An Econometric Analysis of Inventory Turnover Performance in Retail Services

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Abstract

Inventory turnover varies widely across retailers and over time. This variation undermines the usefulness of inventory turnover in performance analysis, benchmarking and working capital management. We develop an empirical model using financial data for 311 public-listed retail firms for the years 1987-2000 to investigate the correlation of inventory turnover with gross margin, capital intensity and sales surprise (the ratio of actual sales to expected sales for the year). The model explains 66.7% of the within-firm variation and 97.2% of the total variation (across and within firms) in inventory turnover. It yields an alternative metric of inventory productivity, Adjusted Inventory Turnover, which empirically adjusts inventory turnover for changes in gross margin, capital intensity and sales surprise, and can be applied in performance analysis and managerial decision-making. We also compute time-trends in inventory turnover and Adjusted Inventory Turnover, and find that both have declined in retailing during 1987-2000.

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1. Introduction

The total inventory investment of all U.S. retailers averaged $449 billion during the year 2003.[1] On average, inventory represents 36% of total assets and 53% of current assets for retailers[2]. Since such a significant fraction of the retailers' assets are invested in inventory, retailers and stock market analysts focusing on retailers pay close attention to inventory productivity. Retailers continuously seek to improve their inventory management processes and systems to reduce inventory levels. Stock market analysts track such practices and reward retailers on gains in their inventory productivity (see, for example, Standard & Poor's surveys on the retailing industry (Sack 2000)).

Inventory turnover, the ratio of a firm's cost of goods sold to its average inventory level, is commonly used to measure performance of inventory managers, compare inventory productivity across retailers, and assess performance improvements over time. However, we find that the annual inventory turnover of U.S. retailers varies widely not only across firms but also within firms from one year to another. For example, during 1987-2000, the annual inventory turnover at Best Buy Stores, Inc. (Best Buy), a consumer electronics retailer, ranged from 2.85 to 8.53. The annual inventory turnover at three peer retailers of Best Buy during the same period shows similar variation: at Circuit City Stores, Inc. from 3.97 to 5.60, at Radio Shack Corporation from 1.45 to 3.05, and at CompUSA, Inc. from 6.20 to 8.65. The factors influencing these variations have not been studied systematically to our knowledge. Thus, the extent to which they indicate better or worse performance in inventory productivity is not known.

In addition, inventory turnover can be correlated with other performance measures in a firm. Figure 1 plots the annual inventory turnover of the above four consumer electronics retailers against their gross margins (the ratio of gross profit net of markdowns to net sales) for the period 1987-2000. The figure shows a strong correlation between inventory turnover and gross margin. Such correlation could

[1] According to the 2003 Monthly Retail Trade Surveys of the U.S. Census Bureau.
[2] These values are computed from our dataset, which contains quarterly values of inventory, total assets, current assets and other variables for all public retailers across 10 product-market segments for the period 1985-2000. The dataset includes 311 firms. It is constructed using Standard and Poor's Compustat database and is summarized in section 2.

possibly be caused by many factors studied in the operations literature, such as differences in variety and price. It raises the question whether inventory turnover should be used per se in performance analysis.

This paper uses public financial data to conduct a descriptive investigation of inventory turnover performance in retail services. We identify the following variables that should be correlated with inventory turnover and can be measured from public financial data: gross margin, capital intensity (the ratio of average fixed assets to average total assets), and sales surprise (the ratio of actual sales to expected sales for the year). Using results from the existing literature, we formulate hypotheses to relate these variables to inventory turnover. We then propose an empirical model to represent these relationships and apply it to a panel of retailing data.

Our paper reports three main findings. First, we find that the explanatory variables explain a significant 66.7% of the *within-firm* variation and 97.2% of the *total* variation (i.e., within and across firms) in inventory turnover. Annual inventory turnover is found to be negatively correlated with gross margin and positively correlated with capital intensity and sales surprise.

Second, we estimate time-trends in inventory turnover in retailing both with and without taking account of the correlations with the explanatory variables. We find that, on average, inventory turnover in retailing has declined during 1987-2000, even though it is positively correlated with capital intensity and capital intensity has increased during this period. However, there are marked differences in the time-trends in inventory turnover across firms: 43% of the firms have increased their inventory turnover with time, and on average, firms that have invested more in capital assets have achieved higher inventory turnover.

Third, using the estimates from our model, we construct an alternative metric of inventory productivity, Adjusted Inventory Turns, which empirically models the tradeoff between inventory turnover and the explanatory variables. This metric can be applied in performance analysis, benchmarking and managerial decision-making, since it enables comparison of inventory productivity across firms and years. We illustrate its interpretation with examples.

There is considerable interest in the operations management community in evaluating time-trends in inventory turnover, and assessing the impact of operational improvements on operational and financial performance. However, there are few empirical studies on these topics. Balakrishnan et al. (1996) compare the performance of a sample of 46 firms that adopted just-in-time processes (JIT) during 1985-89 with a matched sample of 46 control firms, and find that JIT firms achieved larger improvements in their inventory turns. Billesbach and Hayen (1994), Chang and Lee (1995) and Huson and Nanda (1995) also study the impact of JIT on inventory turns for different samples of firms. Hopp and Spearman (1996: chapter 5) summarize the findings of several survey-based studies on whether U.S. manufacturing firms that implemented MRP systems achieved better inventory turns as a result. Hendricks and Singhal (1997, 2001) examine the impact of implementation of total quality management programs on the operating incomes and shareholder values of firms.

In contrast to the above research, Rajagopalan and Malhotra (2001) use aggregate industry-level data from the U.S. Census Bureau for 20 industrial sectors for the period 1961-1994 to determine whether the inventory turns for U.S. manufacturers have decreased with time for each of raw material inventory, work-in-process inventory and finished goods inventory. They find that six sectors show increasing trends in inventory turns for finished goods, and four sectors show larger trends in the years 1980-1994 when JIT became popular compared to the previous period (1961-1979). The results for raw material and work-in-process inventories are marginally better.

Our paper contributes to the operations literature as it studies inventory productivity in retail services, and utilizes firm-level panel data for all public-listed firms in this sector. Panel data are advantageous because they enable us to control for the effects of unobserved firm-specific or time-specific factors in measuring the tradeoffs between the variables of interest. We exploit the flexibility of panel data to compare alternative model specifications and assess their suitability for modeling inventory turnover empirically. We also introduce the variable sales surprise to control for the effect of unexpectedly high sales on inventory turnover. Our model can be used by managers to assess inventory turnover performance, benchmark it against competing firms, and manage working capital requirements.

The model can also be applied in future research to assess the impact of improvements in operations on the inventory productivity of firms.

The rest of this paper is organized as follows. Section 2 summarizes the data and defines the performance variables used. Section 3 develops hypotheses to relate inventory turnover with gross margin, capital intensity and sales surprise using results from the existing literature. In section 4, we discuss the empirical model used in estimation. We present our empirical results in section 5, discuss their managerial implications in section 6, and conclude in section 7 with a discussion of the limitations of our study and directions for future research.

2. Data Description and Definition of Variables

We use financial data for all public-listed U.S. retailers for the 16-year period 1985-2000 drawn from their annual income statements and quarterly and annual balance sheets. These data are obtained from Standard & Poor's Compustat database using the Wharton Research Data Services (WRDS).

