Int. J. Production Economics 133 (2011) 143–153

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

An empirical analysis of inventory turnover behaviour in Greek retail sector: 2000–2005

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ARTICLE INFO

Available online 30 April 2010

Keywords:
Inventory turnover
Product variety
Sales growth
Panel data analysis
Fixed effects

ABSTRACT

In this study we investigate the determinants of inventory turnover. The study is based on an econometric analysis of inventory behaviour using an inventory turnover model. The empirical implementation of the model was conducted on a sample of financial data for 566 Greek retail firms for the period 2000–2005. By employing panel data techniques it was found that inventory turnover ratio is negatively correlated with gross margin and positively correlated with capital intensity and a measure of sales surprise.

Decomposing the variance into its components associated with year, firm and retail segment effects, we found that a substantial amount of inventory turns variability is due to segment-wise effects. Moreover, the inventory turnover reaction to different sales changes was also studied. It was estimated that changes in sales bring on bigger changes when firms operate in sales-declined region. These results are useful in identifying methods and applications to improve inventory performance among firms and over time.

1. Introduction

Inventories have generally been the most difficult asset to be managed both for merchandising and manufacturing firms. Inventory management incorporates purchasing, financing and selling policies. The implementation of these diverse policies comprises conflicting functional objectives; e.g. the financial manager's effort to minimize the inventory level is contradictory to the goal of minimizing the probability of inventory shortage as marketing manager desires. Inventory management deals, on one hand, by specifying, retaining and controlling the desirable inventory level, and on the other, by minimizing the total inventory cost. In other words, the problem of managing inventories is an optimization problem between overstocking and understocking cost. Shortage of inventory implies unsatisfied demand and sales shrinkage. Excessive inventories may lead to the cost of items storage, taxes and insurance, breakage, spoilage, deterioration and obsolescence and the opportunity cost of alternative capital investment as well.

Moreover, in all firms, except those belonging to the financial and service sector, inventories represent a large proportion of current and total assets. For example, Gaur et al. (2005) report that in 2003, inventories in US retailing represent, on average, 36% of total assets and 53% of current assets. Likewise, our dataset on Greek retailers, during the period 2000–2005, show that inventories represent on average 38% of total assets and 51% of current assets. Generally, as it stems from the relevant literature, investment in inventory represents a significant amount of the total funds available in firms. Furthermore, comparison of inventory turns between firms are often the basis for managerial compensation (Shleifer, 1985). For these reasons inventory management receives great attention from market analysts, bankers and investors.

A financial index that combines the cost of goods sold with inventories is the inventory turnover ratio, defined as the ratio of a firm's cost of goods sold to its inventory level. This index shows how many times inventories are turned over during the accounting year. Hence, inventory turnover ratio can often be used as a comparative measure of inventory performance between firms, or in evaluating the effectiveness of inventory management. To our knowledge, there have been only a few research papers that investigate the determinants of inventory management as expressed by inventory turnover ratio. For example, Gaur et al. (2005) set up a methodology, which combines inventory turnover

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doi:10.1016/j.ijpe.2010.04.026

with other performance variables such as the gross margin, capital intensity and sales related variables.

In this study we follow a similar methodology in order to identify the factors that determine inventory behaviour and affect their performance using a large sample of Greek retailing firms operating in the period 2000–2005. Our dataset consists of repeated observations on the same cross section of firms over time drawn from financial data of the firms' annual income statements and annual balance sheets. Econometric analysis is based on the study of Gaur et al. (2005) for the U.S. retail sector. We have further extended this analysis by looking at the sales growth process in association with the inventory turnover ratio.

The results of our econometric analysis confirm the findings of the previous studies as far as the importance of gross margin, capital intensity and sales surprise ratio is concerned. Our model explains 94.10% of the total variation as well as 91.46% of within-firm variation of inventory turnover ratio. Moreover, we estimate the impact of sales growth rate on inventory turns and found that when firms operate in "sales-declined region", sales changes bring on bigger changes to the inventory turnover than in cases where firms operate in "sales-increased region". It was found that a 1% increase in sales growth ratio is associated with an increase in inventory turnover of 0.46% in the former case, and only 0.26% in the latter.

Besides, we investigate the importance of year, firm and segment effects on inventory turnover. By doing so, we find that the variation across segments accounts for 58% of the total variation, while 33% is due to the variation across firms. Finally, we estimated the inventory turnover trend over the entire period examined and found that it varies across firms.

Our results are useful in operation and financial management and could help managers make aggregate level inventory decisions as well as identify the causes of differences in inventory turns between firms and over time. It should be noted that the present panel data econometric study is the first in the Greek literature on inventory behaviour and the results coming from it can stimulate future research into possible ways of effective inventory management.[1]

The remainder of this paper is organized as follows. In Section 2, a review of the relevant literature is presented and the determinants of inventory turnover ratio are discussed. In Section 3, the dataset is explained and a number of descriptive statistics are given. The econometric model is specified in Section 4, while Section 5 contains the main findings. In Section 6 we discuss the implications of our results for operating and financial strategies as well as the limitations of our study. We conclude the paper in Section 7 showing directions for future research.

