy variables for the four quarters to model seasonality. The $(1 - R^2)$ value of this regression is the unexplained variation in sales and is likely to be a good proxy for *Demand Uncertainty*. This is similar to one of the proxies (detrended, deseasonalized noise) used by RN (2007). (2) Starting with the *Sales Surprise* measure in GFR (2005) using trend-adjusted exponential smoothing forecasts for the five years 2001–2005, using 2000–2004 data, we compute the *range* of *Sales Surprise* values over the five years and use it as another proxy for *Demand Uncertainty*.

We consider two alternative measures for *Seasonality*. First, using the quarterly dummy coefficients c_1, c_2, c_3, and c_4 $(=0)$ for each firm from the regression of 10-year quarterly sales discussed above, the seasonality measure is computed as the *range* of the set of values (0, c_1, c_2, c_3) divided by the mean sales over the 10-year period for each firm. This is similar to the ratio of the variance in seasonal dummies divided by mean sales used by Cachon and Olivares (2010) except that we have quarterly instead of monthly dummies, and so we use range rather than variance. Second, we consider a simpler measure of seasonality: the ratio of maximum to minimum quarterly sales over the four quarters of a fiscal year for each firm. This measure is a function of recent seasonal fluctuations unlike the first measure.

Holding Costs. Inventory theory suggests that a firm is likely to hold lower inventory as the cost of carrying inventory (holding cost) increases. In a recent empirical study, Matsa (2011b) found that highly leveraged firms tend to have higher stockout levels (implying lower inventories) in the supermarket industry to protect their cash flows and reduce their working capital. This suggests that their higher capital costs are a key factor influencing inventory levels.

We cannot measure holding costs directly because this information is not available in financial statements. The two major components of holding costs are the cost of capital and space (or storage) cost. We follow a standard approach to measure *cost of capital* (*or weighted cost of capital*). This method requires using information on computing the cost of equity and cost of debt and taking a weighted average where the weights are the proportions of debt and equity in the capital structure. The cost of equity can be computed using the CAPM (capital asset pricing model) or the three-factor model of Fama and French (1993). Details of the approach used to measure *cost of capital* are available from the authors. We cannot compute space cost per unit because we do not know the number of units sold, but a potential proxy for retailers is rent cost per square foot. Although one can obtain data on square footage and rental expenses, some retailers own their stores either partially or fully. So rental expenses may not be a good proxy for space costs; so we restrict ourselves to *cost of capital* as in RN (2007).

Capital Intensity. GFR (2005) pointed out that information technology (IT) and other capital investments help reduce inventories (or increase turns). They used *Capital Intensity* to represent the impact of factors such as warehouses, information technology, and logistics management systems and hypothesized that higher *Capital Intensity* will result in lower inventories. As discussed earlier, we isolate the effects of warehouses on inventories. GFR (2005) used the following formula to measure *Capital Intensity*:

$$\textit{Gross Fixed Assets}/(\textit{Gross Fixed Assets} + \textit{Inventory}).$$

A potential issue with this measure is that it may have a mechanical relationship with the dependent variable. In particular, *Gross Fixed Assets* (*GFA*) is likely to be highly positively correlated *COGS*, especially within the relatively homogenous universe of retailers. The correlation is 0.97–0.99 in the years 2003 to 2005 for the set of retailers considered in the study. So if we let $GFA = k \times COGS$, then we have $GFA/(Inventory + GFA) = k \times COGS/(k \times COGS + Inventory) = 1/(1 + Inventory/(k \times COGS))$. Then this measure of *Capital Intensity* will by definition be negatively correlated with the dependent variable, *Inventory*/*COGS*. GFR (2005) also tested an alternative measure with *Capital Intensity* lagged by one year, but because *Capital Intensity* is highly correlated between successive years (typically around 0.97–0.98), this may not fully mitigate the problem.

Therefore, we consider alternative measures of *Capital Intensity* commonly used in the literature. One of these is *Capital to Sales ratio* and the other is *Capital to Labor ratio*. The *Capital to Labor ratio* is used as a measure of capital intensity in the economics and business literature (Arai 2003, Bettis 1981) and represents the relative usage of capital investments and labor in a business. So, a retailer that incorporates technology (e.g., self-service checkout machines) to substitute for labor has greater *Capital Intensity*. The *Capital to Sales ratio* is used in the business literature (Miller and Bromiley 1990) as a measure of *Capital Intensity.* They are measured as follows:

$$\textit{Capital to Sales ratio} = \textit{FixedAssets}/\textit{Sales},$$

$$\textit{Capital to Labor ratio} = \textit{FixedAssets}/\textit{Employees}.$$

Another possible proxy for investment in such technologies is firm size. Larger retailers like Wal-Mart and Home Depot can make large investments in the latest information technologies that can help reduce inventories, but we have captured the effect of firm size via *Sales*.

3. Data

The focus of this study is on brick-and-mortar retailers that are headquartered and publicly listed in the United States. We considered all retail segments (Standard Industrial Classification (SIC) codes 5200 through 5990) in our study except for the following categories of retailers for the reasons outlined below: (1) Internet and catalog retailers (SIC code 5961) because they have no brick-and-mortar retail stores, one of our key variables; (2) convenience stores (SIC code 5412) such as Unimart because a majority of their sales (approximately 55%) come from gasoline sales, representing a few SKUs, even though they carry approximately 3,000 SKUs, and so SKU count is not an accurate measure of the impact of variety on inventories; (3) retail food stores (SIC code 5400) such as Krispy Kreme because they carry only perishables with negligible inventory; (4) auto dealers and gas stations (SIC code 5500) for reasons similar to those identified for convenience stores that have significant gas sales, and because auto dealers are typically not chains and have a very different profile than other retailers. Furthermore, we eliminated firms that have stores but also significant manufacturing operations (e.g., Sherwin Williams).

