

Demand uncertainty and inventory turnover performance

US retail industry

An empirical analysis of the US retail industry

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Abstract

Purpose – The purpose of this paper is to investigate the impact of demand uncertainty on inventory turnover performance through empirical modeling. In particular the authors use the inaccuracy of quarterly sales forecasts as a proxy for demand uncertainty and study its impact on firm-level inventory turnover ratios.

Design/methodology/approach – The authors use regression analysis to study the effect of various measures on inventory performance. The authors use a sample financial data for 304 publicly listed US retail firms for the 25-year period from 1985 to 2009.

Findings – Controlling for the effects of retail segments and year, it is found that inventory turnover is negatively correlated with mean absolute percentage error of quarterly sales forecasts and gross margin and positively correlated with capital intensity and sales surprise. These four variables explain 73.7 percent of the variation across firms and over time and 93.4 percent of the within-firm variation in the data.

Practical implications – In addition to conducting an empirical investigation for the sources of variation in a major operational metric, the results in this study can also be used to benchmark a retailer's inventory performance against its competitors.

Originality/value – The authors develop a new proxy to measure the demand uncertainty that a firm faces and show that this measure may help to explain the variation in inventory performance.

Keywords Operational performance, Inventory management, Retail industry

Paper type Research paper

Introduction

Managing inventories is at the core of operational performance in many industries. Due to its importance in practice, inventory management has been a well-studied area of research in operations management. Starting with the economic-order quantity model more than a century ago (Harris, 1913), researchers developed mathematical models to guide decision makers on managing their inventories under a variety of settings. Some of these models are now standard material in operation management textbooks (e.g. Nahmias, 2008; Cachon and Terwiesch, 2005) and more advanced



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This study has started when the third author was affiliated with Virginia Polytechnic Institute and State University.

models are available in texts on inventory theory (e.g. Silver *et al.*, 1998; Zipkin, 2000). However, the majority of these models are for a single product or a small set of products and assume away the complexities of industrial supply chains. Therefore, it is important to understand to what extent the prescriptions and predictions of these models are valid in industry. It is also crucial to understand how different factors, other than those studied in these mathematical models, affect the actual inventory performance of firms in practice.

In contrast to the literature on mathematical inventory models, researchers began investigating inventory management practices in industry only in the 1990s. Much of the earlier work focusses on the effects of various production/distribution systems and initiatives on firm-level inventory performance (e.g. Balakrishnan *et al.*, 1996; Hopp and Spearman, 1996). A second stream of empirical research in this area looks at the trends in inventory performance at the industry level (e.g. Rajagopalan and Malhotra, 2001; Chen *et al.*, 2005, 2007) and investigates whether firms improve their inventory management practices over time. A third line of research studies whether inventory outperformance leads to overall financial outperformance or success in the stock market (e.g. Gaur *et al.*, 2014; Capkun *et al.*, 2009).

A final strand of literature attempts to explain differences in inventory performance across firms and to account for various factors that may have an effect on how much inventory a firm needs to carry (e.g. Gaur *et al.*, 2005; Rajagopalan, 2013). Factors that were previously investigated in the literature include gross margin, capital intensity, sales surprise, number of locations, scale economies and product variety. Understanding the effects of different factors on inventory is also important in order to properly benchmark the inventory performance of a firm against other firms in the industry. The empirical papers on inventory management usually adopt the inventory turnover ratio as a measure of the inventory performance of a firm. The inventory turnover ratio is defined as the ratio of the cost of goods sold by a firm to its average inventory level during a given period and is perhaps the most widely used metric in practice as it scales inventory to sales and thus can be used for tracking the performance over time and comparing inventory performance across firms of different sizes.

The objective in this paper is to study the effect of uncertainty on inventory performance of firms in retail industry. Davis (1993) defines three different sources of uncertainty in supply chains: supply uncertainty, process uncertainty and demand uncertainty. The variability of supplier performance due to later or defective deliveries may lead to supply uncertainty. Process uncertainty arises from the unreliability of the production process due to machine breakdowns. Finally, demand uncertainty, which results from unstable demand or inaccurate forecasts, is the most serious of the three (Bhatnagar and Sohal, 2005). Demand uncertainty is an integral dimension of environmental dynamism (Zhou and Benton, 2007; Oh *et al.*, 2012). Inventory theory explains that demand uncertainty is a major reason for carrying inventory (Nahmias, 2008). Considering its importance, seriousness and emphasis in this literature, we focus on demand uncertainty in this paper.

We follow the last line of empirical research on inventory management and study the effect of different factors on firm-level inventory turnover ratios. We have three key contributions to this literature. First, we develop a new metric that can be used to quantify the demand uncertainty a firm faces. This new proxy essentially measures the inaccuracy in forecasts for aggregate quarterly demand and can be easily calculated using quarterly financial data that every public firm reports. In particular, we use the mean absolute percentage error (MAPE) of quarterly forecasts, which are generated

using a fairly standard seasonal forecasting technique. The need for quantifying firm-level demand uncertainty is also evident from earlier literature in this area. Three alternative proxies are suggested in Rumyantsev and Netessine (2007) and Rajagopalan (2013). However, the effect of demand uncertainty (as measured by these proxies) on inventory performance is found to be either insignificant or the opposite of the hypothesized direction (i.e. more uncertainty leads to less inventory) for the retail industry. A fourth proxy, suggested in Shan and Zhu (2013), is based on an assumption that the seasonality and trend affect the demand for each company the same way, which is hard to justify in practice. We propose a more appropriate metric to measure demand uncertainty and attempt to fill this gap in the literature.

Second, we investigate the effect of the demand uncertainty as measured by this new metric on the inventory performance of US retail firms. We believe that the retail industry is an ideal choice for our analysis since a major fraction of the assets of a retail firm is its inventory. The data used in this paper illustrate that in 2009, inventories represented 23.5 percent of total assets and 58.3 percent of current assets for retailers in the US. Retailers pay great attention to inventory productivity, and always try to improve their processes to reduce their inventory levels. Also, starting from the beginning of the 1990s, retailers experimented with different strategies such as larger store formats, mergers and acquisitions, and applied new supply chain technologies. We use financial data for all publicly listed US retailers for the 25-year period 1985-2009, drawn from their quarterly and annual balance sheets and annual income statements. The data are obtained from Standard & Poor's Compustat database using Wharton Research Data Service (WRDS). Using this data, we specify five statistical models to understand the effects of four variables (MAPE, capital intensity, gross margin and sales surprise) on inventory turnover performance. In the three models that we pool the data for all segments, coefficients for MAPE are statistically significant and the hypothesis that the inventory turnover is negatively correlated with MAPE is supported. When we investigated the retail segments separately, the coefficient for MAPE was negative and significant in five out of ten segments. With the addition of MAPE and segment-specific fixed effects in our models, 73.7 percent of the variation across firms and over time and 93.4 percent of the within-firm variation can be explained. These results also show that, the new proxy we propose is robust in measuring demand uncertainty and is associated negatively with inventory turnover ratio as the theory predicts.

Third, we propose a new performance indicator, inventory turnover ratio, which is adjusted for MAPE (in addition to other financial factors considered before) to benchmark a firm's operational performance against others. We believe that since this new proxy measures demand uncertainty more properly, adjusting inventory turnover ratio using it will lead to a better benchmarking of inventory performance in industry.

The rest of the paper is organized as follows. A survey of related literature is presented in the second section. The data and performance variables used throughout this paper are presented in the third section. In the fourth section, hypotheses that relate inventory turnover rate with MAPE in forecasts, gross margin, capital intensity and sales surprise are specified. In the fifth section, empirical models are provided. The statistical results are provided and discussed in the sixth section. Conclusions and avenues for future research are given in the seventh section.

Literature review

Empirical research in operations management, in particular on demand uncertainty and inventory management, received interest only recently. We divide the existing

literature into two parts: inventory management in operations and demand uncertainty and inventory management in retail logistics.

Inventory management in operations

One of the first papers in this area is by Rajagopalan and Malhotra (2001) who explore the inventory trends in US manufacturing firms and the effects of inventory-reduction initiatives on inventory performance using aggregate industry-level data from 1961 to 1994. Their analysis shows that the total manufacturing inventory ratios (which can be roughly defined as the inverse of the inventory turnover rate) decreased from 1961 to 1994, and that these ratios did not improve at a higher rate after the 1980s (when many inventory-reduction initiatives began) compared with the pre-1980 period. Chen *et al.* (2005) study the inventories of publicly traded US manufacturing firms for the period from 1981 to 2000. The authors show that raw material and work-in-process inventories decline over this period; nevertheless, finished-goods inventory remained the same. In addition, they find that firms with higher levels of inventory have poorer long-term stock returns. The relationship between inventory performance and financial performance has been investigated only to a very limited extent.