The selection of firms is based on a four-digit Standard Industry Classification (SIC) code assigned to each firm by the U.S. Department of Commerce according to its primary industry segment. Our dataset includes ten segments in the retailing industry. Table 1 lists the segments, the corresponding SIC codes, and examples of firms in each segment. All segments except apparel and accessories and food stores correspond to unique 4-digit SIC codes. In apparel and accessories, we group together all firms that have SIC codes between 5600 and 5699 because there is substantial overlap between their products. This grouping enables us to increase the number of degrees of freedom by estimating one set of coefficients for all apparel firms instead of estimating separate coefficients for each SIC code. Likewise, in food stores, we group together supermarket chains (SIC code 5400) and convenience stores (SIC code 5411) because of the overlap between their products.

Let S_{sit} denote the sales, net of markdowns, of firm *i* in segment *s* in year *t*, and CGS_{sit} denote the corresponding cost of goods sold. Both sales and cost of goods sold are obtained from the annual income statements of the firms. Let GFA_{sitq} denote the gross fixed assets, comprised of land, property, and equipment, of firm i in segment s at the end of quarter q in year t, NFA_{sitq} denote the net fixed assets, comprised of gross fixed assets less accumulated depreciation, Inv_{sitq} denote the inventory, valued at cost, and TA_{sitq} denote the total assets. These four data items are obtained from the quarterly closing balance sheets of the firms. From these data, we compute the following performance variables for our study:

Inventory turnover (also called inventory turns), $IT_{sit} = \dfrac{CGS_{sit}}{\frac{1}{4}\sum_{q=1}^{4} Inv_{sitq}}$,

Gross margin, $GM_{sit} = \dfrac{S_{sit} - CGS_{sit}}{S_{sit}}$,

Capital intensity, $CI_{sit} = \dfrac{\sum_{q=1}^{4} GFA_{sitq}}{\sum_{q=1}^{4} Inv_{sitq} + \sum_{q=1}^{4} GFA_{sitq}}$, and

Sales surprise, $SS_{sit} = \dfrac{S_{sit}}{\text{Sales Forecast}_{sit}}$.

Here, average inventory and average gross fixed assets are computed using quarterly closing values in order to control for systematic seasonal changes in these variables during the year. The method for obtaining the sales forecast will be described in section 3.3.

We also note that there are alternative measures of capital intensity that could be considered instead of that defined above. In particular, NFA_{sitq}, could be used in place of GFA_{sitq}, to measure capital investment, or TA_{sit} could be used in the denominator as the scaling variable instead of the sum of the average inventory and the average gross fixed assets. We tested our hypotheses with these alternative measures and found that the results are consistent with those reported in this paper. The reader is referred to Stickney and Weil (1999) for detailed descriptions of the income statement and balance-sheet variables.

Our original dataset contains 5088 observations across 576 firms. After computing all the variables, the first two years of data for each firm are omitted. They could not be used in the analysis because the computation of sales forecast required two years of sales data at the beginning of each time-series. We also omit from our dataset those firms that have less than five consecutive years of data available for any sub-period during 1985-2000; there are too few observations for these firms to conduct time-series analysis. These missing data are caused by new firms entering the industry during the period of the dataset, and by existing firms getting de-listed due to mergers, acquisitions, liquidations, etc. Further, we omit firms that had missing data or accounting changes other than at the beginning or the end of the measurement period. These missing data are caused by bankruptcy filings and subsequent emergence from bankruptcy, leading to fresh-start accounting. There were also accounting changes related to the inventory valuation method. Out of ten inventory valuation methods identified by the Compustat database, four are commonly used by retailers: FIFO (first in first out), LIFO (last in first out), average cost method and retail method (see the Compustat data manual for the definitions of these methods). Most retailers in our dataset use a combination of these methods. After removing the firms with missing observations, there were only three firms that switched between exclusively FIFO and exclusively LIFO inventory valuations during the subject time period.

Our final dataset contains 3407 observations across 311 firms, an average of 10.95 years of data per firm. Table 2 presents summary statistics by retailing segment for the performance variables used in our study. It lists the mean and standard deviation for each variable within each segment. For example, the mean of inventory turnover for apparel and accessory stores is 4.57 and the standard deviation is 2.13. The coefficient of variation of inventory turnover ranges from 0.36 for hobby, toy and game shops to 1.92 for home furniture & equipment stores. Thus, the variability of inventory turnover is not limited to a few firms but is widely prevalent. Hereafter, we use IT, GM, CI and SS without the subscripts s, i, t as abbreviations for the respective variable names. We collectively call GM, CI and SS as 'explanatory variables', and IT, GM, CI and SS as 'performance variables' or 'firm-level performance variables'.

3. Hypothesis Development

In this section, we set up the hypotheses to relate inventory turnover with gross margin, capital intensity and sales surprise. An important aspect of our model is that we focus attention on year-to-year variations within a firm, rather than differences across firms. This is done because differences in IT across firms may be associated not only with their GM, CI and SS, but also with factors such as accounting policies, location strategy, management, etc. These factors are exogenous to our dataset. Focusing on variations within a firm enables us to limit their influence. In the empirical analysis in subsequent sections, we control for variation across firms by using firm-specific fixed effects.

We also note that firm-level aggregated variables have several shortcomings that limit their usefulness. We identify these shortcomings at appropriate points in the analysis.

3.1 Gross Margin

We test the following hypothesis:

HYPOTHESIS 1: Inventory turnover is negatively correlated with gross margin.

We motivate this hypothesis in two ways: by observations of managerial practice, and based on results in the academic literature. In surveys of retailing firms conducted by us, we find that managers trade off inventory turns and gross margin in their decision-making. They set their business targets partly in terms of the product of gross margin and inventory turnover (this measure is called gross margin return on inventory, abbreviated as GMROI). Items with higher margins are given lower turns targets than items with lower margins. This tradeoff is commonly referred to by retailing managers as the “earns versus turns” tradeoff. It is consistent with the Du Pont model in accounting, and is prescribed in retailing textbooks, see for example, the strategic profit model in Levy and Weitz (2001: chapter 7). However, no theoretical or empirical justification for this tradeoff is provided in retailing textbooks. Thus, it is not clear whether the practice of trading off earns versus turns is based on observed tradeoffs between inventory turns and gross margin, or whether it is simply a heuristic to allocate a targeted return on investment to different items.

We explain below that the existing literature, even though it is largely based on item-level models, supports a negative correlation between inventory turnover and gross margin, and more importantly, identifies several factors that could explain this correlation. In particular, gross margin can be related to inventory turnover directly because it determines the optimal service level. Further, gross margin can be related to inventory turnover indirectly through price, product variety and length of product lifecycle because they affect both inventory turnover and gross margin. The following discussion explains these relationships.

Service Level: According to the classical newsboy model, an increase in gross margin implies an increase in the average inventory level. It can further be shown that in the newsboy model, an increase in inventory level implies a decrease in expected inventory turnover regardless of the form of the demand distribution. Therefore, an increase in gross margin implies a decrease in expected inventory turnover.

Price: For a given set of items with given costs, an increase in price increases the gross margin of the firm. Further, since demand is negatively correlated with price, an increase in price decreases the demand for the item and increases the coefficient of variation of demand, thus decreasing inventory turnover.

Product Variety: Multiple papers in marketing and economics consider the effect of product variety on price. According to Lancaster (1990), Chamberlin (1950) and Dixit and Stiglitz (1977), higher variety leads to an increase in the consumers' utility, either by reducing the distances of consumers from their perceived 'ideal product' profiles (the Lancaster demand model), or because consumers have an in-built preference for variety (the Chamberlin demand model). Further, from consumer utility theory, higher consumer utility implies higher prices for a given cost (Kotler 1986, Nagle 1987). According to Lazear's model of retail pricing and clearance sales (Lazear 1986), higher variety increases the retailer's uncertainty about price, which further increases the average price.