This study used multiple sources for obtaining data because data on a few variables such as variety are not available from public sources. Variables such as *Sales* (*Net Sales* in Compustat), *COGS*, *Fixed Assets* (*Property, Plant, and Equipment Total* in Compustat), *Number of Employees*, and *Inventory* were collected directly from Compustat (obtained via WRDS). Other measures such as *Gross Margin*, *Demand Uncertainty, Seasonality*, and *Capital Intensity* were computed from the Compustat data. Data on *Number of Stores* are available in 10-K financial statements (accessed via Edgar, http://www.sec.gov/edgar.shtml) and are also available for recent years via Compustat. The 10-K statements also contain information on *Number of Warehouses* for many retailers. The dependent variable *DOS* was computed using *Average Inventory* ($) and *COGS* as described earlier. Retailers use several methods for inventory valuation, but first-in, first-out (FIFO) and last-in, first-out (LIFO) are the most common. We add the "LIFO Reserve" data item in Compustat to average inventory (over four quarters) to obtain the same consistent FIFO valuation of inventory for all retailers.

Data on variety are not available from Compustat or Edgar. Therefore, we collected data in 2005 using a survey questionnaire that was mailed to 180 retailers belonging to the retail segments identified earlier. The 180 retailers are those that had complete financial information on items such as *Sales, COGS*, etc., for the fiscal years 2000–2004, which was necessary to compute some of the measures. The survey was used to obtain information on the two measures *Variety* (*number of SKUs*) and also *Number of Warehouses*, because some retailers did not have this information in the 10-K statements. The survey was followed up with phone interviews to several retailers to obtain information from those who did not respond to the survey as well as to follow up with retailers that responded to the survey to ensure that the written information provided was accurate. Recognizing that some retailers have stores of more than one size or format and the number of SKUs carried may be different, we requested from retailers with multiple store formats a weighted average number of SKUs, with the weights being the number of stores of a particular format. Altogether, 112 retailers provided partial or full information to our questions. Complete, reliable information was obtained for 106 retailers. Furthermore, to validate the data obtained through the survey and phone interviews and to minimize measurement errors, we conducted an extensive online search to obtain information on *Variety* (SKU count) for several retailers and retail categories. In a few cases, the variety data provided by a retailer were inconsistent with the online data. Dropping such cases resulted in 104 as the sample size. Data on *Number of Warehouses* were obtained from 10-K statements for 96 retailers and from the survey for the other 8 retailers (in cases where survey data on *Number of Warehouses* were different from those from the 10-K statement, the 10-K statement was used).

Table 1 Retailer Sample vs. Population

	Sample	Population
Number of Firms	104	180
Sales ($million): Mean	10,885	8,701
Sales ($million): Std. deviation	33,076	26,416
COGS ($million): Mean	7,778	6,258
COGS ($million): Std. deviation	24,715	19,758
Gross Margin %: Mean	34.7	34.6
Gross Margin %: Std. deviation	9.9	11.4
Inventory (days): Mean	105.7	99.4
Inventory (days): Std. deviation	58	63

The 104 retailers represent 57% of the population of retailers in the segments identified earlier. Table 1 provides data on the values of some key variables in both the sample and population; z-tests confirm that the mean values of *Sales*, *COGS*, *Gross Margin*, and *Inventory* for the firms in the sample are not different from those of firms not in the sample.

4. Model Estimation and Econometric Issues

Based on the discussion in §2, the independent variables considered in the study are as follows:

Variables considered in this study are *Variety, Stores*, *Warehouses*, *Warehouses*^{2}, *Seasonality*.

Variables from prior studies are *Gross Margin*, *Capital Intensity*, *Demand Uncertainty*, *Sales*, *Cost of Capital*.

We use both a linear and a squared term for *Warehouses* in the model estimation to capture the U-shaped relationship. The nature of the relationship between number of warehouses and inventories will depend upon factors such as product volume and weight, fuel costs, and storage costs, which are not observable. But this relationship is likely to be similar within the same retail segment. So, using the retailer segment (four-digit SIC code) as a dummy variable helps control for differences across retailers in the nature of this relationship. There are several potential econometric issues with the estimation of the model, and next we discuss these issues and steps taken to address them.

4.1. Simultaneous Causality

One issue to be considered is simultaneous causality bias. Simultaneous causality can lead to the error term being correlated with the independent variables and result in biased and inconsistent estimates of the parameters. Are there independent variables likely to be influenced by the dependent variable? Clearly, inventory levels will not influence decisions about number of stores or warehouse because these are typically based on long-term decisions. However, inventory levels could influence gross margins. Specifically, if inventory levels are high (low), a retailer may reduce (increase) prices, and this will impact gross margins. For instance, many retailers, but especially those selling fashion or seasonal goods, mark down items to deplete inventories. Similarly, inventory levels may influence sales. Low levels of inventory may result in stockouts and therefore impact sales negatively; conversely, high inventory levels may stimulate demand and result in higher sales (Balakrishnan et al. 2008).

We address this issue by using instrumental variables. Specifically, we instrument *Gross Margin* using two-year lag of the *Gross Margin*. Two-year lagged *Gross Margin* will not be impacted by current year inventory levels and is therefore an appropriate instrumental variable. Furthermore, two-year lagged *Gross Margin* is likely to be correlated with current year *Gross Margin*, and so it is a relevant instrument. For similar reasons, we use two-year lagged *Sales* to instrument *Sales*. Cachon and Olivares (2010) used similar lagged variables as instrumental variables. Two-stage least squares was used to implement the instrumental variables method, and the first-stage F-statistic values were high (well above 10), suggesting that the instruments are valid.

Another related issue is that service levels and margins may be influenced by competitive factors. Margins decrease with competition, whereas inventory levels may increase with competition (see Olivares and Cachon 2009, Matsa 2011b). Although we do not measure competitive effects directly, we use retail sector dummies, as discussed in the next subsection, that may partially control for competitive effects. Also, use of instrumental variables discussed earlier helps mitigate the drawback of omitting competitive effects because competitive forces that influence inventory levels in the current year, for example, price reductions or new stores at competing locations, are not likely to influence gross margins in prior years.

4.2. Omitted Variables

Although we have considered many factors that may influence inventory levels, there are some potentially important factors we have not considered. One of these is product perishability. For instance, retailers carrying perishable food products will have lower inventories. Similarly, product obsolescence may impact inventories. Lead time required for replenishment is another factor impacting inventories because longer lead times require higher safety and pipeline stocks (although whether the retailer or supplier owns the pipeline inventory depends on their contractual agreement).