Capkun *et al.* (2009) investigate the relationship between the performance of discrete components of inventory (raw materials, work-in-process, finished goods) and financial performance of US manufacturing firms over the 26-year period from 1980 to 2005. The paper finds a significant positive correlation between inventory performance and measures of financial performance paralleling the results in Rajagopalan and Malhotra (2001) and Chen *et al.* (2007). The strongest effect on financial performance is found to be the effect of finished-goods inventory. Vastag and Whybark (2005) study the relationship between the use of effective inventory management practices (measured by inventory turnover rate) and other manufacturing techniques. Their analysis of data gathered through surveys of manufacturing firms in several countries show that effective inventory management practices have a knock-on effect on the implementation of other practices. Claycomb *et al.* (1999) study the effects of JIT strategy on several performance measures including financial efficiency, inventory levels and organizational efficiency for firms in the logistics industry. Another line of earlier empirical research in inventory management studies the sources of inventory record inaccuracy (see, e.g. DeHoratius and Raman, 2008 and references therein).

Olivares and Cachon (2009) develop an econometric model to investigate how competition influences the inventory holdings of General Motor's 200 dealerships using data over a six-month period. It is found that dealers carry more inventory when they face more competition. Using secondary data covering the years 1996 through 2004, Cachon and Olivares (2010) find that two factors, the number of dealerships in the distribution network and production flexibility, explain almost all of the difference between finished-goods inventories that major US auto manufacturers carry. In Yao *et al.* (2012), the authors investigate the VMI partnership between a major manufacturing company and a set of independent distributors and find that self-learning, learning spillovers from electronic data interchange and learning spillovers from other supply chain dyads have significant positive effects on inventory performance of distributors. Lee *et al.* (2015) examine how a firm's innovation performance is associated with inventory turnover performance. Using data from all non-service US public firms over the period 1976-2005, they show that innovation performance is positively correlated with inventory turnover. They also find that process innovation has a consistent and long-lasting effect, while product innovation has an immediate but temporary effect.

Several papers study inventory performance in countries other than the USA. Johnson and Templar (2011) develop a unified performance proxy composed of various elements in profitability, liquidity and productivity, and explore the impact of improved supply chain management on firm performance. They use data from 117 publicly traded UK manufacturing firms from the period 1995 to 2004. Empirical analysis shows that the proxy provides a good indication for the rate of change in firms' value. Robb *et al.* (2012) investigate the further effect of firm size, industry and location on the inventory performance of firms in mainland China. Shan and Zhu (2013) develop an empirical model to analyze the inventory performance of 1,286 Chinese firms. They find that the level of inventories decreases significantly over time, which is consistent with the studies carried out in the USA.

Demand uncertainty and inventory management in the retail industry

Demand uncertainty has been increasing in recent years due to lengthening supply chains, global recession and macroeconomic events (Kesavan *et al.*, 2013). It can be identified as one of the key sources of variability in any supply chain; therefore, failure to account for major demand fluctuations may either lead to unsatisfied customer demand and loss of market share or excessively high costs (Gupta and Maranas, 2003). Recognition of this fact has motivated us to study the impact of demand uncertainty on inventory performance in the US retail industry. The pioneering work in this area is by Gaur *et al.* (2005) and investigates the sources of variation in inventory turnover performance across firms in the US retail industry. The authors use financial data from 311 publicly listed retail firms for the period 1985-2000 and show that inventory turnover is negatively correlated with gross margin and positively correlated with capital intensity (with some exceptions) and sales surprise. These three variables helped explain 66.7 percent of the within-firm variation and 97.2 percent of the total variation in inventory turnover ratio. The paper also explores time trends in retail inventory and finds that the inventory turnover ratio in the retail industry declined during the 1985-2000 period. Gaur and Kesavan (2008) extend this work to incorporate the effects of firm size and sales growth rate. This paper uses data from 353 publicly listed US retail firms for the period 1985-2003. The authors find that inventory turnover is positively correlated with firm size and sales growth rate. Their results regarding the effects of gross margin, capital intensity and sales surprise on inventory turnover performance are consistent with those of Gaur *et al.* (2005). Gaur *et al.* (2014) propose a new metric, which they call adjusted inventory turnover, to measure the inventory performance of firms in the US retail industry. This new metric accounts for the effects of gross margin and capital intensity on inventory performance and is shown to be useful when different stakeholders evaluate retailers. Alan *et al.* (2014) use a set of data similar to Gaur *et al.* (2014) and show that inventory productivity can be successfully used to predict future stock returns. It is also shown that the predictive power of inventory productivity is robust to the way it is measured.

Inventory performance of US retailers and wholesale firms over the period 1981-2004 is investigated by Chen *et al.* (2007). They find that the inventory performance of these firms improve over these years. As in Chen *et al.* (2005), it is found that poorer inventory performance leads to poorer long-term stock market performance. Rumyantsev and Netessine (2007) analyze the panel data from 722 public US firms including retail firms for the period 1992-2002. The authors show that many of the predictions of inventory theory at the item level extend to the aggregate firm level; firms that are subject to higher demand uncertainty, longer lead times and higher gross

margins have larger inventories. The authors also find evidence that larger firms tend to carry less inventory as they benefit from economies of scale. Mishra *et al.* (2013) develop a conceptual model outlining the relationships between the information technology capability of firms and inventory efficiency. The model is tested using data for 394 US firms, which represent various industries including the retail trade, over the ten-year time period from 2000 to 2009. The authors find evidence that information technology capability improves the inventory efficiency of firms. They also show that this indirectly leads to higher stock market returns. Rajagopalan (2013) explores the impact of product variety, number of stores, number of warehouses, seasonality and demand uncertainty (in addition to the previously studied factors) on inventory levels at US retailers. Using data from primary and secondary sources for 104 retailers in the years 2000-2004, the paper finds that only variety and number of stores have significant effects on inventory levels.

Johnston (2014) studies the inventory performance of US retailers and shows that firm size and net margin also have significant effects on inventory turnover. Shockley *et al.* (2014) present an empirical study of 219 US retail firms and find that retailers that fail to invest in their structural and human capital exhibit short-term financial benefits, but suffer in their ongoing operational performance. Shockley and Turner (2014) explore an empirical link between the inventory management of 336 US retail firms and their competitive operational performance. The authors show that in general better inventory performance leads to better operational performance. However, the authors also note that there may be no universal measure of inventory performance in the retail industry; one may have to use a specialized indicator of inventory performance when evaluating a firm in a particular segment of the retail industry. Kolias *et al.* (2011) use the data of 566 Greek retail firms for the period 2000-2005 and show that the results in Gaur *et al.* (2005) also hold for the Greek retail industry.

Our review of the literature shows that there is no consistent metric that can be obtained from aggregate firm-level financial data to measure the demand uncertainty that a firm faces. Previous research also has conflicting conclusions on how demand uncertainty affects a retailer's inventory performance. Our main contribution in this study is to develop a metric to quantify the demand uncertainty that a firm faces and to use this metric to understand the effect of demand uncertainty on that firm's inventory turnover performance. In particular, we use Winter's triple exponential method to obtain quarterly sales forecasts, and use the MAPE of these forecasts as a proxy for demand uncertainty. Our data source is similar to Gaur *et al.* (2005), except that we include the period 2001-2009 in our analysis. Our results show that the effect of this new metric is more robust in comparison to the previously proposed proxies for demand uncertainty. MAPE has a significant negative effect on inventory performance when we pool the data for all segments of the US retail industry. When the analysis is carried out individually for each of the ten retail segments, we find that MAPE has a significant negative effect on inventory in five segments. We believe that our models and metrics can be effectively used to understand the impact of various factors (demand uncertainty in particular) on inventory performance and to benchmark a firm's inventory performance against its competitors in the marketplace and over time.

Data description and definition of variables

We obtained the financial data for all publicly listed US retailers for the 25-year period 1985-2009 from "Compustat North America Quarterly Updates" and "Compustat North America Annually Updated" available at Standard & Poor's Compustat database

using WRDS. The US Department of Commerce assigns a Standard Industry Classification (SIC) code to each firm according to its primary industry segment. Five segments correspond to unique four-digit SIC codes. For example, the SIC code 5311 represents “Department stores.” For the rest of the SIC codes, we group together firms in similar product groups as there are substantial overlaps among their products. For example, all firms with SIC codes between 5600-5699 are collected in a segment called “Apparel and accessory stores.” The categorization that we use is the same as that was used in Gaur *et al.* (2005). Table I lists all segments, corresponding SIC codes, and a few examples of firms in each segment.

The original dataset contained 6,561 annual and 25,142 quarterly observations across 623 firms. There were several firms whose quarterly data are available but whose annual data are missing and similarly there are several firms whose annual data are available but the quarterly data are missing. We eliminated these firms as we need both annual and quarterly results. We omit from our dataset the firms that have less than seven consecutive years of data. Our final dataset contains 3,628 annual and 14,512 quarterly observations across 304 firms for the period 1985-2009.

Based on the data, we define and compute the following performance variables: inventory turnover, gross margin, capital intensity, sales surprise and MAPE. These performance variables are used in developing hypotheses in the fourth section and empirical models in the fifth section. Inventory turnover is the cost of goods sold divided by the average inventory. Gross margin is defined as the percent of total sales revenue that the company retains after incurring its direct costs. Capital intensity is the ratio of a firm’s gross fixed assets to its total assets and measures a firm’s investment in warehouses, information technology and inventory/logistics management systems that may have a direct effect on how effectively it can manage its inventory. Sales surprise is the ratio of actual sales to forecasted sales. These four variables are defined exactly the same way as they are defined in Gaur *et al.* (2005). The detailed formulae are provided in the Appendix.