In empirical research, Pashigian (1988) shows that price is positively correlated with variety in a study of time-series price and sales data for department stores, and Kekre and Srinivasan (1990) show that firms with higher variety have higher relative prices in a cross-sectional study of over 1,400 business units. Thus, according to the above papers, price increases with variety for given cost. Therefore, variety has a positive effect on gross margin through price. We note that these papers do not address the cost of variety.

Numerous papers and case studies using risk pooling as the basis of their argument have examined the impact of product variety on inventory turnover. Lower variety through delayed differentiation is used to increase inventory turnover in the Benetton case study (Heskett and Signorelli 1989), at Hewlett-Packard (Feitzinger and Lee 1997), and in research articles that explore these relationships (Lee and Tang 1997, Swaminathan and Tayur 1998). Zipkin (2000: chapter 5) constructs an index of product variety, and observes from experience with a large firm that an increase in variety is associated with a decrease in inventory turnover. van Ryzin and Mahajan (1999) also analyze the effects of variety on price and inventory using a model of assortment choice. While they do not explicitly consider inventory turnover, they show that total inventory increases with variety, and that variety under market equilibrium is increasing in price given fixed procurement costs.

Length of the product lifecycle: The length of product lifecycle has a similar effect on gross margin and inventory turnover as product variety. A shorter product lifecycle implies rapid changes to products to better match consumer requirements, and thus, increased consumer utility (Pashigian 1988). As discussed above, higher consumer utility implies higher prices and higher gross margin. A shorter product lifecycle also implies less availability of historical data for forecasting. Since the accuracy of demand forecasts increases with the availability of historical data, products with longer lifecycle and greater availability of historical data should have lower demand uncertainty, less safety stock requirement, and higher inventory turnover than products with shorter product lifecycle and less availability of historical data.

Since service level, price, variety and lifecycle length are not measured in our model, separate tests of the linkages of these factors with inventory turns and gross margin are beyond the scope of our study. Instead, Hypothesis 1 is limited to estimating the correlation of inventory turnover with gross margin.

3.2 Capital Intensity

Investments in warehouses, information technology, and inventory and logistics management systems involve capital investment by a firm, which is accounted as fixed assets, and is therefore measured by an increase in CI. Thus, we formulate the following hypothesis:

HYPOTHESIS 2: Higher capital intensity increases inventory turnover.

We expect that the addition of a new warehouse should result in a decrease in total inventory at the retailer, and thus, an increase in its inventory turnover because of two reasons. First, the warehouse enables the retailer to reduce safety stock over the supplier lead-time by postponing the decision to allocate inventory across stores (‘the joint ordering effect’, see Eppen and Schrage 1981). Second, the warehouse enables the retailer to centralize safety stock and re-balance store inventories between shipments from the supplier (‘the depot effect’, see Jackson 1988).

We also expect inventory turns to increase with investment in information technology. According to Cachon and Fisher (2000), the benefits of implementing information systems for the management of inventory include better allocation of the inventory to the stores, shorter ordering lead times, smaller batch sizes, and a lower cost of processing orders. Clark and Hammond (1997), in a cross-sectional study, show that food retailers who adopt a continuous replenishment process (CRP) enabled by the adoption of electronic data interchange (EDI) achieve 50-100% higher inventory turns than traditional ordering processes. For further documentation of the benefits of information technology, see Kurt Salmon Associates (1993), Campbell Soup Company (Cachon and Fisher 1997), Barilla SpA (Hammond 1994), H. E. Butt Grocery Co. (McFarlan 1997), and Wal-Mart Stores, Inc. (Bradley, et al. 1996).

Since capital intensity is measured from gross fixed assets, it does not isolate the effects of different kinds of capital investments made by a firm. Further, it includes other capital investments of a retailer as well, for example, investments in stores. These could dilute the effect of capital intensity on inventory turnover.

3.3 Sales Surprise

Inventory turnover can be affected by unexpectedly high sales. If the sales realized by a retailer in a given period are higher than its forecast, then the average inventory level for the period will be lower than expected, and realized inventory turnover, which is a ratio of realized unit sales to the average inventory for the period, will be higher than expected. The outcome will be reversed if realized sales are lower than expected sales.

Therefore, we use sales surprise as defined in §2 to measure unexpectedly high sales, and formulate the following hypothesis.

HYPOTHESIS 3: Inventory turnover is positively correlated with sales surprise.

Sales surprise should, ideally, be measured with respect to the management's forecast of sales since inventory decisions taken by the management are based on these forecasts. Since managements' sales forecasts are not publicly reported, we estimate sales forecasts from historical data using Holt's linear exponential smoothing method[3]. The sales forecast for period *t* is as

$$\text{Sales Forecast}_{sit} = L_{si,t-1} + T_{si,t-1},$$

where $L_{si,t\text{-}1}$ and $T_{si,t\text{-}1}$ are smoothed series defined as

$$\begin{aligned} L_{sit} &= \alpha S_{sit} + (1-\alpha)(L_{si,t-1} + T_{si,t-1}), \\ T_{sit} &= \gamma(L_{sit} - L_{si,t-1}) + (1-\gamma)T_{si,t-1}, \end{aligned}$$

and α ($0 < \alpha < 1$) and γ ($0 < \gamma < 1$) are weighting constants. We compared the forecast errors for several values of α and γ. The best forecasts were obtained for $\alpha = \gamma = 0.75$. Thus, these values are used to compute all the results reported in this paper. We also computed sales forecasts using simple exponential smoothing and double exponential smoothing. These forecasts had higher forecast errors and were biased compared to Holt's linear exponential smoothing.

[3] Alternatively, one could use the I/B/E/S dataset to obtain sales forecasts. This dataset provides analysts' forecasts of sales for a subset of the public-listed firms for the period 1997 onwards. For the time-period used in this paper,

4. Model Specification and Analysis

We propose the following log-linear model to test the hypotheses:

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

Here, F_i is the time-invariant firm-specific fixed effect for firm i, c_t is the year-specific fixed effect for year t, b^1_s, b^2_s, b^3_s are the coefficients of log GM_{sit}, log CI_{sit}, and log SS_{sit}, respectively, for segment s, and ε_{sit} denotes the error term for the observation for year t for firm i in segment s. Hypotheses 1, 2 and 3 imply that, for each segment s, b^1_s must be less than zero, and b^2_s and b^3_s must be greater than zero.

We use a log-linear specification for three reasons: (1) A log-linear relationship between the variables is suggested by plotting IT against GM, CI and SS. (2) Retail industry reports (see, for example, Sack 2000) and surveys of retailers that we have conducted show that multiplicative measures such as GMROI and return on assets are widely used to measure and reward the performance of inventory planners and merchants. (3) We simulated a periodic review inventory model with stationary demand for different values of gross margin, lead-time and variance of demand, and collected data on the variables of interest to compare log-linear and linear model specifications. We found that the log-linear specification had significantly lower prediction errors than the linear specification.

The following aspects of the model need elaboration:

Firm-specific fixed effects, F_i: Inventory turnover can be correlated with factors that are omitted in our dataset, such as managerial efficiency, marketing, location strategy, accounting policy, etc. These factors can result in biased and inconsistent estimates of the parameters (see Hausman and Taylor 1981). Therefore, we minimize their effect by using firm-specific control variables, F_i. These control variables can be modeled either as fixed effects or as random effects. We model them as fixed effects because they can be used to compare average inventory turnover performance across firms over the period of analysis.

I/B/E/S provides forecasts only for a few firms, giving a total of less than 300 observations. However, this dataset could be useful in future research.