Information on product perishability and lead time are not available in financial statements or other online sources. Also, these factors vary substantially across items depending on numerous factors. For instance, lead time depends on whether the item is supplied from the retailer's or supplier's warehouse, location of the supplier and their shipment policies, etc. Furthermore, there is no aggregate measure of lead time or perishability or a good proxy for them. Roumiantsev and Netessine (2007) use *Accounts Payable* (days) or *AP* as a proxy for lead time but there are two issues with this proxy. First, discussion with retailers suggests that it may not be a good proxy because accounts payable is a function of payment terms and not lead time. Second, $AP(t) = AP(t-1) + Purchases(t) - Payments(t)$, and $Inventory(t) = Inventory(t-1) + Purchases(t) - COGS(t)$. Both *Payments* and COGS are simply functions of past purchases for a retailer because they simply sell the items they purchase without any processing. So, changes in accounts payable will be mechanically correlated with changes in inventory. Thus, even though *Accounts Payable* may be highly correlated with *Inventory* and may be significant, this may mislead us into thinking that we are measuring lead time and its effect on inventory.

The cross-sectional nature of the data together with the unobservable factors discussed above suggest the potential for omitted variable bias. Based on discussions with retailers, it appears that the omitted variables mentioned earlier are often a function of the retailer segment. For example, grocery stores carry a significant proportion of perishable products, whereas jewelry stores do not carry any. So, the variation in perishability within grocery stores will be small compared to the variation between grocery and nongrocery stores. Similarly, lead times are somewhat segment specific. For instance, most clothing stores get their supplies from the Far East and so their lead times may be similar. On the other hand, grocery stores tend to get many of their supplies domestically and have shorter lead times. Hence, we use *Retailer Segment* as a control variable in our second model specification. Specifically, we use the four-digit SIC segment classification to identify the retailer segments. But *Retailer Segment* may not fully capture all the omitted variables. For instance, we could not include space costs, which may not be the same for all retailers within a segment and may be correlated with a variable such as gross margin in the model. To better control for the impact of omitted variables, we explore another approach using panel data, which is discussed next.

Data on many of the variables for multiple time periods can be obtained from secondary sources, but data on *Variety* are available only for one year. But the change in *Variety* is negligible over a short time span, say, one to two years, although it may change significantly over a longer time span, and the same is true for *Warehouses*. Hence, we collected data on the time-varying variables for the fiscal years 2004 and 2006, which adjoin 2005. We did not consider longer time periods because *Variety* may change over time at different rates across firms, resulting in omitted variable bias even in the panel data. We considered random effects estimation because we are interested in the effects of variables such as *Variety* and *Warehouses*, which are time invariant in the short run (e.g., two to three years) and hence cannot be estimated using fixed effects estimation. However, random effects estimation requires the more restrictive assumption that the regressors be uncorrelated with the unobserved firm effects. We use the Hausman specification test to choose between these two specifications (Cameron and Trivedi 2009).

5. Results and Discussion

Table 2 provides key descriptive statistics for the sample for the 2005 fiscal year. Table 3 provides details on the number of retailers in each segment. A list of all retailers in the sample is in the online appendix (available at http://dx.doi.org/10.1287/msom.1120.0407).

Table 2 Descriptive Statistics for U.S. Retailer Sample ($N = 104$)

Variable	Mean	Std. deviation	Median
Inventory (days of supply)	106.6	58.1	97
Gross Margin %	0.347	0.099	0.335
Variety (number of SKUs)	32,439	125,335	20,000
Sales (million $)	10,885	33,076	2,383
Stores	1,074	1,270	563
Warehouses	4.4	4.6	3

Table 3 Number of Firms in Each SIC Retailer Segment

SIC	Segment description (example firm)	No. of firms
5200	Bldg matl, hardwr, retail (Tractor Supply Co)	2
5211	Lumber and oth bldg matl, retail (Lowe's)	2
5311	Department stores (Kohl's)	6
5331	Variety stores (Dollar General)	12
5399	Misc general mdse stores (Costco)	2
5411	Grocery stores (Kroger)	17
5531	Auto and home supply stores (AutoZone)	2
5600	Apparel and accessory stores (Men's Wearhouse)	2
5621	Women's clothing stores (Ann Taylor)	7
5651	Family clothing stores (Nordstrom)	10
5661	Shoe stores (Foot Locker)	5
5700	Home furniture and equip store (Cost Plus)	5
5731	Electronics stores (Best Buy)	5
5734	Comp and comp software stores (GameStop)	1
5735	Record and tape stores (Hastings)	1
5912	Drug and proprietary stores (Walgreens)	3
5940	Misc shopping goods stores (Staples)	10
5944	Jewelry stores (Zales)	3
5945	Hobby, toy, and game shops (Toys "R" Us)	3
5990	Retail stores (Petco)	6
	Total	104

Table 4 provides pairwise correlations for the explanatory variables. A log transform was used for the dependent variable *Inventory* and for all the independent variables except for *Warehouse* and *Warehouse*^{2} variables to deal with potential skewness in data and to reduce heteroskedasticity (Gujarati 1995). The standard errors reported in the tables are heteroskedasticity-adjusted standard errors.

As discussed earlier, some of the measures used here for variables considered in prior studies are different (e.g., *Capital Intensity*). So, we need to carefully understand whether differences if any in our results relative to prior studies are due to differences in the measures used or due to the new variables added. So, we first began by reestimating models (1) and (2) of GFR (2005) using an almost identical data set for the period 1985–2000 with the new measures suggested here.[1] Specifically, we used *Capital to Labor ratio* (alternatively *Capital to Sales ratio*) as a measure of *Capital Intensity* and an instrumental variable for *Gross Margin* as discussed earlier. We also used lagged *Sales Surprise* as instrumental variable for *Sales Surprise*—inventory levels may influence *Sales Surprise* because lower inventory levels may result in lower *Sales Surprise* because the firm is not able to meet forecasted demand. The results of this reestimation, labeled as Model 1, are in Table 5. Comparing these results to the pooled model (2) of GFR (2005), we find that

[1] We are grateful to Vishal Gaur for providing the list of firms used by GFR (2005). We do not report the results with segment-specific coefficients because our goal is to check the robustness of the pooled coefficients when we add the new variables using 2005 data.