In this paper we use a new metric, MAPE, as a new measure for demand uncertainty. We provide the following justification for its use in this study. First, notice that a direct approach to measure demand uncertainty would be to use item level detailed demand data. However, this is not possible since the demand data of retail firms is usually not publicly available and capturing and measuring variability over thousands of stock keeping units for hundreds of companies would not be possible computationally. Therefore, one needs to use a proxy to measure demand variability.

Retail industry segment	SIC codes	Examples
Apparel and accessory stores	5600-5699	Gap, Ann Taylor, Foot Locker
Catalog, mail-order houses	5961	Amazon.com, Lands’ End, Spiegel
Department stores	5311	Macy’s, Neiman Marcus, J.C. Penney
Drug and proprietary stores	5912	CVS, Rite Aid, Eckerd
Food stores	5400, 5411	Albertson’s, Kroger, Safeway
Hobby, toy and game shops	5945	Toys R US, Michaels Stores, Noodle Kidoodle
Home furniture and equip. stores	5700, 5712	Bed Bath & Beyond, Cost Plus, Pier 1 Imports
Jewelry stores	5944	Zale, Tiffany, Finlay Fine Jewelry
Radio, TV, consumer electronics stores	5731, 5734	Best Buy, Circuit City, Radio Shack
Variety stores	5331, 5399	Wal-Mart, Target, 99 Cents Only

Table I.
Classification of retail segments

The use of a forecast inaccuracy measure for this purpose is in line with how firms traditionally make inventory decisions when they face uncertainty in demand. In practice, firms first forecast their random demand using historical data and then use this forecast to decide their inventory levels. Demand uncertainty is usually tackled by considering the errors in forecasting which are usually measured using a performance metric such as mean square error, mean absolute deviation or MAPE. We use MAPE in our analysis as it scales to the level of demand, which obviously varies across retail segments and firms and over time.

Potentially, there are two problems with using this particular proxy (these issues are also valid for other proxies suggested in the literature for this purpose, see a discussion of these other proxies below). First, due to aggregation of all stock keeping units for a company, variability in quarterly sales, and thus MAPE of quarterly sales forecasts is an approximate measure. Second, it assumes that sales correctly represent the original demand, while in fact there could be some censoring of data due to stock-outs.

We note that alternative proxies are used in the literature to quantify demand uncertainty. In Rumyantsev and Netessine (2007), the authors run a regression model for each firm to characterize the demand in each quarter as a linear function of time and quarter dummies. The variance of the residuals of this model is then used as a proxy for demand uncertainty. The results show that, at the aggregate level, inventory levels increase with demand uncertainty. When the analysis is carried out at the industry level, however, the predictions of the inventory theory fail to be supported. In particular, the demand uncertainty has a significant negative effect on relative inventory level for the retail industry as a whole. This result bears similarity with the findings of Eroglu and Hofer (2014) who conclude that demand uncertainty has no significant impact on the inventory leanness-performance even though demand uncertainty has a significant negative effect on firm performance. An explanation for this statement may be that in some sectors, capacity rather than inventory is used to buffer against demand uncertainty. However, note that the demand uncertainty in this study is measured at the industry level, not at the firm level.

The variable that is used for demand uncertainty in Shan and Zhu (2013) is slightly different. Rather than fitting a separate regression model for each firm, the authors used pooled estimates for the effect of time and quarter with firm-specific fixed effects. While this approach is much simpler than the one in Rumyantsev and Netessine (2007), it may be difficult to justify the assumption that the quarter and time effects are the same for all firms in China. Nevertheless, Shan and Zhu (2013) show that their data supports the positive association between the demand uncertainty (as they measure it) and inventory levels at the aggregate level, and for most of the industries in China (their industry classification does not specify retail industry as a separate industry).

Rajagopalan (2013) suggests two alternative measures for demand uncertainty. The first alternative is similar to what is used in Rumyantsev and Netessine (2007). Rather than using the variance of residuals obtained from the regression model explained above, Rajagopalan (2013) uses $(1-R^2)$ of the regression model. The second alternative is the range of sales surprise as defined above. Rajagopalan's study shows that $(1-R^2)$ measure of demand uncertainty has a significant effect on inventory levels, but does not have the hypothesized sign; more demand uncertainty leads to lower inventory. Range of sales surprise had a significant positive effect only in some of the models proposed by Rajagopalan (2013).

Given weak and mixed results regarding other metrics suggested in the literature, and in the absence of any other proxy that can be calculated using publicly available

data sources, we believe that MAPE of quarterly sales forecasts should be a good candidate to capture at least some of the demand uncertainty that a firm faces. In obtaining the quarterly forecasts, we use Winter's triple exponential method. The formulae and the choice of parameters for this method are presented in the Appendix.

Table II shows the descriptive statistics for each retailing segment for the performance variables (the standard deviations are provided in parentheses). We see that there is a great level of variation in inventory turnover (minimum average at 2.323 in jewelry stores and maximum average at 11.379 in food stores) across different segments of the retail industry. Likewise, MAPE also varies substantially across segments (minimum average at 5.5 percent in department stores and maximum average at 12.8 percent in catalog and mail-order houses).

Hypothesis development

The hypotheses that we develop in this section are mainly inspired by the mathematical models of inventory theory. As mentioned before, many of these models are now part of standard textbooks in operations management (e.g. Nahmias, 2008; Cachon and Terwiesch, 2005). However, we note that most are for managing the inventory of a single item or a small group of items, while our analysis is for firm-level aggregate inventories. The data we use are aggregated for all products and locations that a firm manages. In addition, we consider the snapshots of data at the end of quarters or years while inventory decisions are made on a daily basis in practice. Thus, we are primarily interested in finding out whether the predictions of inventory theory are valid at the aggregate level through the hypotheses. Testing these hypotheses is crucial in understanding sources of variation in inventory performance across US retailers and over time. Once the sources of variation are clearly identified, one can benchmark a retailer's performance against others or over time by controlling for these sources.

We present four hypotheses. The first three hypotheses relate inventory turnover to gross margin, capital intensity and sales surprise. As we briefly review in the second section, some of these hypotheses are presented and tested earlier in other empirical papers including Gaur *et al.* (2005), Rumyantsev and Netessine (2007), Gaur and Kesavan (2008), Koliias *et al.* (2011), Shan and Zhu (2013), Rajagopalan (2013), Johnston (2014) and Lee *et al.* (2015). The fourth hypothesis relates inventory turnover to demand uncertainty as it is measured by the new metric we propose: MAPE of quarterly demand forecasts:

H1. Inventory turnover is negatively correlated with gross margin.

The main motivation for this hypothesis is the fundamental trade-off between underage and overage costs encountered in stochastic inventory models. In the simplest of these models, the newsvendor model, the optimal-order quantity is the critical fractile of the demand distribution, where the critical fractile is defined as the ratio of the underage cost to the sum of underage and overage costs (Nahmias, 2008; Cachon and Terwiesch, 2005). Underage cost, i.e., the cost of not satisfying a customer demand is often defined as a product's gross margin (in some cases the cost due to loss of goodwill is also added to gross margin). Therefore as the gross margin of a product increases, so does the critical fractile, leading to a higher order quantity and more expected inventory for the newsvendor at the end of the period. This reasoning is also valid for more advanced inventory models that involve multiple periods, products, echelons or setup costs. Even when unsatisfied demand is fully backordered, one can

argue that the backorder penalties are increasing in gross margin since customers for high-margin products are expected to be more demanding and sensitive to stock-outs. In cases where it is difficult to quantify underage costs precisely and retailers use service levels to drive their inventory decisions, it is clear that retailers would set higher target service levels for products with higher gross margins.

Higher margins or higher product prices may lead to lower inventory turns due to other reasons as well. Some of these reasons are stated in Gaur *et al.* (2005). First, an increase in price leads to lower average demand resulting in a higher coefficient of variation, which translates into higher inventory in the form of safety stocks. Second, consumers derive additional utility from increased variety. Thus higher product variety allows a firm to charge a higher price for its products leading to an increase in the gross margin (Lancaster, 1990; Chamberlin, 1950; Dixit and Stiglitz, 1977). However, as the product variety increases, the average demand for each product goes down, again resulting in a higher coefficient of variation (or higher forecast inaccuracy) and lower inventory turnover. Third, firms can charge higher prices for products with shorter life cycles since designs for these products better match changing customer needs. However, firms can no longer rely on historical sales data to accurately forecast demand for these products, leading to more safety stock or lower inventory turns.

Several other arguments are mentioned in the literature in favor of *H1*. Johnston (2014) suggests that faster and more reliable forms of transportation lead to shorter lead times and hence lower inventory for retailers. However, these forms of transportation also increase direct costs, leading to a lower gross margin. Alan *et al.* (2014) and Gaur *et al.* (2014) state that higher gross margins are associated with higher quality products, which leads to slower inventory turns.

Gaur *et al.* (2005) also report observations from their survey of retailing businesses that support this hypothesis in practice. In particular, they state that retailing managers use the “earn vs turns trade-off” where they set lower inventory turnover targets for those products with higher margins. Based on all these reasons, we hypothesize that higher gross margins lead to firms carrying more inventory.