Omitted variables also imply that cross-sectional data for a single year or longitudinal data for a single firm are unsuitable for estimating the model because they cannot distinguish the effects of the explanatory variables from differences in F_i (see Hoch 1962).

Time-specific fixed effects, c_t**:** These variables control for changes in secular characteristics over time, such as in economic conditions, in the interest rates, in price level, etc., and thus, enable us to compare inventory turnover across years. They also enable us to measure trends in average inventory turnover in the retailing industry over time after controlling for the effects of the other explanatory variables.

Segment-specific coefficient estimates, b^1_s, b^2_s, b^3_s**:** The coefficients of the explanatory variables might differ across retailing segments. Thus, we estimate segment-specific coefficients to test for heterogeneity across segments.

It is useful to estimate other model specifications with different combinations of the control variables to ascertain the correctness of the model and draw further insights. First, to test whether the coefficients of the explanatory variables differ across segments, we compare (1) with the following specification (with pooled coefficients of explanatory variables instead of segment-wise coefficients):

$$\log IT_{sit} = F_i + c_t + b^1 \log GM_{sit} + b^2 \log CI_{sit} + b^3 \log SS_{sit} + \varepsilon_{sit}. \tag{2}$$

Second, to test whether the firm-wise fixed effects F_i are statistically significant, we compare (1) with the following specification (with segment-wise fixed effects instead of firm-wise fixed effects):

$$\log IT_{sit} = F_s + c_t + b_s^1 \log GM_{sit} + b_s^2 \log CI_{sit} + b_s^3 \log SS_{sit} + \varepsilon_{sit}. \tag{3}$$

Here, F_s is the segment-wise fixed effect, and the other terms have their usual meaning. Both (2) and (3) are useful because they have fewer parameters, and hence can allow more precise estimation. However, (3) should not be used if firm-wise fixed effects are statistically significant.

Third, since IT and GM are both functions of cost of goods sold, it is possible that we observe a negative correlation between IT and GM even if inventory levels are independent of the gross margin realized by a firm. A similar argument could be applied to IT and CI since they are both functions of average annual inventory. To test for this problem, we estimate an alternative model using average annual inventory level, Inv_{sit} $\left(= \frac{1}{4} \sum_q Inv_{sitq} \right)$, as the dependent variable instead of IT_{sit}. We add CGS_{sit} to the list of explanatory variables in this model to control for scale.

$$\log Inv_{sit} = F_s + c_t + b_s^1 \log GM_{sit} + b_s^2 \log CI_{sit} + b_s^3 \log SS_{sit} + b^4 \log CGS_{sit} + \varepsilon_{sit}. \quad (4)$$

For this model, we measure capital intensity as the ratio of GFA to TA rather than as defined in §2 to avoid having a term in the explanatory variables that is a function of Inv_{sit}. Further, we also test for this problem using models (1) and (2). We estimate these models with values of gross margin and capital intensity lagged by one year, log $GM_{si,t-1}$ and log $CI_{si,t-1}$, as the explanatory variables instead of log GM_{sit} and log CI_{sit}.

Other model specification can be constructed to test if $b^1{}_s$, $b^2{}_s$ and $b^3{}_s$ change with time or if the time-specific fixed effect c_t differs across segments. We compare the results of different specifications in section 5. The main results of the paper are based on (1) and (2). We estimate all models assuming that the error term, ε_{sit}, has first-order autocorrelation, and is segment-wise heteroscedastic, i.e., the variance of ε_{sit} varies by segment. The estimation process and statistical tests of assumptions are presented in the Appendix. The reader is referred to Greene (1997: chapter 14), Hsiao (1986) and Judge, et al. (1985: chapter 13) for further discussion of the specification and estimation of panel data models such as ours.

5. Results

5.1 Basic Results

Table 3 shows the fit statistics for models (1) and (2) estimated using MLE. The overall fit of model (1) is statistically significant ($p<0.0001$). The coefficients of all the explanatory variables, log GM_{sit}, log CI_{sit} and log SS_{sit}, are also significantly different from zero ($p<0.0001$). Comparing the results for models (1) and (2), we find that the likelihood ratio test that model (1) is preferred to model (2) is statistically significant ($p<0.0001$). Separate F-tests to determine whether each coefficient differs across segments are also significant (p<0.0001 for each of log GM_{sit}, log CI_{sit} and log SS_{sit}). Therefore, the coefficients' estimates differ significantly across segments.

We determine the fraction of variation in log IT_{sit} explained by each model by computing the overall prediction accuracy and the within-firm prediction accuracy of each model using the usual formula for R^2:

$$\text{Overall prediction accuracy} = 1 - \frac{\sum_{s,i,t}\left(\log IT_{sit} - \widehat{\log IT}_{sit}\right)^2}{\sum_{s,i,t}\left(\log IT_{sit} - \overline{\log IT}\right)^2},$$

$$\text{Within-firm prediction accuracy} = 1 - \frac{\sum_{s,i,t}\left(\log IT_{sit} - \widehat{\log IT}_{sit}\right)^2}{\sum_{s,i,t}\left(\log IT_{sit} - \overline{\log IT}_{si}\right)^2},$$

where $\widehat{\log IT}_{sit}$ is the predicted value of $\log IT_{sit}$ obtained from (1) or (2), $\overline{\log IT}$ is the overall mean of $\log IT_{sit}$, and $\overline{\log IT}_{si}$ is the within-firm mean of $\log IT_{sit}$[4]. The overall prediction accuracy for model (1) is 97.16% and for model (2) is 96.83%. The within-firm prediction accuracy for model (1) is 66.7% and for model (2) is 62.8%. The within-firm accuracy is remarkable because it shows that year-to-year changes in the IT of a firm are highly correlated with simultaneous changes in GM, CI and SS. The overall prediction accuracy is higher than the within-firm accuracy because the between-firm variation in inventory turnover is larger than the within-firm variation, and is fully explained by the firm-specific fixed effects.

Table 4 shows the coefficients' estimates for models (1) and (2). The pooled coefficient for log GM_{sit} is –0.285 (p<0.0001), and strongly supports hypothesis 1. The segment-wise coefficients also support hypothesis 1 for nine of the ten segments. Thus, inventory turns are negatively correlated with gross margin. Since we have a log-linear model, the coefficient of log GM_{sit} gives the elasticity of

[4] There are several measures of R-square for the generalized regression model. One alternative would be to apply the formula for R-square to the transformed model obtained in FGLS estimation. Since the R-square thus determined need not lie between 0 and 1, we do not use this procedure. See Kmenta (1996: chapter 12) for details.

inventory turns with respect to gross margin. Thus, a 1% increase in gross margin (for example, from 0.5 to 0.505) is associated with an estimated –0.285% change in inventory turns.

Across segments, the coefficient estimate for log GM_{sit} varies from –0.153 for apparel and accessories retailers to –0.571 for hobby, toy and game shops. From the discussion in §3, there can be several reasons for this variation. For example, for the same value of GM, product variety, lifecycle length and demand uncertainty may vary across segments, resulting in different coefficients. Since price, variety and lifecycle length are not included in our dataset, we cannot ascertain the causes of the differences in coefficients' estimates across segments. These could be investigated in a further study.

The pooled coefficient for log CI_{sit} is 0.252 ($p<0.0001$), and strongly supports hypothesis 2. Segment-wise estimates of the coefficient of log CI_{sit} also strongly support hypothesis 2 for seven of the ten segments. The value of the coefficient ranges from 0.106 to 1.085 across segments where it is statistically significant ($p<0.02$). Thus, investment in capital assets is positively correlated with inventory turnover.