Table 4 Pairwise Correlations Using 2005 Data

	Variety	*Warehouses*	*Seasonality*	*Capital Intensity*	*Sales*	*Gross Margin*	*Cost of Capital*	*Demand Uncertainty*	*Stores*
Variety	1								
Warehouses	0.1017	1							
Seasonality[a]	−0.0101	−0.2714	1						
Capital Intensity[b]	0.1056	0.3221	−0.0700	1					
Sales	0.0716	0.56	−0.0229	0.4482	1				
Gross Margin	0.097	−0.2136	0.0587	−0.2723	−0.3151	1			
Cost of Capital	0.4088	−0.0131	0.0555	−0.1066	−0.003	−0.0651	1		
Demand Uncertainty[c]	−0.0884	−0.0524	−0.0929	−0.1654	−0.2468	0.0187	−0.0322	1	
Stores	0.0344	0.4049	0.0575	−0.0238	0.6012	0.0987	0.0165	−0.2076	1

[a]Measure using seasonal dummies.
[b]*Capital/Labor* measure.
[c]$(1 - R^2)$ measure of demand uncertainty.

Gross Margin is associated with lower inventory turns and *Sales Surprise* with higher inventory turns as hypothesized by GFR (2005); the coefficients for *Gross Margin* are almost identical to those of GFR (2005). The coefficient for *Capital Intensity* (using the measure *Capital/Labor*), although statistically significant, is the opposite of that hypothesized in Model 1, i.e., it leads to lower turns. We also estimated the model using *Retailer Segment* dummies rather than firm fixed effects—see Model 2 in Table 5. The qualitative conclusions with respect to *Gross Margin* and *Sales Surprise* are unchanged if individual firm dummies are replaced by *Retailer Segment* dummies; however, the individual coefficients do change. Also, we find that the *Capital to Labor ratio* measure for *Capital Intensity* is significant and has the hypothesized sign, i.e., increases inventory turns, when *Retailer Segment* dummies are included instead of firm effects (Model 2). The difference in the coefficients between Models 1 and 2 suggests that excluding firm fixed effects may result in biased estimate of the coefficients. Overall, the qualitative conclusions with regard to *Gross Margin* and *Sales Surprise* are consistent with GFR (2005), but the evidence is mixed for *Capital Intensity*.

Table 5 Coefficient Estimates in Models 1–3

Variable	Model 1	Model 2	Model 3
Dependent variable	Inventory turns	Inventory turns	Inventory (DOS)
Regressors			
Gross Margin	−0.322 (0.020)***	−0.667 (0.034)***	0.454 (0.133)***
Capital Intensity[a]	−0.091 (0.014)***	0.116 (0.023)***	−0.134 (0.047)***
Sales Surprise	0.099 (0.015)***	0.799 (0.220)***	1.598 (0.782)**
Firm fixed effects	Yes	No	N.A.
Retailer segment effect	No	Yes	Yes
Year effects	Yes	Yes	N.A.
Sample years	1987–2000	1987–2000	2005
N	2,905[b]	2,905[b]	104
R^2[c]	0.139	0.50	0.81

Note. Standard errors are in parentheses and represent heteroskedasticity robust standard errors.
[a]The results reported here are for the *Capital/Labor* measure of capital intensity. For the *Capital/Sales* measure, the coefficients in Models 1, 2, and 3, respectively, were −0.218 (0.013)***, −0.088 (0.026)***, and −0.099 (0.069); in Models 1 and 2, the signs are the opposite of those hypothesized. The coefficients for *Gross Margin* and *Sales Surprise* were also correspondingly different but were statistically significant and had the hypothesized sign.
[b]$N = 2{,}905$ is the number of observations over the period 1987–2000 for the 307 firms.
[c]The R^2 value provided for Model 1 is overall R^2 (within, 0.117; between, 0.18) and for Models 2 and 3 as well. The R^2 for Model 3 without *Retailer Segment* effect was 0.37. The adjusted R^2 values for Models 2 and 3 were 0.496 and 0.755, respectively.
$^{**}p < 0.5$; $^{***}p < 0.01$.

The main objective of this study is to understand the influence of the new variables such as variety, stores and warehouses on inventories. To this end, we estimate and compare (i) a model with control variables identified in prior studies (GFR 2005, RN 2007, Gaur and Kesavan 2009) and (ii) a model with the control variables *and the new variables* identified in this study. We first estimated these models using only 2005 data, both without and with *Retailer Segment*. Table 6 provides the results from estimating these models (Models 4 and 5) with *Retailer Segment* dummies, which help control for omitted variable bias as discussed earlier. We used Cook's D statistic to identify outliers in the data, and two observations appeared to be influential. But excluding these two points changed the coefficient estimates by less than one-third of the standard error. Another potential issue is multicollinearity. Although one of the pairwise correlations is greater than 0.5 in Table 4, Judge et al. (1988, p. 869) pointed out that when more than two explanatory variables are involved, "pairwise correlations can give no insights into more complex interrelationships." So, we considered variance inflation factors, which are all less than 2.5, and multicollinearity does not appear to be an issue.

Table 6 Coefficient Estimates in Models 4 and 5

Variable	Model 4 (2005)	Model 5 (2005)	Model 6 Random effects (2004–2006 data)	Model 7 Random effects (2004–2006 data)
Variety		0.161 (0.021)***		0.166 (0.023)***
Stores		0.172 (0.031)***		0.155 (0.026)***
Seasonality[a]		0.009 (0.013)		0.014 (0.01)
Warehouses		−0.004 (0.016)		−0.01 (0.018)
$(Warehouses)^2$		0.00004 (0.0008)		0.0004 (0.0009)
Gross Margin	0.641 (0.141)***	0.46 (0.111)***	0.459 (0.082)***	0.449 (0.073)***
Sales	−0.062 (0.022)***	−0.231 (0.032)***	−0.057 (0.022)***	−0.223 (0.029)***
Demand Uncertainty[b]	−0.024 (0.029)	0.0 (0.022)	−0.03 (0.015)**	−0.023 (0.014)*
Cost of Capital	0.214 (0.117)*	0.028 (0.092)	−0.009 (0.036)	−0.036 (0.034)
Capital Intensity[c]	−0.052 (0.051)	0.05 (0.04)	−0.02 (0.042)	0.043 (0.035)
Retailer Segment dummy	Yes	Yes	Yes	Yes
Sample year	2005	2005	2004–2006	2004–2006
N (observations)	104	104	308	308
$R^{2\,d}$	0.82	0.905	0.799	0.892

Note. Standard errors are in parentheses and represent heteroskedasticity robust standard errors.