We note here that *H1* is supported in all papers that we have reviewed: Gaur *et al.* (2005), Gaur and Kesavan (2008), Rajagopalan (2013) and Johnston (2014) for the US and Koliass *et al.* (2011) for the Greek retail industries; Rummyantsev and Netessine (2007) and Lee *et al.* (2015) for the US and Shan and Zhu (2013) for Chinese public firms across different industries:

H2. Inventory turnover is positively correlated with capital intensity.

Capital intensity measures the amount of fixed assets a company owns in comparison to its total assets. Higher capital intensity is an indication that a retailer invests more on warehouses, information technology, supply chain infrastructure and logistics, all of which have substantial effects on inventory productivity at retail organizations. A warehouse may lead to lower inventories in three ways for a retail firm. First, carrying inventory at a warehouse in a nearby location (closer than the supplier) effectively reduces the replenishment lead time a store faces and this clearly leads to reductions in safety inventory. Second, by allowing multiple stores to replenish jointly through a warehouse rather than directly from suppliers individually, a retailer can benefit from risk pooling and reduce its total inventory. These two types of benefits of warehouses under stochastic demand are called “depot effect” and “joint ordering effect” and are discussed in Eppen and Schrage (1981). Even when the demand is relatively stable, a warehouse may be used to consolidate shipments from multiple

suppliers to multiple stores, allowing stores to increase the frequency of their replenishments leading to a reduction in cycle inventories. An example is Wal-Mart which benefits tremendously from its warehouses through a strategy called cross-docking (Apte and Viswanathan, 2000). Investing in warehouse technologies such as automated storage and retrieval systems may also lead to reductions in a retailer's inventory through improved accuracy and lead times of orders which replenish stores.

Information technology can also offer substantial improvements for inventory management at retail firms. Examples of information technology that may help reduce inventory include enterprise resource planning solutions, which may improve accuracy of inventory and transactional records and reduce lead times and frequency of replenishment orders, supply chain management software that may improve forecast accuracy and determine inventory targets optimally and Markdown Optimization software that can be used to liquidate end of season inventories more effectively. Cachon and Fisher (2000) state that implementing information systems leads to more efficient allocation of inventory to stores, shorter lead times, lower cost of processing orders and higher inventory turns. Further improvements are possible by using information technology that allows a virtual integration between retailers and their suppliers. For example, Clark and Hammond (1997) report that compared to traditional ordering process, implementation of electronic data interchange in food retailers leads to a 50 percent increase in inventory turns. Achabal *et al.* (2000) report that two retailers improved their inventory turnover in the range of 18-76 percent by implementing a decision support system for vendor managed inventory. Based on these reasons, we hypothesize that firms with higher capital intensity carry less inventory, which leads to a higher inventory turnover rate.

We note that *H2* is supported in almost all papers that we have reviewed: Gaur *et al.* (2005) and Gaur and Kesavan (2008) for the US and Koliass *et al.* (2011) for the Greek retail industries; Rumyantsev and Netessine (2007) and Lee *et al.* (2015) for the US public firms in general. In Rajagopalan (2013), when new variables are included in addition to what is suggested in Gaur *et al.* (2005), the effect of capital intensity is no longer significant. In Johnston (2014), capital intensity has a surprising negative effect on inventory turnover. The author attributes this to increased number of stores at US retailers (instead of increased technology investment to support existing stores):

H3. Inventory turnover is positively correlated with sales surprise.

Sales surprise is the ratio of actual sales to forecasted demand. A firm is underestimating its demand if sales surprise is larger than one. The larger the sales surprise the larger the actual demand in comparison to the firm's projections for that year. This unexpectedly high demand leads to less inventory for the firm and higher inventory turnover rate for that year. Conversely, if a firm overestimates its demand, the sales surprise for that year is less than one. This unexpectedly low demand leads to an inventory level more than what is planned and thus lower turnover rate for that year. The effect of sales surprise on inventory turnover is investigated empirically in other papers starting with Gaur *et al.* (2005). All of these papers hypothesize that inventory turnover is positively correlated with sales surprise and find partial support for this hypothesis in the retail industry.

Gaur and Kesavan (2008) and Alan *et al.* (2014) define sales surprise slightly differently. Sales surprise or sales ratio as defined in Gaur and Kesavan (2008) in these papers is simply the ratio of current year's sales to previous year's sales. This is

essentially equivalent to using the previous year's sales as a forecast for this year's demand. Our definition of sales surprise is the same as that given in Gaur *et al.* (2005) and we also test the same hypothesis.

We note that *H3* is supported in all papers that we have reviewed: Gaur *et al.* (2005), Gaur and Kesavan (2008) and Johnston (2014) for the US and Koliass *et al.* (2011) for the Greek retail industries; Rummyantsev and Netessine (2007) and Lee *et al.* (2015) for the non-service US public firms across different industries:

H4. Inventory turnover is negatively correlated with demand uncertainty.

The fourth hypothesis we propose is based on the role of demand uncertainty identified clearly in stochastic inventory theory. The most fundamental model in stochastic inventory theory is the newsvendor problem. In the newsvendor problem, the optimal-order quantity is the critical fractile of the demand distribution. For a symmetric distribution and a critical fractile, which is more than 50 percent (which is equivalent to underage costs being more than overage costs; a condition that holds in almost all practical situations), this means that as the demand uncertainty increases so does the optimal-order quantity. Ordering more at the beginning of the period obviously leads to more leftover inventory at the end of the period (Nahmias, 2008; Cachon and Terwiesch, 2005). The effect of demand uncertainty on inventory is similar when the inventory/ordering decisions are driven by a service level instead, given that the service level is sufficiently high (e.g. more than 50 percent when the service level is defined as the probability of no stock-out).

The need to buffer more stock when faced with more demand uncertainty can also be shown in more complex models that involve multiple periods, multiple products, multiple echelons or setups. In fact, an important part of operations/supply chain management literature is devoted to how one can reduce exposure to or cope better with demand uncertainty and decrease inventory. Examples include push-pull systems (Simchi-Levi *et al.*, 2007), product postponement (Lee, 1996) and efforts to mitigate the bullwhip effect (Lee *et al.*, 2004).

As we discuss in the third section, we decide to use MAPE of quarterly sales forecasts in a given year to measure the demand uncertainty that a firm faces in that year. One can argue that MAPE of quarterly sales forecasts and annual sales surprise are very closely defined metrics. Our purpose for defining a new explanatory variable is as follows. Sales surprise only captures the "after the fact," one time impact of forecast errors on inventory. If in one year, a firm sold more than what it projected; its inventory would be less than what was projected. Alternatively, if a firm sold less than what it projected, its inventory would be more than was projected. With MAPE of quarterly forecasts, we would like to measure the impact of demand uncertainty on firm-level inventory decisions. If a firm knows that it is exposed to high forecast inaccuracy (or high demand uncertainty), it would stock more safety stock to maintain its service level (which is assumed to be high in retail). On the other hand, if a firm's forecasts are usually accurate, it would not plan for too much stock.

While the effect of demand uncertainty on a given inventory model is rather clear, we also need to mention its possible effect on operational practices of retail firms. Retailers that are exposed to high demand uncertainty may choose to work with suppliers with shorter lead times or may want to adopt pull-based strategies. This may lead to better inventory performance for such retailers. The testing of *H4* will help us to understand whether and where this effect dominates the classical effect of uncertainty on inventories across US retail segments.

We note again that $H4$ is tested in three earlier papers using different proxies for demand uncertainty. In the earliest of these papers, Rumyantsev and Netessine (2007) use the variance of the residuals from a regression model that fits each firm's sales as a function of seasonal and trend variables. Their results from 722 US public firms in various industries show that inventory turnover is negatively associated with demand uncertainty overall. However, the analysis for the retail industry (focus of this paper) separately shows a surprising positive association. Rajagopalan (2013) uses two different proxies and tests this hypothesis using data from the US retail industry. When $(1-R^2)$ of a regression model (similar to what is used in Rumyantsev and Netessine, 2007) is used as a proxy, the effect of demand uncertainty is either insignificant or the opposite of the direction hypothesized here. When the range of sales surprise is used as a proxy, the effect of demand uncertainty is either insignificant or weakly significant in the hypothesized direction. In Shan and Zhu (2013), the proxy used is similar to what is used in Rumyantsev and Netessine (2007), however the regression model is a pooled model with fixed effects for each firm. We believe that this proxy is hard to justify as it assumes that seasonality and time affects each firm the same way. The test of the hypothesis using data from Chinese retail firms shows a strong association between this measure of demand uncertainty and aggregate inventory.

Model specification

We develop linear regression models by performing a logarithmic transformation on all independent variables and the dependent variable, in order to accommodate the skewness in data and reduce heteroskedasticity. This is in line with the previous work of Gaur *et al.* (2005), Rumyantsev and Netessine (2007) and Rajagopalan (2013) who also use log-linear specification to obtain a better fit to the data with lower prediction errors. In order to further justify the log-linear specification, Gaur *et al.* (2005) compare the prediction errors of both linear and log-linear models by simulating a periodic-review inventory model with stationary demand for various values of gross margin, lead time, and variance of demand and find that log-linear models lead to smaller prediction errors. Lee *et al.* (2015) show with retail data that the distributions of the log-transformed variables are closer to normal. Hence, log-linear transformation is more appropriate for empirical tests and statistical inferences. We note that when we have logarithmic transformation on both a dependent variable Y and an independent variable X and postulate a model $\ln Y = b^0 + b^1 \ln X$, a p percent increase in the independent variable X will lead to $100 \times (\exp(b^1 \times \ln(1 + 0.01 \times p)) - 1)$ percent change in the dependent variable Y .