The pooled and segment-wise estimates of the coefficient of log SS_{sit} are all positive and statistically significant at $p<0.001$. They strongly support hypothesis 3. The value of the pooled coefficient is 0.143 and the segment-wise coefficients range between 0.053 and 0.279. These estimates are useful since they enable us to control for the effect of surprisingly high sales on inventory turnover.

5.2 Time-trends in inventory productivity

The year-specific fixed effects, c_t, in our model can be used to estimate the time-trend in inventory productivity *after* adjusting for the correlation with gross margin, capital intensity and sales surprise. Table 5 shows the estimates of c_t obtained from models (1) and (2), and figure 2 shows a time-series plot of c_t for model (2). Note that these estimates are decreasing with time. Taking the standard errors of the estimates into account, we find that the estimates of c_t for the initial years, t = 1987,…,1993, are significantly larger than the estimates of c_t for the latter years, t = 1996,…,2000 ($p<0.01$). This shows that controlling for sales surprise and changes in capital intensity and gross margin, inventory turns have decreased with time during 1987-2000.

The trend in c_t can be compared with the 'unadjusted' time trend in inventory turns (i.e., ignoring the correlation with GM, CI and SS) by fitting the following model:

$$y_{sit} = g_i + ht + \nu_{sit}\,. \tag{5}$$

Here, y_{sit} equals IT_{sit} to estimate a linear time-trend and log IT_{sit} to estimate an exponential time-trend, g_i is the intercept for firm i, and h is the common slope with respect to time across all firms. We also apply this model to CI_{sit}, GM_{sit}, log CI_{sit} and log GM_{sit} to estimate the trends in their values. Table 6 gives the results obtained. We find that inventory turns have decreased significantly with time ($p<0.0001$), capital intensity has increased significantly with time ($p<0.0001$), and gross margin has no significant time-trend.

Now consider the trends in inventory turns for individual firms. These trends can be estimated with the following models, after slight changes to (1) and (5):

$$y_{sit} = g_i + h_i t + \nu_{sit}\,. \tag{6}$$

$$\log IT_{sit} = F_i + h_i' t + b_s^1 \log GM_{sit} + b_s^2 \log CI_{sit} + b_s^3 \log SS_{sit} + \varepsilon_{sit}. \tag{7}$$

Here, (6) measures the 'unadjusted' time-trend, h_i, in the inventory turns for each firm i, and (7) measures the 'adjusted' time-trend, h'_i, after controlling for the correlation with the explanatory variables. We find that the estimate of h_i is negative for 176 firms (of these, 76 are statistically significant ($p<0.05$)), and positive for 135 firms (59 statistically significant ($p<0.05$)). The estimate of h'_i is negative for 193 firms (83 statistically significant ($p<0.05$)), and positive for 118 firms (49 statistically significant ($p<0.05$)).

In summary, the overall trend in inventory turns in the retailing industry is downward sloping during 1987-2000. This result is consistent with the result obtained by Rajagopalan and Malhotra (2001) for several sectors in the manufacturing industry. However, we additionally find that capital intensity has increased significantly during this period, and is positively correlated with inventory turnover. Thus, even though the overall trend in inventory turns is negative, firms with a greater increase in capital intensity have shown a larger increase in inventory turns over time compared to their peers. Further, as shown using (6) and (7), we also find that the trend in inventory turns varies across firms. During the subject period, 43% of the firms have shown an increase in inventory turns, and 38% of the firms have shown an increase in inventory turns controlling for the changes in capital intensity, gross margin and sales surprise.

Rajagopalan and Malhotra offer several conjectures to explain the observed downward trends in inventory turns, for example, product variety may have increased with time, product lifecycles may have become shorter with time due to faster introduction of new products, average lead times may have increased due to greater global sourcing. While these conjectures apply to retailing as well, like Rajagopalan and Malhotra, we currently cannot offer conclusive evidence.

5.3 Econometric Issues

We find that models (1) and (2) are more suitable for our analysis than model (3) because the firm-wise fixed effects F_i are statistically significant as shown in Table 3. We also find that the estimates from model (4) and from models (1) and (2) with lagged explanatory variables, log $GM_{si,t-1}$ and log $CI_{si,t-1}$, support hypotheses 1, 2 and 3 at $p<0.0001$. Therefore, the estimated correlations between inventory turns and gross margin, and between inventory turns and capital intensity are not artifacts of the way the variables are defined.

Please see the Appendix for the results regarding heteroscedasticity and autocorrelation in the dataset.

6. Managerial Implications

Our results show that inventory turnover should not be used per se in performance analysis. For example, if a firm realizes an increase in inventory turnover with a concurrent decrease in gross margin, it does not necessarily indicate an improvement in its capability to manage inventory. Likewise, if two firms have similar inventory turnover and gross margin values but different capital intensities, then the firm with the lower capital intensity could possibly have a better capability to manage inventory than the other firm. Finally, if a firm realizes an increase in inventory turnover with an unexpected increase in sales, then the increased inventory turnover may not indicate an improved capability to manage inventory. Thus, changes in gross margin, capital intensity and sales surprise should be incorporated in the evaluation of inventory productivity of a firm.

Our results give a tradeoff curve that computes the expected inventory turnover of a firm for given values of sales surprise, gross margin and capital intensity. We term the distance of the firm from its tradeoff curve as its A*djusted Inventory Turnover*, denoted AIT. The value of AIT for firm *i* in segment *s* in year *t* is computed as

$$\log AIT_{sit} = \log IT_{sit} - b^1 \log GM_{sit} - b^2 \log CI_{sit} - b^3 \log SS_{sit} \,,$$

or, equivalently, as

$$AIT_{sit} = IT_{sit} \left(GM_{sit}\right)^{-b^1} \left(CI_{sit}\right)^{-b^2} \left(SS_{sit}\right)^{-b^3} . \tag{8}$$

Adjusted Inventory Turnover is an empirical measure to compare inventory productivity across firms and across years by controlling for differences in gross margin, capital intensity and sales surprise.

According to our results, managers of firms with low AIT should investigate whether their firms are less efficient than their peers, and identify steps they might take in order to improve their inventory productivity. Firms with higher inventory turnover may differ systematically from firms with lower inventory turnover. On the one hand, such differences may be attributed to differences in accounting policies and may not have operational implications. On the other hand, they may indicate differences in efficiency that cannot be rectified simply by increased spending. This possibility is supported in our discussions with managers. Fisher, Raman and McClelland (2000) discuss differences between retailers and identify best practices in retail operations through on-site interviews, surveys and workshops in a four-year study of 32 retailers.

We present two examples to illustrate the interpretation of Adjusted Inventory Turns. The first example shows that inventory turns may overstate differences in inventory productivity across firms. The second example shows that time-trends in inventory turns can be misleading.

Example 1: Consider again the example of four consumer electronics retailers in Figure 1. We apply (8) to find the AIT for these firms. For example, in year 1996, the inventory turns of these firms are 5.9 (Best

Buy), 4.1 (Circuit City), 8.2 (CompUSA) and 3.0 (Radio Shack). The corresponding values of gross margin are 0.15, 0.26, 0.14 and 0.32, respectively, and the corresponding values of capital intensity are 31%, 47%, 33% and 42%, respectively. After applying these values and sales surprise, we find that the Adjusted Inventory Turns of the four firms are 3.1, 2.6, 4.1 and 2.2, respectively. Thus, we observe that the differences between the Adjusted Inventory Turns of Best Buy, Circuit City, CompUSA and Radio Shack are smaller than the differences between their inventory turns because the differences in inventory turns are partly compensated by the differences in gross margin. For example, the inventory turns of CompUSA are 2.8 times those of Radio Shack, but the Adjusted Inventory Turns of CompUSA are 1.9 times those of Radio Shack.