[a]The results reported here are for the measure of *Seasonality* obtained from seasonal dummies as described in the main body of the paper. For the max-min ratio measure of *Seasonality*, the cofficient in Model 5 was 0.542 (0.114)***, and in Model 7 it was 0.12 (0.07)*.

[b]The results reported here are for the $(1 - R^2)$ measure of *Demand Uncertainty*, as described in the main body of the paper. The *Sales Surprise Range* measure of *Demand Uncertainty* was not significant in Models 4 or 5, but was significant at the 5% level with the hypothesized sign in Models 6 and 7. We also explored *Sales Surprise* (instrumented), the measure used by GFR (2005) to estimate forecast error. It was significant at the 1% level, but the sign was the opposite of that hypothesized in Model 4, and it was not significant in Models 5–7.

[c]The results reported here are for the *Capital/Labor* measure of capital intensity. The *Capital/Sales* measure was not significant in Models 4–7.

[d]The R^2 values for Models 4 and 5 without *Retailer Segment* dummies were 0.45 and 0.63, respectively. The adjusted R^2 values for Models 4 and 5, respectively, were 0.762 and 0.866.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

The results for Model 5 indicate that *Variety* and *Stores* are significant at the 1% level, and the signs are consistent with the hypotheses, but *Warehouses* and its squared term are not significant. The results for Model 4 and 5 show that *Gross Margin* and *Sales* are significant at the 1% level in both models and have the hypothesized signs. The remaining variables in either model are not significant at even the 10% level, except for *Cost of Capital* in Model 4, but it does not have the hypothesized sign. Comparing the results of Models 4 and 5, there is no change in the significance level of the control variables, although the coefficients do change when the new variables are included. Furthermore, based on results not reported here to be concise (available from the authors), *Gross Margin*, *Sales, Variety*, and *Stores* are significant at the 1% level and have the hypothesized signs when *Retailer Segment* dummies are *excluded*. The model *without* retailer segment dummies explains 63% of the variation in inventories. But we find that the standard errors are lower and *t*-values higher for the significant variables *Variety*, *Sales*, *Stores*, and *Gross Margin* when *Retailer Segment* dummies are included. So, these variables appear to be robust regressors in explaining inventory levels, and their effects are stronger if we control for characteristics common to the retailers in a segment. However, the results of Models 1 and 2 suggested that excluding firm fixed effects may result in biased estimates of the coefficients, and so caution has to be exercised in using the coefficient estimates.

We also estimated the models without and with the new variables using the panel data set with three time periods (2004–2006) as discussed in §4 to check the robustness of the results and to mitigate omitted variable bias. Also, we added *Retailer Segment* dummies because this helps "control for a certain amount of heterogeneity that might be correlated with the time-constant elements" in the regressors (Wooldridge 2002, p. 288). The null hypothesis of the Hausman test is not rejected (the corresponding *p* values were 0.186 and 0.564, respectively, in the models without and with the new variables), and so the random effects model is the preferred estimator, and we present the random effects estimation results without and with the new variables, respectively, as Models 6 and 7 in Table 6.

Among the new variables, *Variety* and *Stores* are again significant at the 1% level and have the hypothesized signs. The coefficients for *Gross Margin* and *Sales* are significant at the 1% level and have the hypothesized signs in both models, with the coefficient for *Gross Margin* almost the same, but the coefficient for *Sales* changing when the new variables are introduced. The coefficient for the *Unexplained Variance* $(1 - R^2)$ measure of *Demand Uncertainty* is significant at the 5% and 10% levels, respectively, in the models without and with the new variables but does not have the hypothesized signs, i.e., more variance is associated with lower DOS. RN (2007) also found that a similar measure for *Demand Uncertainty* was significant but did not have the hypothesized sign in the retail and wholesale sectors. The remaining variables such as *Cost of Capital* and *Capital Intensity* are not significant at the 10% level in either model. Comparing the results of Models 5 and 7 (i.e., cross-sectional and panel data with all the variables), we find that the coefficients of *Variety*, *Sales*, *Stores*, and *Gross Margin* are quite similar in both models and change by at most half the standard error, and in most cases by less than one-fourth of the standard error. This provides further evidence that the significance of these four variables and, in particular, the new variables *Variety* and *Stores* is robust.

As discussed in §2, we considered alternative measures for *Capital Intensity*, *Demand Uncertainty*, and *Seasonality*, and we briefly discuss our main findings without providing the detailed results (available from the authors). The *Capital/Sales* measure of *Capital Intensity* was not significant in any of the models. *Sales Surprise Range*, an alternative measure for *Demand Uncertainty*, was not significant in Models 4 and 5—the cross-sectional analysis using 2005 data. However, it was significant at the 5% level and had the hypothesized sign in Models 6 and 7—the random effects models. *Sales Surprise*, which measures forecast error that results from demand uncertainty, was significant at the 1% level but did not have the hypothesized sign in Model 4 and was not significant in the other models. The max-min ratio measure of *Seasonality* was significant in Model 5 at the 1% level and was significant at the 10% level in Model 7. We also estimated a specification with fewer (six) retail segment dummies by combining similar segments such as women's clothing stores and family clothing stores, and the results are similar. Given the mixed results for the measures of *Demand Uncertainty* and *Seasonality*, we also performed F-tests to check the null hypothesis that *Seasonality* and *Demand Uncertainty* are both jointly insignificant using alternative measures. The null hypothesis is rejected at the 1% level in the 2005 data and at the 5% level in the panel data when the max-min ratio is used for *Seasonality*, and is rejected in the panel data when the measure based on seasonality dummies is used for *Seasonality*. This suggests that increased demand fluctuations do appear to be associated with higher inventories, but the effect is not robust across different specifications. Based on a careful observation of the underlying data, some of these fluctuations are partly captured by the retailer segment dummies. Finally, *Variety* and *Stores* continue to be significant at the 1% level, and the coefficients change by less than half the standard error if alternative measures are used for *Capital Intensity*, *Demand Uncertainty*, and *Seasonality*. The same is true for *Gross Margin* and *Sales*.