We now present our empirical models. The first three models pool the data from all segments of the retail industry, whereas the last two models include regressions for each segment.

Model 1

Model 1 uses firm- and time-specific fixed effects and uses all of the variables GM , CI , SS and $MAPE$ as independent variables. Using firm-specific fixed effects allows us to account for factors that are specific to each firm but that are omitted in our dataset. Some of these factors such as managerial efficiency, location strategy or marketing may have an impact on inventory turnover. Similarly, time-specific fixed effects are used to control for general changes over time such as economic conditions or

interest rates. Let F_i denote time-invariant firm-specific fixed effect for firm i , c_t denote year-specific fixed effect for year t , b^1 , b^2 , b^3 and b^4 denote the pooled estimates for the coefficients for $\ln GM_{sit}$, $\ln CI_{sit}$, $\ln SS_{sit}$ and $\ln MAPE_{sit}$, respectively; and ε_{sit} denotes the error term for the observation for year t for firm i in segment s . *H1-H4* imply that, b^1 and b^4 must be less than 0, and b^2 and b^3 must be greater than 0:

$$\ln IT_{sit} = F_i + c_t + b^1 \ln GM_{sit} + b^2 \ln CI_{sit} + b^3 SS_{sit} + b^4 \ln MAPE_{sit} + \varepsilon_{sit} \quad (1)$$

Model 2

Model 2 also uses pooled estimates. In contrast to Model 1, Model 2 uses segment-specific fixed effects, F_s , rather than firm-specific fixed effects. Using segment-specific fixed effects, we allow the coefficients of independent variables to be different in different segments. We expect Model 2 to explain less of the total variability in inventory turnover ratios as firm-specific fixed effects are now dropped. However, Model 2 is useful in explaining the variability across different firms and can be used for benchmarking purposes. Again, our four hypotheses imply that $b^1 < 0$, $b^2 > 0$, $b^3 > 0$ and $b^4 < 0$:

$$\ln IT_{sit} = F_s + c_t + b^1 \ln GM_{sit} + b^2 \ln CI_{sit} + b^3 SS_{sit} + b^4 \ln MAPE_{sit} + \varepsilon_{sit} \quad (2)$$

Model 3

Model 3 also uses pooled estimates but drops both the firm-specific and segment-specific effects. We only have a time-specific fixed effect in Model 3. Again, the four hypotheses imply that $b^1 < 0$, $b^2 > 0$, $b^3 > 0$ and $b^4 < 0$:

$$\ln IT_{sit} = c_t + b^1 \ln GM_{sit} + b^2 \ln CI_{sit} + b^3 SS_{sit} + b^4 \ln MAPE_{sit} + \varepsilon_{sit} \quad (3)$$

Model 4

In Model 4, we have separate regressions for each segment of the retail industry. In this case, b_s^1 , b_s^2 , b_s^3 and b_s^4 denote coefficients for $\ln GM_{sit}$, $\ln CI_{sit}$, $\ln SS_{sit}$, and $\ln MAPE_{sit}$ for segment s . Similar to Model 1, we have firm-specific and time-specific fixed effects. The four hypotheses imply that $b_s^1 < 0$, $b_s^2 > 0$, $b_s^3 > 0$ and $b_s^4 < 0$ for each segment s :

$$\ln IT_{sit} = F_i + c_t + b_s^1 \ln GM_{sit} + b_s^2 \ln CI_{sit} + b_s^3 SS_{sit} + b_s^4 \ln MAPE_{sit} + \varepsilon_{sit} \quad (4)$$

Model 5

Model 5 is also specific to each retail segment. Different from Model 4, we remove the firm-specific fixed effects in this model. Again our hypotheses imply that $b_s^1 < 0$, $b_s^2 > 0$, $b_s^3 > 0$ and $b_s^4 < 0$ for each segment s :

$$\ln IT_{sit} = F_s + c_t + b_s^1 \ln GM_{sit} + b_s^2 \ln CI_{sit} + b_s^3 SS_{sit} + b_s^4 \ln MAPE_{sit} + \varepsilon_{sit} \quad (5)$$

Results

We use ordinary least squares (OLS) method to estimate the parameters in Models 1-5. OLS estimators are used in almost all papers cited above. The pooled estimates for the coefficients of $\ln GM$, $\ln CI$, $\ln SS$ and $\ln MAPE$ and R^2 for Models 1-3 are reported

in Table III. The standard errors are reported in parentheses for each estimate. *H1-H3* are supported in all three models with $p < 0.01$. *H4* is supported with $p < 0.01$ in Model 1 and with $p < 0.05$ in Models 2 and 3. When firm-specific fixed effects are included (Model 1), the four variables are able to explain 93.4 percent of the variation in inventory turnover ratios in our data. As variation across firms is captured with firm-specific fixed effects, this means that the four variables explain 93.4 percent of the within-firm variation using pooled estimates. When segment-specific fixed effects are considered (Model 2), the four variables can explain 73.7 percent of the variation (within and across firms) in inventory turnover ratio. We believe that this is a substantial portion of the variation and shows that the variables GM, CI, SS and MAPE can be used to adequately benchmark a firm's inventory performance against its competitors and over time. Using the multiplicative model in (2) and coefficient estimates for Model 2, one can show that a one percent increase in GM and MAPE lead to 0.5692 and 0.0169 percent reduction in inventory turnover rate while the same one percent increase in CI and SS lead to 0.3989 and 0.1610 percent increase in inventory turnover rate (note again that for a log-log model like ours, a p percent increase in the independent variable will lead to $100 \times (\exp(b \times \ln(1 + 0.01 \times p)) - 1)$ percent change in the dependent variable where b is the parameter estimate for the logarithm of the independent variable). While 0.0169 seems small in absolute terms, a more appropriate judgment should be based on considering the fact that there is large variation in MAPE within and across segments. A one standard deviation increase in MAPE (equivalent to 128 percent increase in MAPE, see Table II) of an average retailer leads to a 1.388 percent decrease in its inventory turnover rate.

The segmentwise coefficient estimates for Model 4 (where we have firm-specific fixed effects) are reported in Table IV. *H1* is supported with $p < 0.01$ in all segments of the retail industry. *H2* is supported in eight segments with $p < 0.01$. The effect of capital intensity is insignificant in two segments. *H3* is supported in five segments, three with $p < 0.01$ and two with $p < 0.05$. *H4* is supported in five segments, three with $p < 0.01$ and two with $p < 0.05$. The most pronounced negative effect of demand uncertainty on inventory turnover rate is in drug and proprietary stores, where a one percent increase in MAPE leads to a 0.0643 percent decrease in inventory turnover rate. A 1 SD increase in MAPE of an average retailer in this segment leads to 6.769 percent decrease in inventory turnover rate. Surprisingly, demand uncertainty as measured by MAPE, has a significant ($p < 0.01$) positive effect on inventory turnover rate in hobby, toy and game shops. While similar results are reported in Rumyantsev and Netessine (2007) and Rajagopalan (2013) for the retail industry as a whole, we seem to isolate this interesting result for a specific segment of the retail industry. (We will explain the results in detail for each segment below once we also provide the results for Model 5). With firm-specific effects, the four variables can explain 85.1-96.3 percent of the within-firm variation.

The segmentwise coefficient estimates for Model 5 (where we have no firm-specific fixed effects) are reported in Table V. In this case, *H1* and *H2* are supported in all ten

Model	ln GM	ln CI	ln SS	ln MAPE	R ²
1	-0.2675 (0.0118)***	0.2293 (0.0108)***	0.1079 (0.0135)***	-0.0167 (0.0051)***	93.4
2	-0.5737 (0.0145)***	0.4001 (0.0111)***	0.1617 (0.0248)***	-0.0170 (0.0077)**	73.7
3	-0.7255 (0.0170)***	0.5823 (0.0119)***	0.1672 (0.0314)***	-0.0216 (0.0092)**	57.3

Table III.
Coefficient estimates
for Models 1-3

Notes: Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table IV.
Coefficient estimates
for Model 4