The gross margins of these firms might differ due to any one or more of the factors listed in §3. Indeed, the annual reports to shareholders of these firms show that their product mixes differ from each other. CompUSA has a higher proportion of personal computers in its sales (high turns, low margins), Best Buy and Circuit City have higher proportions of home electronics and appliances (mid-range turns and margins), and Radio Shack has a higher proportion of spare parts and accessories in its sales (low turns, high margins). Since the Adjusted Inventory Turns of these firms are less disparate than their inventory turns, it suggests that the differences in inventory turns between these firms may not indicate better or worse inventory productivity. Figure 3 shows the tradeoff between inventory turns and gross margin for the four firms obtained using (8) (assuming constant capital intensity and no sales surprise to avoid year-to-year variations in these variables).

Example 2: Ruddick Corp. is a holding company that owns Harris Teeter, a regional supermarket chain in the southeastern United States with 137 stores and sales of $2.7 billion in the year 2000. Figure 4 shows time-series plots and linear trends of IT and AIT for Harris Teeter for the years 1987-2000. The inventory turns of Harris Teeter do not show any significant time-trend. During the same period, the gross margin of Harris Teeter has increased steadily from 23.4% to 30.9%, and its capital intensity has increased marginally. After applying (8), we find that the Adjusted Inventory Turns of Harris Teeter have increased significantly at an average rate of 0.055 per year. Thus, the Adjusted Inventory Turns show that the lack of time-trend in inventory turnover may not imply that the inventory productivity of the firm has not improved with time. Indeed, we discovered from retailing managers that Harris Teeter switched to private label brands during this period. Since private label brands have higher gross margins, Harris Teeter increased the service level for private label merchandise in its stores, affecting its inventory turns.

7. Limitations and Directions for Future Research

We have shown that inventory turns in retail services have a high correlation with gross margin, capital intensity and sales surprise. Therefore, inventory turns should not be used per se in performance analysis. Instead, we have proposed an empirical metric derived from our model, Adjusted Inventory Turns, which controls for the correlation between these variables and enables comparison of inventory productivity across firms and across years. We have also computed time-trends in inventory turns in the retailing industry for the period 1987-2000. We find that inventory turns in the industry, on average, have declined during this period even though they are positively correlated with capital intensity, and capital intensity has increased during this period. Further, there are marked differences between the time-trends in inventory turnover across firms. Inventory turns of 43% of the firms in our dataset have improved with time while the rest have declined.

Since our paper is based on aggregate financial data, it has many limitations that can be addressed in future research using more detailed datasets. The first is the issue of omitted variables. Operational characteristics such as product variety, length of product life cycle and price are omitted in our model. Thus, our results are limited to estimating the structural relationship between inventory turns and gross margin; they do not explain the causes of this relationship. Our model can be enriched by including the omitted variables and directly measuring their effects on inventory turns and gross margin.

A second limitation of our study is that the variables are measured at an aggregate level. The variable for capital intensity does not distinguish between the relative merits of different kinds of investments, such as in information technology, warehouses, logistics management systems, etc. Disaggregated data could be used to extend our analysis and test for the effectiveness of different kinds of investments made by a firm. Further, some firms have more than one retail chain under one corporate ownership (for example, Gap, Inc.), or own stores in many countries. Data at the level of retail chain and country of location for such firms would be useful to analyze the tradeoffs between the performance variables more accurately.

A third limitation of our study is related to the measurement of accounting data. We have sought to minimize the effects of accounting policies by focusing only on intra-firm variation in inventory turns. Further, we have controlled for firms that report changes in accounting policies, mergers, acquisitions and filing of bankruptcy during the period of the study. However, the constitution of the variables measured in our study may change even when accounting policies remain unchanged. Therefore, our results need to be interpreted with caution.

Our paper identifies opportunities for future research on inventory productivity. One valuable area of research is to investigate why some firms realize higher inventory productivity than others even after controlling for differences in capital investment, gross margin and sales surprise. This question could be of relevance to both the operations and the business strategy literature. In the latter, it would contribute to research on the role of industry, corporate-level strategy and firm-level strategy on the operating performance of firms (see, for example, Beard and Dess 1981, McGahan and Porter 1997, Rumelt 1991 and Schmalensee 1985). A related research question is to understand why the elasticities of inventory turns with respect to the explanatory variables differ across segments. We have hypothesized some plausible reasons for these differences, which could be tested in future research. Finally, we have tested our model for many alternative specifications, datasets, and time periods. We have found the estimates to be very robust with respect to these variations. This model could be applied to control for correlations between performance variables in future research as to how operational improvements affect operating performance and financial performance of firms.

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Appendix: Estimation and Econometric Issues

Since our data contain observations across firms and years, it is likely that the variance of ε_{sit} varies across firms, and that ε_{sit} is correlated across years. Further, we find that the standard deviations of all the variables differ substantially across segments. For example, as shown in table 2, the standard deviation of inventory turnover ranges from a low of 0.58 for jewelry stores to a high of 10.42 for home furniture and equipment stores. Likewise, the standard deviation of gross margin ranges from a low of 0.12 for food stores to a high of 1.02 for catalog and mail-order houses. Therefore, we consider a flexible structure of the variance-covariance matrix of ε_{sit} with segment-wise heteroscedasticity and first-order autocorrelation. Segment-wise heteroscedasticity implies that the variance of ε_{sit} is identical across firms within a retailing segment but differs across segments. Autocorrelation is also a common characteristic of financial time-series data. Since our data are annual time-series, we use a first-order autoregressive process; higher order autoregressive processes would be suitable for monthly or quarterly data.

For this variance structure, ordinary least squares (OLS) estimators are not efficient and the tests of significance performed on OLS estimators are not valid. Therefore, we use maximum likelihood estimation (MLE) to estimate the parameters of our model[5]. See Greene (1997: chapter 13) for a description of the estimation methodology, and Judge, et al. (1985) for a survey of the research on the asymptotic properties of various estimation methods.

[5] Other estimation techniques that may be used include feasible generalized least squares (FGLS) estimation omitting the first observation for each firm (the Cochrane-Orcutt procedure or the Hildreth-Liu procedure) or full FGLS estimation using the Prais-Winsten transform. We do not omit the first observation in the time-series of each firm because our data have relatively short time-series and it has been shown that discarding the first observation can adversely affect the efficiency of the estimates when the length of the time-series is short. Instead, we apply the transformation $\varepsilon_{si1} = u_{si1} / \sqrt{1-\rho_s^2}$ to the first observation.

We obtain the following results regarding the specification of the error term. We find that segment-wise heteroscedasticity and first order autocorrelation are also statistically significant in our dataset[6]. The standard error ranges from 0.011 for department stores to 0.145 for home furnishings and equipment stores. The autocorrelation coefficient ranges from 0.29 for hobby toys and games stores to 0.92 for home furnishings and equipment stores. Thus, the use of MLE with segment-wise heteroscedastic and AR(1) autocorrelated errors is suitable for our analysis.

Further, we find that the coefficients' estimates for the explanatory variables are robust with respect to changes in model specification if the assumptions of heteroscedastic and AR(1) autocorrelated errors are applied. For example, even though firm-wise fixed effects F_i are statistically significant, model 3 with segment-wise fixed effects gives similar coefficients' estimates as models (1) and (2). (The autocorrelation coefficient becomes very large and captures some of the differences across firms.) However, model 3 does not give the same results when errors are assumed to be homoscedastic and independent. We think that this indicates the presence of a correlation between the firm-wise fixed effects and the explanatory variables as discussed in §4. Other changes, such as segment-specific year effects or linear time-trends also do not have any significant effect on the coefficients of the explanatory variables.