5.1. Discussion and Implications

The results of the study suggest that *Variety* and *Stores* are significant factors in explaining aggregate inventory levels among U.S. retailers. The standardized or beta coefficients from Model 5 show that a one standard deviation increase in *Variety* increases inventories by 0.34 standard deviations, whereas a one standard deviation increase in *Stores* increases inventories by 0.36 standard deviations. The number of *warehouses* does not have an effect on inventory levels. The study also confirms the impact of *Gross Margin* on inventories found in GFR (2005) and other prior studies and the effect of scale economies, measured via *Sales*, on inventory levels identified by RN (2007) and Gaur and Kesavan (2009). A one standard deviation increase in *Gross Margin* increases inventories by 0.17 standard deviations, whereas a one standard deviation increase in *Sales* decreases inventories by 0.54 standard deviations. The overall picture that emerges is that *Sales*, *Variety*, *Stores*, and *Gross Margin* are key factors in explaining inventory levels at U.S. retailers. Greater variation in demand, due to uncertainty or seasonal fluctuations, also has an effect on inventories, although the effect is less robust.

Product variety is a critical factor influencing inventory levels as per the inventory literature, and our study confirms this intuition in the retail setting. This is also consistent with prior results of Fisher and Ittner (1999) in the automobile industry, Cachon and Olivares (2010) among auto dealers, and Cachon et al. (2005), who found variety to be a significant predictor of finished goods inventory and total inventories in manufacturing firms but found mixed evidence with respect to its impact on raw material and work-in-process inventories.

Retailers often try to expand their sales by increasing the variety of items they carry and by expanding the number of stores. Although this is clearly necessary for growth, they also need to recognize the impact on inventory levels because inventory is the largest investment for most retailers. Increasing variety and breakneck store growth can result in excessive inventories, and the return on this inventory investment may suffer. The idea of limiting variety and controlling store growth may seem anathema to a retailer, but many retailers have been cutting back on variety (see Brat et al. 2009) to reduce inventories and thus increase profits. Many retailers expand their store count too quickly and then cut them back, sometimes only when facing financial distress (Johnson and Batt 2008). Similarly, scale economies play a substantial role in influencing inventory levels, as is clear from the impact of *Sales* on DOS. Hence, retailers should monitor and expect to see reductions in their inventories as sales grow. Our results about the impact of *Variety* and *Stores* confirm theoretical predictions and suggest that a retailer's high inventory may be due to having too many low volume items or too many stores.

Next, we provide some plausible reasons for the factors that were not found to be significant. Considering *Warehouses* first, perhaps the number of warehouses does not impact inventory levels because most of the inventory is held at the store level. Alternatively, this may be due to the limited variation in the number of warehouses: 49 (almost half) of the firms in our sample have one or two warehouses. Furthermore, the replenishment policies and other stocking policies not observed in the study may confound the potential effects of number of warehouses on inventories.

Our results also suggest that holding cost, measured using *Cost of Capital* may not be a significant predictor of inventory levels, and this is surprising. This may be because our measures are not accurate, but there may be other reasons. Holding costs need not be significant in determining order quantities and inventory levels even in theoretical inventory models if quantity discounts dominate the order quantity decision or if storage or transportation capacity constraints are binding. Also, many firms use rules of thumb such as a "25% cost of carrying inventory" (REM Associates 2008), in which case inventories may not be sensitive to *Cost of Capital*. *Cost of Capital* has not been found to be significant in several previous studies too. Evans (1969, p. 214), in his survey of the aggregate inventory investment literature, noted "the absence of virtually any positive empirical evidence on the role of credit factors influencing inventory investment." Randall et al. (2006) and RN (2007) both found the impact of *cost of capital* on inventories to be inconclusive. On the other hand, Matsa (2011b) found that a highly leveraged firm that is likely to have higher cost of capital tends to have higher stockout levels.

Our results relating to *Capital Intensity* differ from those of GFR (2005). Focusing on the *Capital/Labor* measure for *Capital Intensity*, it was significant and had the hypothesized sign in models where only the three variables of GFR (2005) were used along with retailer dummies (Models 2 and 3), but it was not significant once additional variables were added using either 2005 or 2004–2006 data (Models 4–7). Further analysis reveals that when *Sales* is included as a regressor, the effect of the *Capital/Labor* measure is no longer significant, and this is true independent of whether retailer segment dummies are added or not. *Sales* is a potential proxy for firm size and may be capturing the effects of capital intensity.

Our results suggest that greater demand fluctuations are associated with higher inventories, although the evidence is a bit mixed, unlike for *Variety* or *Stores*. Given the results for the *Sales Surprise Range* measure for *Demand Uncertainty* and *Seasonality* in some model specifications and the results of specifications without retailer segment dummies and other tests, it appears that demand variation does impact inventory levels, although its effects are partially captured by the retailer segment dummies.

An interesting outcome of this study is the high proportion of variance in DOS explained by the variables in the model with retailer segment dummies. So, the model could be used by retailers for benchmarking their inventory levels. Retailers often compare their inventory levels with other firms in the same or related segments, and the empirical model presented here can provide deeper insights. For example, if a retailer is similar to another retailer along the dimensions identified here but nevertheless has much higher or lower inventories, then this suggests an investigation of their inventory policies. Table 7 presents actual and fitted DOS values for eight representative firms in our sample. Both Wet Seal and Destination Maternity are in the apparel sector, but Wet Seal has much lower inventories than predicted, and the converse is true for Destination Maternity. This may be partly because the apparel business is very fickle with considerable demand uncertainty, and so inventories in a particular year are difficult to predict. Alternatively, it may be due to differences in inventory policies and Wet Seal may be carrying too little inventory, potentially losing sales, whereas Destination Maternity may be carrying too much inventory that eats into its margins. Wet Seal is known for its tight inventory controls, and this may partly explain its much lower inventories (SAS Institute 2012). A comparison of key variables for the two firms indicates that Wet Seal had similar sales (500.8 versus 561.6 million dollars), far fewer stores (400 versus