Segment	ln GM	ln CI	ln SS	ln MAPE	R ²
Apparel and accessory stores	-0.2082 (0.0159)***	0.2132 (0.0231)***	0.0462 (0.0309)	-0.0259 (0.0084)***	89.5
Catalog, mail-order houses	-0.3101 (0.0653)***	0.2074 (0.0353)***	0.2387 (0.0642)***	-0.0464 (0.0295)	85.6
Department stores	-0.2609 (0.0273)***	0.3046 (0.0453)***	0.1880 (0.0311)***	-0.0242 (0.0112)**	84.1
Drug and proprietary stores	-0.6429 (0.0748)***	0.2413 (0.0493)***	0.0937 (0.0243)***	-0.0646 (0.0219)***	94.3
Food stores	-0.2054 (0.0200)***	0.2623 (0.0324)***	0.0878 (0.4168)**	0.0134 (0.0084)	85.9
Hobby, toy, and game shops	-0.1468 (0.0377)***	-0.0203 (0.0661)	0.1076 (0.1140)	0.0912 (0.0308)***	91.0
Home furniture and equip. stores	-0.4153 (0.0887)***	0.5517 (0.0487)***	-0.0224 (0.0951)	0.0005 (0.0243)	85.1
Jewelry stores	-0.8382 (0.0921)***	0.2962 (0.0475)***	0.1140 (0.0788)	-0.0029 (0.0276)	92.2
Radio, TV, consumer electronics stores	-0.1234 (0.0300)***	-0.0039 (0.0360)	-0.0228 (0.0683)	-0.0408 (0.0171)**	88.4
Variety stores	-0.2826 (0.0514)***	0.0734 (0.0139)***	0.0924 (0.0377)**	-0.0295 (0.0087)***	96.3

Notes: Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table V.
Coefficient estimates
for Model 5

Segment	ln GM	ln CI	ln SS	ln MAPE	R ²
Apparel and accessory stores	-0.3392 (0.0242)***	0.4266 (0.0206)***	0.0281 (0.0599)	-0.0059 (0.0144)	54.6
Catalog, mail-order houses	-0.9488 (0.0473)***	0.3767 (0.0300)***	0.3382 (0.0942)***	-0.1132 (0.0341)***	59.8
Department stores	-0.2444 (0.0346)***	0.2210 (0.0293)***	0.1964 (0.0556)***	-0.0502 (0.0159)***	42.2
Drug and proprietary stores	-1.0119 (0.0717)***	0.5052 (0.0385)***	0.0546 (0.0766)	-0.0377 (0.0267)	78.4
Food stores	-0.2730 (0.0285)***	0.4559 (0.0397)***	-0.0844 (0.0879)	-0.0306 (0.0141)**	25.8
Hobby, toy, and game shops	-0.2537 (0.0602)***	0.1725 (0.0443)***	0.2269 (0.2147)	0.1033 (0.0454)**	56.4
Home furniture and equip. stores	-0.7739 (0.1178)***	0.5246 (0.0564)***	0.2411 (0.2067)	0.1985 (0.03413)***	49.4
Jewelry stores	-0.9791 (0.0651)***	0.4226 (0.0567)***	0.2351 (0.1234)*	-0.0469 (0.0377)	78.2
Radio, TV, consumer electronics stores	-0.4011 (0.0483)***	0.1826 (0.0506)***	0.1567 (0.1341)	-0.0947 (0.0313)***	46.1
Variety stores	-1.0100 (0.0376)***	0.2666 (0.0177)***	0.1463 (0.0746)*	-0.0492 (0.0147)***	82.4

Notes: Standard errors are in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

segments of the retail industry with $p < 0.01$. $H3$ is supported in four segments, two with $p < 0.01$ and two with $p < 0.1$. $H4$ is supported in five segments, four with $p < 0.01$ and one with $p < 0.05$. The most significant negative effect of demand uncertainty on inventory turnover rate is in catalog and mail-order houses, where a one percent increase in MAPE leads to a 0.113 percent decrease in inventory turnover rate.

A 1 SD increase in MAPE of an average retailer in this segment leads to 6.736 percent decrease in inventory turnover rate. R^2 without the firm-specific fixed effects are substantially lower. Nevertheless, the four variables explain more than 50 percent of the variation inventory turnover rate within and across firms in six segments.

Once again, we also see a surprising significant positive effect of MAPE. This time we have two segments, home furniture and equipment stores and hobby, toy and game

shops, where the inventory turnover rate increases with higher MAPE (with $p < 0.01$ and $p < 0.05$, respectively). Since we do not have firm-specific fixed effects in Model 5, this positive association can be explained by how different retailers respond to uncertainty using different practices.

There are important differences between the effects of MAPE on the inventory turnover performance across different segments and in Models 4 and 5. Therefore, we provide more detailed explanations for these differences. The results of Models 4 and 5 along with summary data on different segments are provided in Table VI.

In apparel and accessory stores segment, MAPE has a significant effect on inventory turnover when fixed effects for the firms are considered (Model 4). This shows that, as expected, the apparel and accessory retailers respond to higher demand uncertainty by carrying more inventory. However, this segment is rather diverse and there seems to be significant differences in capabilities and practices across different firms which cannot be explained by capital intensity. For example, firms that are subject to higher demand uncertainty may be using pull approach predominantly, leading to lower inventory for those firms. These differences dominate the effect of uncertainty on within-firm variation. Therefore, when the firm-specific effects are removed, the effect of MAPE is no longer significant.

The effect of demand uncertainty in catalog and mail-order houses seems to be entirely different. In this case, MAPE does not have a significant effect on inventory performance when the firm-specific effects are considered. This is perhaps due to the fact that changes in MAPE are rather small from one period to the other. This is plausible since these are usually mass retailers (e.g. Amazon.com, Lands' End) that offer huge numbers of SKUs in many different categories and our metric is an

Segment	Number of firms	Examples	Average IT	Model 4 ln MAPE	Model 5 ln MAPE
Apparel and accessory stores	73	Gap, Ann Taylor, Foot Locker	4.111 (1.691)	Negative***	
Catalog, mail-order houses	39	Amazon.com, Lands' End, Spiegel	8.741 (7.828)		Negative***
Department stores	21	Macy's, Neiman Marcus, J.C. Penney	3.222 (0.816)	Negative**	Negative***
Drug and proprietary stores	23	CVS, Rite Aid, Eckerd	9.574 (12.305)	Negative***	
Food stores	54	Albertson's, Kroger, Safeway	11.379 (4.487)		Negative**
Hobby, toy, and game shops	7	Toys R US, Michaels Stores, Noodle Kidoodle	2.652 (0.905)	Positive***	Positive**
Home furniture and equip. stores	19	Bed Bath & Beyond, Cost Plus, Pier 1 Imports	3.942 (5.132)		Positive***
Jewelry stores	14	Zale, Tiffany, Finlay Fine Jewelry	2.323 (4.303)		
Radio, TV, consumer electronics stores	17	Best Buy, Circuit City, Radio Shack	3.776 (1.382)	Negative**	Negative***
Variety stores	37	Wal-Mart, Target, 99 Cents Only	4.154 (2.398)	Negative**	Negative***

Table VI.
Summary results for
Models 4 and 5

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

aggregate metric. When the firm-specific effects are removed, the effect of MAPE is significant. This shows that, in this segment, firms that face higher uncertainty also carry more inventory; differences in operational practices or capabilities seem to be small.

In the department stores segment, MAPE has a significant negative effect on inventory turnover rate with or without firm-specific effects. An individual firm carries more inventory when it faces more uncertainty and firms that face more uncertainty than their counterparts carry more inventory. This shows that there are no significant differences in the way that firms operate in this segment (presumably more push) and changes in the level of uncertainty do not usually lead to changes in operational practices of individual firms. Firms respond to more uncertainty by simply increasing their inventory, as predicted in theory and hypothesized in this study.

Results for the drug and proprietary stores are similar to what is seen in apparel and accessory stores. When only within-firm variability is considered, the effect of MAPE is significant. When the firm-specific effects are dropped, the relationship between MAPE and inventory turnover is not significant. This may show that there may important differences between operational practices of the firms in this segment. In addition, there may be important differences in the product categories (aside from drugs) that are carried in these firms.

Results for the food stores are similar to catalog and mail-order houses segment except that the effect of MAPE when the firm fixed effects are removed is less significant. Again, we can argue that the level of exposure to overall uncertainty is not likely to change over time for these firms since they are selling products (food) for which the demand is rather stable. Therefore the effect of MAPE on individual inventory turnover is insignificant. However, in general, firms that are subject to more uncertainty carry more inventory than their counterparts.

The segment for hobby, toy and game shops exhibit the most counter-intuitive results. The effect of MAPE is significant in both models. However the sign is the opposite of what is hypothesized. First, Model 4 shows that firms that face more uncertainty than their counterparts carry less inventory. Note that this segment is a diverse segment (Michaels Stores vs Toys R Us). It appears that firms that are exposed to more uncertainty operate in significantly different ways than those firms that face less uncertainty. This even leads to carrying less inventory. Second, Model 5 shows that as an individual firm exposes to more uncertainty, it changes its own operational practices. Given that some of the industries that are listed in this segment are in constant change (toy and game shops), it may be argued that firms also change their operational practices to better respond to demand uncertainty along the way, leading to less inventory even though they are exposed to more uncertainty. For example, when faced with high uncertainty, some of the firms in this segment may be choosing to work with vendors with shorter lead times or move from push-based strategies to pull-based strategies. It is also possible that some of the firms in this segment operate under newsvendor-like settings (e.g. toy shops) and operate under very low service levels.

The effect of MAPE on home furniture and equipment stores is similar when the firm-specific effects are controlled. Again, one can argue that in this segment there is diversity in operational practices leading to more inventory turnover for those firms that have larger MAPE. For example, a furniture retailer which is exposed to higher demand uncertainty may use a pull-based model, while another with less demand uncertainty adopts a push system, perhaps leading to a higher inventory turnover ratio for the former. However, when the firm-specific effects are accounted for, the effect of

MAPE is no longer significant. Given these results in the last two segments, it may be also worthwhile to consider other factors (that are not captured by our existing independent variables) that moderate the effect of demand uncertainty on inventory performance of a firm in these segments.