[6] Upon estimating models 1-3 with and without the assumptions of segment-wise heteroscedasticity and AR(1) autocorrelation, we find that the value of the log likelihood function improves significantly (likelihood ratio test $p<0.0001$) after these assumptions. White's General Test for heteroscedasticity and Durbin-Watson test for AR(1) autocorrelation are also statistically significant.

Table 1: Classification of data using SIC codes into retailing segments

Retail Industry Segment	SIC Codes	Examples of firms
Apparel And Accessory Stores	5600-5699	Ann Taylor, Filenes Basement, Gap, Limited
Catalog, Mail-Order Houses	5961	Amazon.com, Lands End, QVC, Spiegel
Department Stores	5311	Dillard's, Federated, J. C. Penney, Macy's, Sears
Drug & Proprietary Stores	5912	CVS, Eckerd, Rite Aid, Walgreen
Food Stores	5400, 5411	Albertsons, Hannaford Brothers, Kroger, Safeway
Hobby, Toy, And Game Shops	5945	Toys R Us
Home Furniture & Equip Stores	5700	Bed Bath & Beyond, Linens N' Things
Jewelry Stores	5944	Tiffany, Zale
Radio,TV,Cons Electr Stores	5731	Best Buy, Circuit City, Radio Shack, CompUSA
Variety Stores	5331	K-Mart, Target, Wal-Mart, Warehouse Club

Table 2: Summary Statistics of the Variables for each Retail Segment: 1985-2000

(The values for each variable are its mean and standard deviation across all observations in the respective segment.)

Retail Industry Segment	Number of firms	Number of annual observations	Average Annual Sales ($ million)	Average Inventory Turnover	Average Gross Margin	Average Capital Intensity	Median Annual Sales ($ million)	Median Inventory Turnover	Median Gross Margin	Median Capital Intensity
Apparel And Accessory Stores	72	786	979.1	4.57	0.37	0.59	301.9	4.22	0.35	0.62
				2.13	0.08	0.14				
Catalog, Mail-Order Houses	45	441	439.9	8.60	0.39	0.50	142.0	5.38	0.40	0.51
				9.11	0.17	0.18				
Department Stores	23	309	6,058.6	3.87	0.34	0.63	1364.8	3.55	0.35	0.65
				1.45	0.08	0.10				
Drug & Proprietary Stores	23	256	2,309.5	5.26	0.28	0.48	667.6	4.38	0.29	0.51
				2.90	0.07	0.12				
Food Stores	57	650	4,573.6	10.78	0.26	0.75	1300.1	9.79	0.26	0.77
				4.58	0.06	0.08				
Hobby, Toy, And Game Shops	10	98	1,455.5	2.99	0.35	0.46	220.5	2.73	0.36	0.44
				1.08	0.07	0.14				
Home Furniture & Equip Stores	13	125	391.2	5.44	0.40	0.55	224.0	2.90	0.41	0.54
				10.43	0.07	0.16				
Jewelry Stores	15	156	475.2	1.68	0.42	0.36	223.2	1.48	0.47	0.35
				0.58	0.13	0.11				
Radio,TV, Cons Electr Stores	17	200	1,585.0	4.10	0.31	0.44	460.2	3.93	0.29	0.45
				1.54	0.11	0.09				
Variety Stores	36	386	6,548.7	4.45	0.29	0.51	781.9	3.71	0.29	0.51
				2.92	0.09	0.15				
Aggregate statistics	311	3407	2,791.4	6.08	0.33	0.57	508.1	4.36	0.31	0.58
				5.41	0.11	0.17				

Table 3: Fit statistics for the maximum likelihood estimates of models (1) and (2)

	Model (1)	Model (2)
-2·Log likelihood ratio	-4283.1	-3894.4
	(chi-sq = 2332.51)	(chi-sq = 2221.97)
AIC	-3537.1	-3202.4
AICC	-3420.9	-3103.5
BIC	-2143.4	-1909.5
Tests of significance of variables (F-tests)		
Firm	12.24	20.13
Year	6.09	4.18
log GM	119.28	290.99
log CI	129.14	139.05
log SS	448.12	403.16
Differences in coefficient estimates across segments (F-tests)		
log GM	4.19	
log CI	30.26	
log SS	12.20	

Note: All the statistics are significant with p<0.0001.

Table 4: Coefficients' estimates for models (1) and (2) obtained from MLE
(Pooled coefficients are for model (2) and segment-wise coefficients are for model (1).)

	log GM		log CI		log SS	
	Estimate	Std Err	Estimate	Std Err	Estimate	Std Err
Coefficients from model (1)						
Apparel And Accessory Stores	-0.153[a]	0.034	0.977[a]	0.069	0.053[a]	0.011
Catalog, Mail-Order Houses	-0.226[a]	0.048	-0.039	0.102	0.225[a]	0.021
Department Stores	-0.310[a]	0.029	0.861[a]	0.103	0.189[a]	0.020
Drug & Proprietary Stores	-0.186[a]	0.061	0.361[a]	0.093	0.143[a]	0.024
Food Stores	-0.351[a]	0.042	1.085[a]	0.097	0.179[a]	0.016
Hobby, Toy, And Game Shops	-0.571[a]	0.145	-0.015	0.151	0.215[a]	0.033
Home Furniture & Equip Stores	-0.017	0.174	0.562[b]	0.241	0.174[a]	0.030
Jewelry Stores	-0.438[a]	0.085	0.038	0.065	0.279[a]	0.035
Radio,TV,Cons Electr Stores	-0.500[a]	0.089	0.268[a]	0.059	0.140[a]	0.034
Variety Stores	-0.313[a]	0.047	0.106[a]	0.028	0.176[a]	0.027
Pooled coefficients from model (2)	-0.285[a]	0.017	0.252[a]	0.021	0.143[a]	0.007

[a, b] Statistically significant at p<0.001 and p<0.02, respectively, for two-tailed tests.

Table 5: Estimates of time-specific fixed effects c_t for models (1) and (2)

Year	Model (1)		Model (2)	
	Estimate	Std. Error	Estimate	Std. Error
1987	0.1297[a]	0.0171	0.1009[a]	0.0181
1988	0.0890[a]	0.0168	0.0611[a]	0.0177
1989	0.0774[a]	0.0164	0.0423[a]	0.0173
1990	0.0697[a]	0.0160	0.0375[a]	0.0169
1991	0.0681[a]	0.0155	0.0460[a]	0.0164
1992	0.0586[a]	0.0150	0.0388[a]	0.0159
1993	0.0517[a]	0.0146	0.0363[a]	0.0155
1994	0.0380[a]	0.0141	0.0276[b]	0.0150
1995	0.0287[b]	0.0136	0.0174	0.0145
1996	0.0109	0.0129	0.0008	0.0139
1997	0.0119	0.0121	-0.0009	0.0129
1998	0.0044	0.0108	-0.0024	0.0116
1999	0.0000	0.0086	-0.0024	0.0093
2000	-		-	

[a, b] Statistically significant at $p<0.01$ and $p<0.10$, respectively, for two-tailed tests.