Table 7 Fitted vs. Actual Inventories for a Sample of Firms

Retailer	Fitted inventory (DOS)	Actual inventory (DOS)	% Deviation (fitted – actual)/fitted (%)
Wet Seal	68.2	37	46
Petco	65.6	52.7	20
Home Depot	81.9	77.4	5
Charming Shoppes	76.9	75.8	1.4
Radio Shack	137.8	136.8	0.7
Big Lots	121	126.3	−4
Dick's Sporting Goods	100.6	113	−12
Destination Maternity	85.8	132.7	−55

Notes. The list of firms represent the entire range of percentage deviations in our sample, including the firms with the largest positive and negative percentage deviations. The fitted values were based on the coefficients in Model 5.

1,591), a lower gross margin (35% versus 51%), and more SKUs (5,100 versus 3,100). These factors partly explain the lower predicted inventory for Wet Seal, but the actual inventory is much lower for Wet Seal and alarmingly higher for Destination Maternity. The analysis here can be a starting point to more carefully explore the reasons for these differences and investigate their inventory policies.

The approach presented here can also be appropriately adapted to benchmark store performance within a retail firm. Stores may differ in their sales, variety, and gross margin, as well as demand fluctuations depending on the product mix carried. So, a retailer may expect stores with higher sales to have lower inventories (ceteris paribus), and if this is not the case, they could investigate further. In fact, a retailer may be able to replicate the analysis conducted here and estimate the impact of the factors identified here across the store network. This will help them to create more accurate benchmarks for comparing the inventory performance of their stores.

5.2. Limitations

Despite the care taken to measure many of the variables and mitigate potential econometric issues, there are some limitations to the study. First, we may not be capturing accurately the impact of IT investments on inventories. A potential limitation of using fixed assets (numerator in the *Capital Intensity* measure we used) is that IT expenditures constitute only about 5% or so of total capital expenditures for retail firms (Doms et al. 2003). However, to the best of our knowledge, there is no public source of information on technology spending by individual retail firms.

Second, there may be sources of measurement error. For instance, sales for some retailers come from services or products that are not stocked at the stores. Home Depot offers services such as roofing or floor installation, the sales of which involve labor as well as materials. However, this effect tends to be somewhat retail segment specific (for instance, both Home Depot and Lowe's have such sales from services whereas apparel retailers do not), and so the *Retailer Segment* variable may have controlled for this effect. Similarly, some retailers have online sales, and the inventories carried for online sales may be lower than inventories at brick-and-mortar stores. Unfortunately, most retailers do not report their online sales in 10-Ks. If the proportion of online sales or sales from services is not correlated with the other regressors, then our results or conclusions are still valid. Inventories are carried at stores as well as in warehouses and in the pipeline. Although we have included *Stores* and *Warehouses* as independent variables, this may not capture the variation among retailers in where this inventory is carried, how frequently they are replenished, cross-docking efforts, etc. The number of SKUs may not be a good measure of variety if there is significant consumer substitution among SKUs within a product category.

There also may be unobserved firm-specific events or factors that may influence inventory performance but are not captured. Supply chain disruptions such as those mentioned by Hendricks and Singhal (2003) are examples of such events. Similarly, as mentioned earlier, increase in capital costs after a leveraged buyout has a significant effect on inventories held by supermarkets (Matsa 2011b). Management changes and weather could be other factors. However, if the impact of these factors is similar across retailers or the unobserved firm-specific events are random events, then our conclusions are still valid. Chen et al. (2005) pointed out that only a small fraction of retail inventories is held by public firms, and public retailers typically tend to be larger, so our sample may not be representative. Hence, the results and conclusions of this study, which is restricted to a sample of publicly listed retailers, may not hold for the larger population of retailers in the United States.

6. Conclusion

This study finds that the number of items carried and number of stores are critical factors associated with higher inventory levels at U.S. retailers, as predicted by theory. On the other hand, the number of warehouses is not significant in explaining inventory levels. The study confirms previous findings that gross margin and scale economies (with sales as proxy) do have a significant influence on inventory levels and contributes to the literature by proposing alternative measures for some of these variables that address econometric concerns. Despite some limitations of the study identified in the previous section, the study sheds light on many key factors that impact inventories at U.S. retailers. The study also found that a few key variables can explain a substantial fraction of the variance in inventory levels and can be useful to retailers in benchmarking inventory levels and in turn examining their inventory policies.

This study answers some questions but raises several interesting ones that require additional work. What has been the impact of variety over time on inventories? Have firms counteracted the impact of variety with better information systems, as postulated by Gao and Hitt (2004)? GFR (2005) found that inventories have declined in several but not all retail segments during 1987–2000. Are the predictor variables identified in this study responsible for the differential changes in inventory levels over time?

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/msom.1120.0407.

Acknowledgments

The author is grateful to the editor, associate editor, and anonymous referees for valuable comments and suggestions that have improved this paper significantly. The author is also grateful to Avinash Nayak, Angela Shockley, Amit Agrawal, and Guiyuan Li for their research assistance.

References

Arai M (2003) Wages, profits, and capital intensity: Evidence from matched worker-firm data. *J. Labor Econom.* 21(3):593–618.

Balakrishnan A, Pangburn M, Stavrulaki E (2008) Integrating the promotional and service roles of retail inventories. *Manufacturing Service Oper. Management* 10(2):218–235.

Berman B (2010) Products, products everywhere. *Wall Street Journal* (August 22), http://tiny.cc/flknlw.

Bettis RA (1981) Performance differences in related and unrelated diversified firms. *Strategic Management J.* 2(4):379–393.

Brat I, Byron B, Zimmerman A (2009) Retailers cut back on variety, once the spice of marketing. *Wall Street Journal* (June 26), http://tiny.cc/doknlw.

Cachon G, Olivares M (2010) Drivers of finished goods inventory performance in the U.S. automobile industry. *Management Sci.* 56(1):202–216.