In jewelry stores segment, MAPE does not seem to have any significant effect on inventory turnover. In the US jewelry industry, 80 percent of the sales come from fast selling items while only 10 percent of the inventory is for such items. Therefore, the volatility in total demand seems to have a negligible effect on how much inventory is kept in total. This happens even when the firm-specific fixed effects are not accounted for.

The segments for radio, TV, consumer electronics stores and variety stores are very similar to the department stores segment. All of these industries are well established and changes in operational practices from one firm to the other or from one period to the other are rather limited. Firms simply respond to higher uncertainty by carrying more safety stock.

Our results show that gross margin, capital intensity, sales surprise and demand uncertainty have significant effects on inventory turnover rate, and one has to control for differences in these factors when comparing the performance of a firm with its competitors. To do this, one can use the residuals from Model 5, where we have a segment-specific regression without firm-specific fixed effects. We first predict the inventory turnover of firm i in segment s in year t using:

$$\ln \widehat{IT}_{sit} = \widehat{F}_s + \widehat{c}_t + \widehat{b}_s^1 \ln GM_{sit} + \widehat{b}_s^2 \ln CI_{sit} + \widehat{b}_s^3 \ln SS_{sit} + \widehat{b}_s^4 \ln MAPE_{sit} \quad (6)$$

where \widehat{F}_s is the estimate of the constant for segment s , \widehat{c}_t the estimate of the time effect for period t and $\widehat{b}_s^1, \widehat{b}_s^2, \widehat{b}_s^3$ and \widehat{b}_s^4 are the coefficient estimates for $\ln GM, \ln CI, \ln SS$ and $\ln MAPE$, respectively, given in Table V. The residual for firm i in segment s in year t is then $\ln IT_{sit} - \ln \widehat{IT}_{sit}$. Firms with positive residuals are considered to overperform and firms with negative residuals are considered to underperform compared to their peers in the same segment. We illustrate this approach for six retail segments in Figures 1-6 by plotting the residuals of some of the well-known retailers over time.

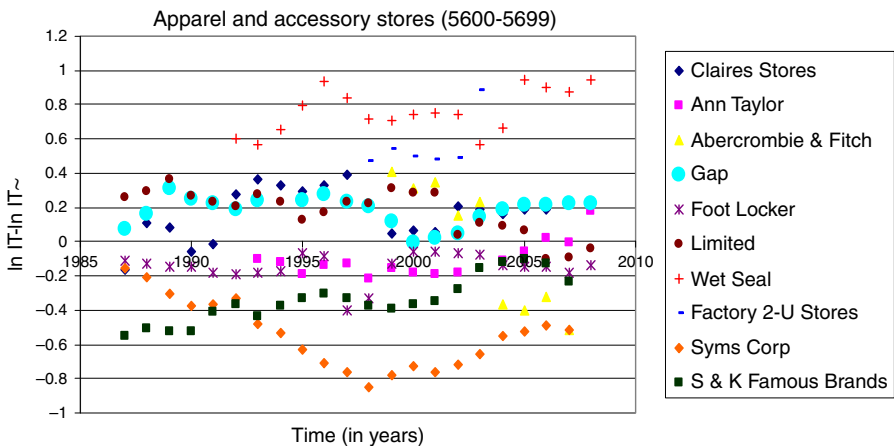


Figure 1.
Apparel and
accessory stores

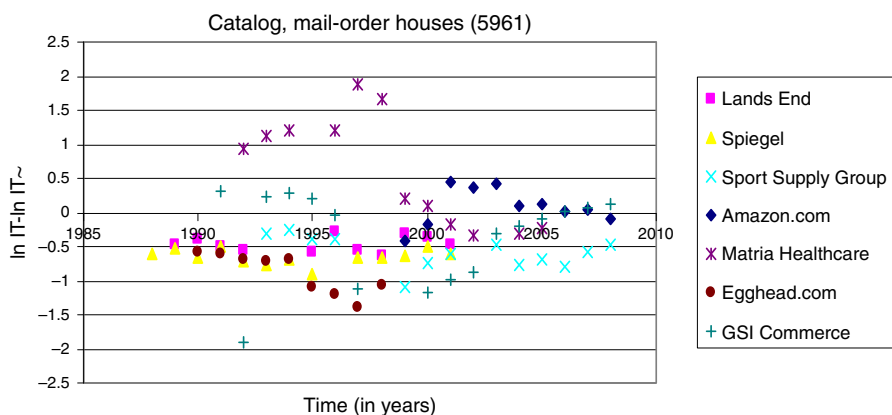


Figure 2.
Catalog, mail-order houses

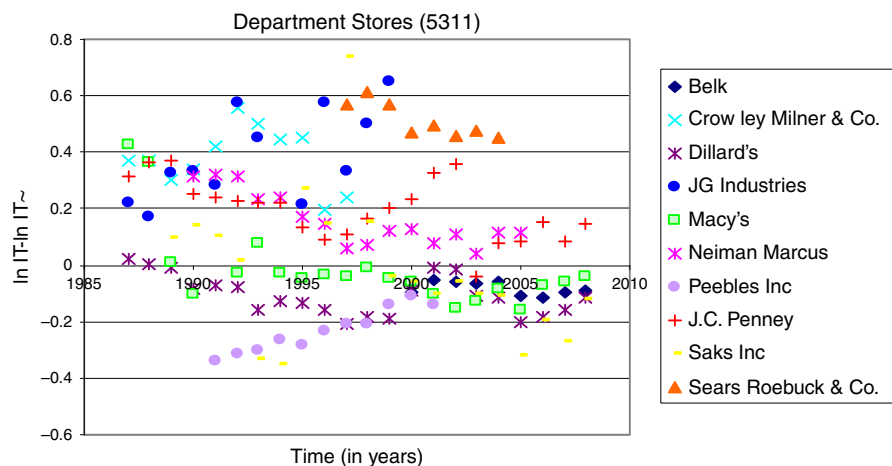


Figure 3.
Department stores

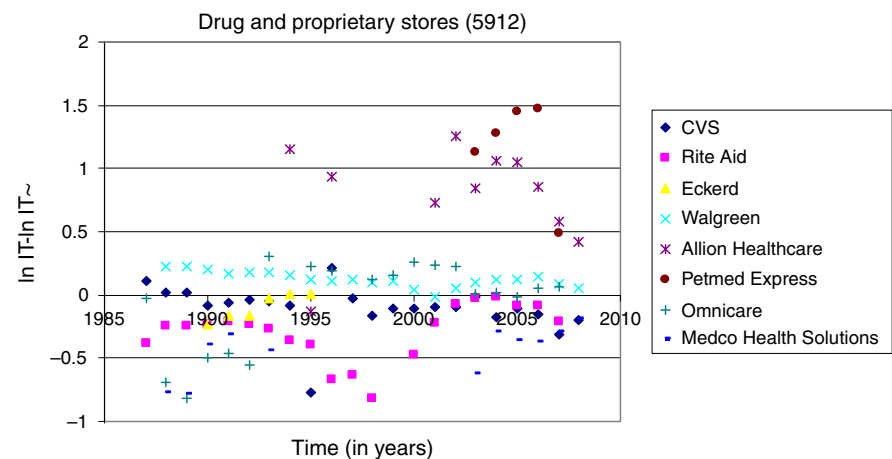


Figure 4.
Drug and proprietary stores

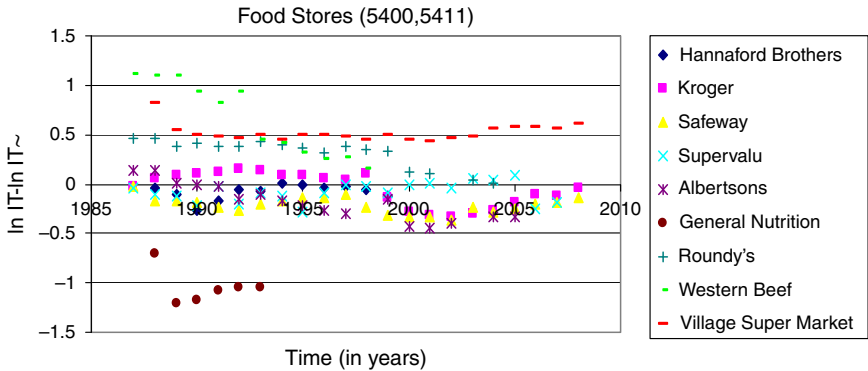


Figure 5.
Food stores

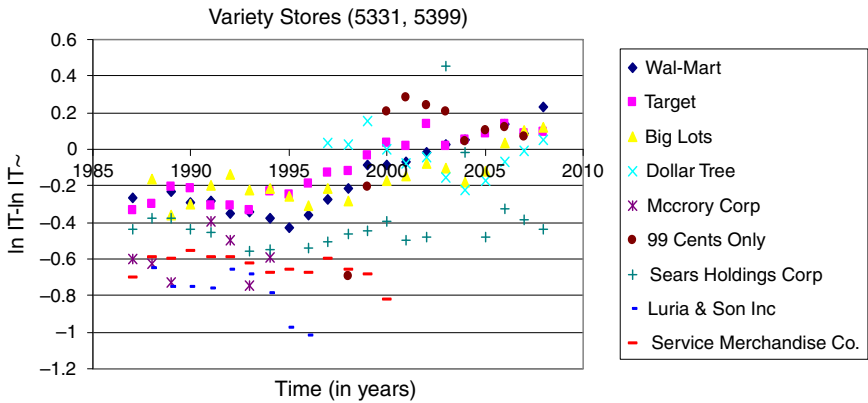


Figure 6.
Variety stores

Conclusion

In this paper, we empirically investigate the effects of gross margin, capital intensity, sales surprise and demand uncertainty on the inventory turnover rates in the US retail industry. The first three factors are suggested in earlier literature and are shown to have significant effects on the inventory performance of a retail firm. In order to measure demand uncertainty, we define a new proxy, MAPE (MAPE) of quarterly sales forecasts obtained through times series forecasting. Empirical models using these variables are tested on sample financial data for 304 publicly listed US retail firms for the 25-year period 1985-2009 obtained from Standard & Poor's Compustat database using WRDS.