Table 6: Time trends in IT, CI and GM estimated using equation (5)

Variable	Coefficient	Std Error	t-statistic	p-value
IT	-0.05460	0.01354	-4.03	<0.0001
log IT	-0.00454	0.00110	-4.11	<0.0001
CI	0.00568	0.00030	19.00	<0.0001
log CI	0.01250	0.00077	16.23	<0.0001
GM	-0.00018	0.00031	-0.59	0.5568
log GM	0.00093	0.00130	0.72	0.4736

Figure 1: Plot of annual inventory turns vs. annual gross margin for four consumer electronics retailers for the years 1987-2000

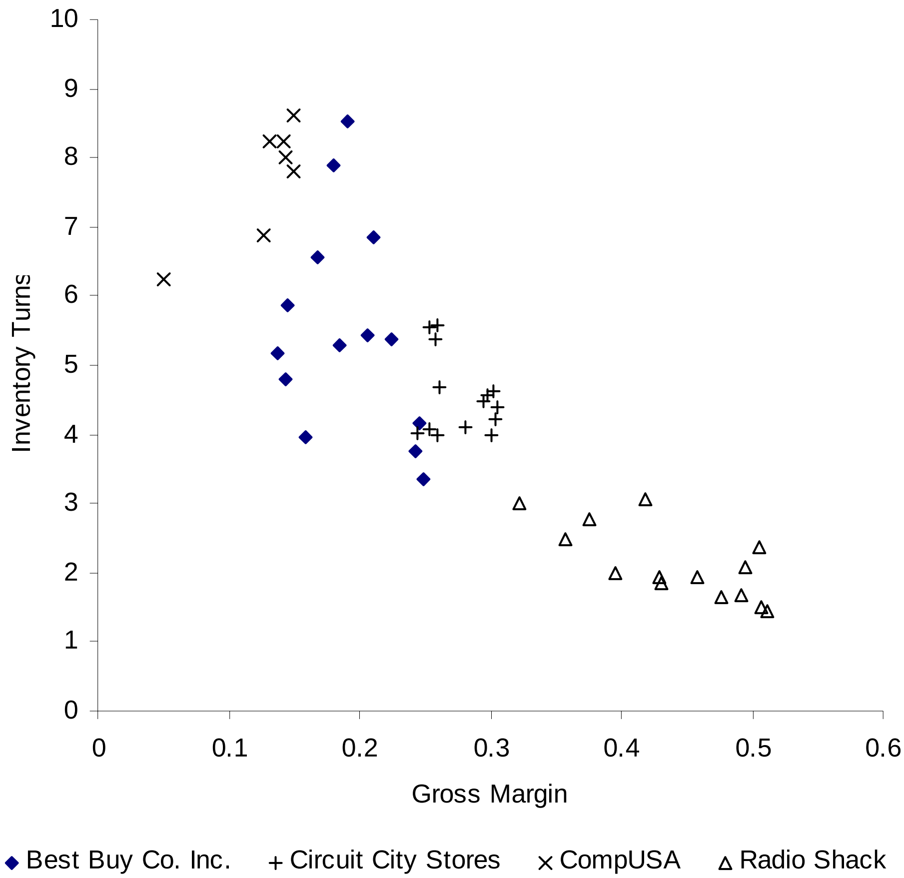


Figure 2: Plot of time-specific fixed effects c_t for model (2)
(the error bars show intervals of 2×standard error)

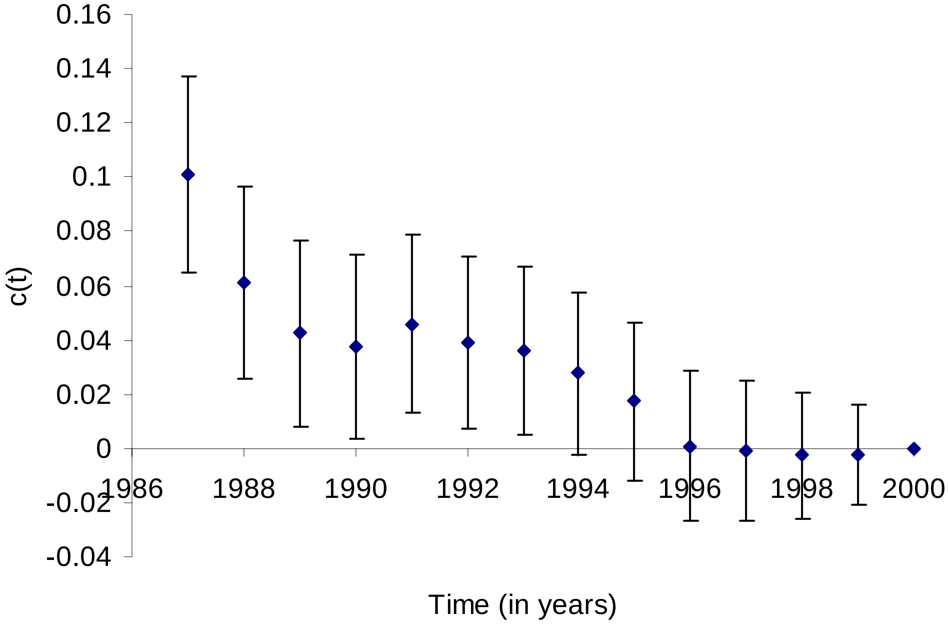
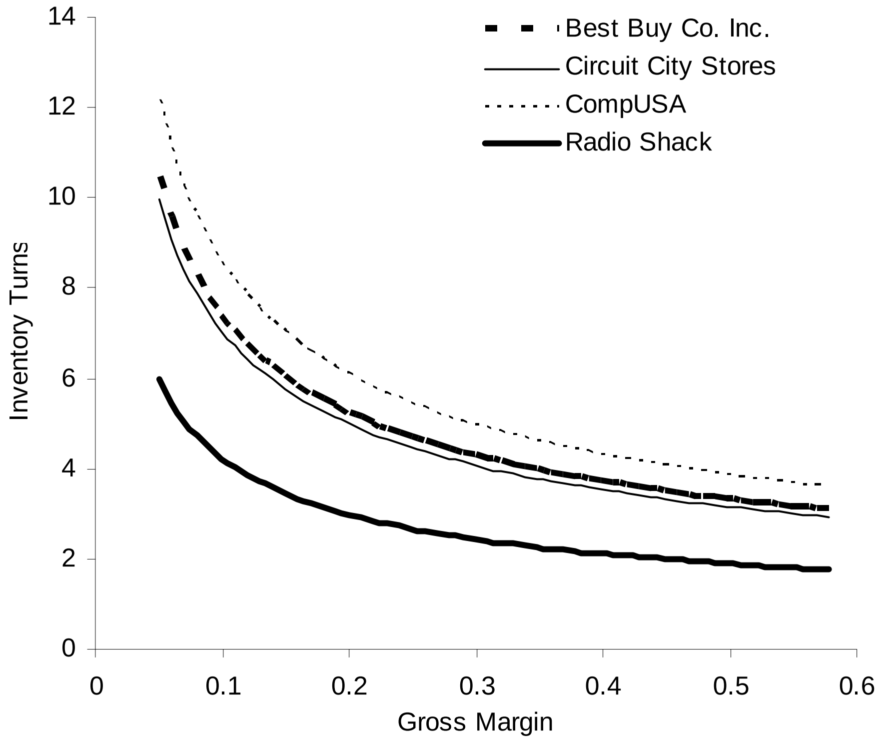


Figure 3: Tradeoff curves between inventory turnover and gross margin estimated for the four consumer electronics retailers in Figure 1 for the years 1987-2000



Note: These curves are computed using (8). CI is set to its average value for each firm and SS is set to 1 to avoid year-to-year variations in these variables.

Figure 4: Plot of Inventory Turnover and Adjusted Inventory Turnover for Ruddick Corp.