Cachon G, Gao G, Hitt L (2005) Product variety, inventory management and firm performance. Working paper, The Wharton School, University of Pennsylvania, Philadelphia.

Cameron CA, Trivedi PK (2009) *Microeconometrics Using Stata* (Stata Press, College Station, TX).

Chen H, Frank MZ, Wu OQ (2005) What actually happened to the inventories of American companies between 1981 and 2000? *Management Sci.* 51(7):1015–1031.

Doms ME, Jormin RS, Klemek SD (2003) IT investment and firm performance in retail trade. Working Paper 2003-19, Federal Reserve Bank of San Francisco, San Francisco.

Ellickson PB (2006) Quality competition in retailing: A structural analysis. *Internat. J. Indust. Organ.* 24(3):521–540.

Evans MK (1969) *Macroeconomic Activity: Theory, Forecasting, and Control; An Econometric Approach* (Harper and Row, New York).

Fama E, French K (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33(1):3–56.

Fisher ML, Ittner CD (1999) Impact of product variety on automobile assembly operations. *Management Sci.* 45(6):771–786.

Gao G, Hitt LM (2004) IT and product variety: Evidence from panel data. Working paper, The Wharton School, University of Pennsylvania, Philadelphia.

Gaur V, Kesavan S (2009) The effects of firm size and sales growth rate on inventory turnover performance in U.S. retail services. Agrawal N, Smith S, eds. *Retail Supply Chain Management*, Chap. 3 (Springer, New York), 25–52.

Gaur V, Fisher ML, Raman A (2005) An econometric analysis of inventory turnover performance in retail services. *Management Sci.* 51(2):181–194.

Gujarati DN (1995) *Basic Econometrics*, 3rd ed. (McGraw-Hill, New York).

Hendricks KB, Singhal VR (2003) The effect of supply chain glitches on shareholder value. *J. Oper. Management* 21(5):501–522.

Hwang MY, Weil D (1998) Who holds the bag? The impact of information technology and workplace practices on inventory. *Proceedings of the Industrial Relations Research Association*, Vol. 1 (Industrial Relations Research Association, Madison, WI), 68–77.

Iyer A, Radhakrishnan A (2009) Data analysis and supply chain design for a company. *INFORMS Annual Meeting 2009* (INFORMS, Hanover, MD).

Johnson EJ, Batt RJ (2008) How to make dealerships strong—and happy. *Wall Street Journal* (October 20), http://tiny.cc/gyknlw.

Judge GG, Hill RC, Griffiths WE, Luetkepohl H, Lee TC (1988) *Introduction to the Theory and Practice of Econometrics* (Wiley, Hoboken, NJ).

Kekre S, Srinivasan K (1990) Broader product line: A necessity to achieve success? *Management Sci.* 36(10):1216–1231.

Kesavan S, Gaur V, Raman A (2010) Do inventory and gross margin data improve sales forecasts for U.S. public retailers? *Management Sci.* 56(9):1519–1533.

Kök AG, Fisher AG, Vaidyanathan R (2008) Assortment planning: Review of literature and industry practice. Agrawal N, Smith SA, eds. *Retail Supply Chain Management* (Springer, New York), 99–154.

Lieberman MB, Helper S, Demeester L (1999) The empirical determinants of inventory levels in high-volume manufacturing. *Production Oper. Management* 8(1):44–55.

Luttrell KL (2007) Wholesale and retail trade division dominates S corporations since 1959. Accessed October 20, 2009, http://www.irs.gov/pub/irs-soi/59scorp.pdf.

Matsa DA (2011a) Competition and product quality in the supermarket industry. *Quart. J. Econom.* 126(3):1539–1591.

Matsa DA (2011b) Running on empty? Financial leverage and product quality in the supermarket industry. *Amer. Econom. J. Microeconomics* 3(1):137–173.

Miller KD, Bromiley P (1990) Strategic risk and corporate performance: An analysis of alternative risk measures. *Acad. Management J.* 33(4):756–779.

Olivares M, Cachon G (2009) Competing retailers and inventory: An empirical investigation of general motors' dealerships in isolated markets. *Management Sci.* 55(9):1586–1604.

Rajagopalan S, Malhotra A (2001) Have inventories declined in the U.S.: An empirical study. *Manufacturing Service Oper. Management* 3(1):14–24.

Randall T, Ulrich K (2001) Product variety, supply chain structure, and firm performance: Analysis of the U.S. bicycle industry. *Management Sci.* 47(12):1588–1604.

Randall T, Netessine S, Rudi N (2006) An empirical examination of the decision to invest in fulfillment capabilities: A study of Internet retailers. *Management Sci.* 52(4):567–580.

REM Associates (2008) Methodology of calculating inventory carrying costs. Report, REM Associates, Princeton, NJ. Accessed October 10, 2009, http://www.remassoc.com/portals/0/remprecc.pdf.

Ren J, Willems SP (2007) An empirical study of inventory policy choice and inventory level decisions. Working paper, School of Management, Boston University, Boston.

Roumiantsev S, Netessine S (2007) What can be learned from classical inventory models: A cross-industry exploratory investigation? *Manufacturing Service Oper. Management* 9(4):409–429.

SAS Institute (2012) The Wet Seal Inc. accelerates fast fashion with SAS® size profiling. Accessed February 20, 2012, http://www.sas/com/success/wetseal.html.

Softletter (1992) The SKU explosion. Report, Softletter, Killingworth, CT. Accessed October 17, 2011, http://www.thefreelibrary.com/The+SKU+explosion.-a011982481.

Teo CP, Shu J (2004) Warehouse-retailer network design problem. *Oper. Res.* 52(3):396–408.

Van Ryzin G, Mahajan S (1999) Inventory costs and variety benefits in retail assortments. *Management Sci.* 45(11):1496–1509.

Vidyarthi N, Celebi E, Elhedhli S, Jewkes E (2007) Integrated production-inventory-distribution, system design with risk pooling. *Transportation Sci.* 41(3):392–408.

Wooldridge JM (2002) *Econometric Analysis of Cross-Section and Panel Data* (MIT Press, Cambridge, MA).

Zipkin PH (2000) *Foundations of Inventory Management*, 1st ed. (McGraw-Hill/Irwin, New York).