We show that these four variables can explain 73.7 percent of the variation across firms and over time and 93.4 percent of the within-firm variation in the retail industry as a whole. Demand uncertainty, as defined by the new proxy that we propose, has a significant negative effect on the inventory turnover rate, confirming the predictions of inventory theory. When the analysis is carried out separately for each segment, the negative effect of the MAPE of quarterly sales forecasts is found to be statistically significant in five of the ten retail segments. Surprisingly, our proxy has a significant positive effect on inventory performance in the home furniture and equipment and hobby, toy and game shops segments of the industry. This shows that the effect of

certain operational practices that some retailers use when they face demand uncertainty may dominate the classical effect of demand uncertainty on inventory performance. Given these rather surprising results, future research may be required to study these two segments in more detail. This can be done by finding other factors that may moderate the inventory performance in these segments (and quantifying them by publicly available data). Another approach may be to study a group of individual firms in these segments and investigate the differences in their operational practices and changes over time.

Our empirical results show that the new proxy we propose is more robust in capturing the demand uncertainty that firms face when making inventory decisions in comparison to other proxies suggested in Rumyantsev and Netessine (2007) and Rajagopalan (2013). This new proxy can be easily calculated by using financial data that public firms report in their quarterly and annual income statements. We also believe that it better captures the uncertainty each firm faces individually as it is based on running time series forecasting separately for each firm using sales data from only that firm (unlike the proxy suggested in Shan and Zhu, 2013 which requires data from every firm in the industry). The new proxy can also be used for other empirical investigations. For example, it may be interesting to study the effect of demand uncertainty on operational practices of firms and on key financial performance indicators or operational metrics other than inventory turnover rate. In addition, it may be used to quickly measure a firm's exposure to demand uncertainty using publicly available data and see how this changes over time and guide retailers in designing supply chains that cater to the level of demand uncertainty they face (Fisher, 1997).

This paper contributes to the growing empirical literature that investigates the sources of variation in inventory productivity across different firms and over time. In particular, we extend the literature (e.g. Gaur *et al.*, 2005; Gaur and Kesavan, 2008; Rajagopalan, 2013) that studies the effect of various financial measures on inventory turnover ratio in the retail industry. We show that the three hypotheses tested in Gaur *et al.* (2005) prevail with a more recent and larger dataset and even after we account for a new variable that measures demand uncertainty. Gaur *et al.* (2014) note that it is crucial to refine the traditional metrics of inventory productivity (e.g. inventory turnover rate or days of inventory) to account for different financial factors so that lenders, suppliers and investors can better assess whether a particular retailer carries too much or too little inventory compared to its peers or compared to its own prior performance. Earlier research also shows that inventory productivity may be used successfully to predict future stock returns (e.g. Alan *et al.*, 2014). Since we add a new explanatory variable and show that its effect is significant on inventory performance, we argue that the adjusted inventory turnover ratio that also accounts for this variable will be a more useful metric for benchmarking or predicting future stock performance. Benchmarking using this metric may help firms in improving their operations to better cope with demand uncertainty and improve their inventory management practices in general. It may be also interesting to study whether this new metric leads to better predictions than those made in Alan *et al.* (2014).

This study can be extended in a number of ways. One may investigate to see whether a more appropriate measure can be developed for demand uncertainty. In this study, we use a statistical time series forecasting method to determine forecasts and use the resulting errors to quantify demand uncertainty. An alternative way could be to use the forecasts that are developed by the firms themselves or by independent financial analysts. One can also investigate other factors such as replenishment lead

time, supplier reliability and product variety that may be affecting inventory performance of a firm jointly with demand uncertainty. Additional factors such as competition may have separate effects and may help to explain more of the variation in inventory performance of retail firms.

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Appendix

We obtain the data from Compustat to calculate the independent variables that we use in our study. All data are in units of million US dollars. S_{sit} : sales, net of markdowns in dollars for firm i in segment s in year t ; CGS_{sit} : cost of goods sold in dollars for firm i segment s in year t ; INV_{sitq} : inventory valued at cost for firm i segment s at the end of quarter q in year t ; GFA_{sitq} : gross fixed assets for firm i segment s at the end of quarter q in year t ; A_{sitq} : total assets for firm i segment s at the end of quarter q in year t ; C_{sitq} : current assets for firm i segment s at the end of quarter q in year t .

Based on the data above, we define and compute the following performance variables: inventory turnover, gross margin, capital intensity, sales surprise and MAPE.

Inventory turnover rate is the ratio of cost of goods sold to average inventory levels:

$$IT_{sit} = \frac{CGS_{sit}}{\frac{1}{4} \sum_{q=1}^4 INV_{sitq}}$$

Gross margin is the ratio of gross profit net of markdowns to actual sales:

$$GM_{sit} = \frac{S_{sit} - CGS_{sit}}{S_{sit}}$$

Capital intensity is the ratio of average fixed assets to average total assets:

$$CI_{sit} = \frac{\sum_{q=1}^4 GFA_{sitq}}{\sum_{q=1}^4 INV_{sitq} + \sum_{q=1}^4 GFA_{sitq}}$$

where $GFA_{sitq} = A_{sitq} - C_{sitq}$.

Sales surprise is the ratio of actual sales to expected sales for the year:

$$SS_{sit} = \frac{S_{sit}}{SF_{sit}}$$

where SF_{sit} is the annual sales forecast for firm i in segment s in year t . In order to calculate F_{sit} , we follow Gaur *et al.* (2005) and use Holt's double exponential smoothing method. We use the formulae in Nahmias (2008) and compute the one-step-ahead forecast SF_{sit} for given smoothing constants α ($0 \leq \alpha \leq 1$) and β ($0 \leq \beta \leq 1$) as follows:

$$T_{sit} = \alpha S_{sit} + (1 - \alpha)(T_{si,t-1} + G_{si,t-1}),$$

$$G_{sit} = \beta(T_{sit} - T_{si,t-1}) + (1 - \beta)G_{si,t-1},$$

$$SF_{sit} = T_{si,t-1} + G_{si,t-1},$$

where T_{sit} and G_{sit} are the estimates for the intercept and slope, respectively for firm i in segment s in year t . In order to be consistent with the results in Gaur *et al.* (2005), we use $\alpha = \beta = 0.75$ in our method.

MAPE is the MAPE of quarterly forecasts for a year and is given as follows:

$$MAPE_{sit} = \frac{1}{4} \sum_{q=1}^4 100 \times \frac{|S_{sitq} - SF_{sitq}|}{S_{sitq}},$$

where SF_{sitq} is the quarterly sales forecast for firm i in segment s in quarter q of year t . In order to determine SF_{sitq} , we use Winter's triple exponential smoothing method. We use the formulae in Nahmias (2008) and calculate the one-step-ahead forecast SF_{sit} for given smoothing constants α ($0 \leq \alpha \leq 1$), β ($0 \leq \beta \leq 1$) and γ ($0 \leq \gamma \leq 1$) as follows:

$$T_{sitq} = \alpha \left(\frac{S_{sitq}}{c_{sit,q-4}} \right) + (1 - \alpha)(T_{sit,q-1} + G_{sit,q-1}),$$

$$G_{sitq} = \beta(T_{sitq} - T_{sit,q-1}) + (1 - \beta)G_{sit,q-1},$$

$$c_{sitq} = \gamma \left(\frac{S_{sitq}}{T_{sitq}} \right) + (1-\gamma)c_{sit,q-4},$$

$$SF_{sitq} = (T_{sit,q-1} + G_{sit,q-1})c_{sit,q-4},$$

where T_{sitq} , G_{sitq} and c_{sitq} are the estimates for the intercept, slope and seasonality, respectively, for firm i in segment s in quarter q of year t . We initialize the Winter's method as described in Nahmias (2008). In order to determine the values of α , β , and γ , we tried five different values for each parameter from the set (0.1, 0.3, 0.5, 0.7, 0.9) and evaluated 125 different alternatives for each firm. For each firm, we selected the combination that minimizes the MAPE over the setup period.

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