2. Literature review

Over the past decades, especially after the development of Japanese inventory management systems (e.g. just-in-time process), it has been argued that successful inventory management, mostly in the manufacturing sector, is associated with the reduction of inventory level. Chen et al. (2005) conclude that the inventory holding period of American manufacturing firms had been reduced from 96 days to 81 days between 1981 and 2000. The average rate of inventory holding period was 2% per year. In addition, according to their study, the greatest reduction, 6% per year, was found for work-in-process inventory. Raw materials declined by about 3% while finished-goods inventories did not decline. In fact, in certain sectors (leather, drugs and tobacco industries) finished-goods inventories had increased. Rajagopalan and Malhotra (2001) mentioned that, from 1961 to 1994, raw materials and work-in-process inventory of U.S. manufacturing firms had been reduced. During the same period there were no significant trends in finished-goods inventories.

To evaluate inventory management it is desirable to obtain appropriate performance measures. An accounting based performance variable is the inventory turnover ratio. To our knowledge a few empirical studies (e.g. Gaur et al., 2005; Roumiantsev and Netessine, 2007) investigate inventory management efficiency with a focus on accounting concepts considering that balance sheet and income statement may adequately categorize some activities related to operation and financial management. Gaur et al. (2005) conclude that inventory turnover varies widely across firms and over time. For this reason "…inventory turns should not be used, per se, in performance analysis". Instead, an empirical model could be used that combines the inventory turnover ratio with appropriate explanatory variables.

Empirical estimates have shown that inventory turnover ratio is negatively correlated with gross margin and positively correlated with capital intensity (Gaur et al., 2005). The negative correlation can be explained through the classical newsboy model[2] according to which an increase in gross margin implies an increase in the inventory level and, consequently, a decrease in inventory turns. Roumiantsev and Netessine (2007), analyzing a sample of 722 public US companies for the period from 1992 to 2002, found empirical evidence that firms operating with higher gross margins have higher inventory levels, thus lower inventory turns.

Furthermore, inventory turnover can be indirectly related to gross margin because of the impact of other factors like price, product variety and length of the product life cycle (Gaur et al., 2005). According to the demand theory, an increase in price reduces the volume of demand and increases its variability so that inventory level is being increased. In terms of product variety, according to both Lancaster's (1990) and Chamberlin's (1950) demand models, higher variety leads to an increase in consumer's utility either because the consumer easily spots the good he prefers through a wide variety, or because she has a built-in preference for variety, respectively, (Gaur et al., 2005). An increase in consumer's utility explains the increase in price which in turn increases gross margin.

In relation to the length of the product life cycle, short length implies rapid and repeated changes in product characteristics with a view to fulfilling the consumer's preferences (Pashigian, 1988) which justifies higher price level and thus increasing gross margin. Moreover, for those products with short life cycle the availability of historical datasets is limited to a few years' period. Consequently, the accuracy of demand forecasts is small which implies high demand uncertainty requiring a higher level of safety stocks, and as result a decrease in inventory turns.

Furthermore, gross margin is associated with stockout costs. These include both lost profits from the immediate order because of cancellations, and long-run costs if stockouts reduce the likelihood of future orders. In practice, customers do react substantially and negatively to poor service (e.g. stockouts), which may lead them to switch retailers on subsequent trips

[1] For a recent cross-sectional econometric study on Greek inventories see Dimelis and Lyriotaki (2007).

[2] Fundamental stochastic inventory model, in which it is assumed that the demand is a random variable, normally distributed with mean μ and standard deviation σ. According to the newsboy model (or news vendor model) the optimum size of the quantity order S can be determined from the eqquation. $\varphi\left(\frac{S-\mu}{\sigma}\right)=\frac{c_u}{c_0+c_u}$ where c is the cost per unit of unsatisfied demand and c_0 the cost per unit of positive inventory remaining at the end of the period (see, e.g. Axsater (2006) pp. 114–116).

(Fitzsimons, 2000) with a significant adverse effect on future demand (Anderson et al., 2003) increasing the loss-of-goodwill cost. On the other hand, satisfied customers are likely to continue to buy from the same firm (Anderson and Sullivan, 1993). Hence, the higher the gross margin the higher the lost profits associated with stockouts. As a result, higher gross margin may lead firms to increase the inventory levels to avoid facing higher lost profits.

The positive correlation between inventory turns and capital intensity results from the nature of investments. Capital investments (including investments in warehouses, equipments, information technology and logistics management systems) lead to a better inventory allocation as well as to a more efficient implementation of customer orders increasing inventory turns (Cachon and Fisher, 2000). A positive influence of information technologies on inventory performance is well supported at the firm level. For example, previous studies (Frohlich and Westbrook, 2002; Vickery et al., 2003; Barua et al., 1995; Mukhopadhyay et al., 1995) find that an increase in IT investment results in higher inventory turns and lower inventory holding costs. Rabinovich et al. (2003) state that the adoption of enterprise-wide information systems may be linked to a reduction in inventory turnover.

Investments in information technologies have helped firms to cut back on the volume of inventories as a precaution against glitches in their supply chain or as a hedge against unexpected increase in aggregate demand (Ferguson, 2001). Moreover, information technology investments may increase inventory turns due to improvement in the replenishment process (e.g., Garry, 1994; Robins, 1995; Casper, 1996). Clark and Hammond (1997) show that with the adoption of a continuous replenishment process by food retailers, their inventory turns increased up to 100%. However, automatic replenishment is not limited to the grocery industry; apparel retailers utilized automatic replenishing programs to improve the inventory efficiency (King and Maddalena, 1998).

Econometric analysis shows that inventories are largely driven by forecasts, especially those concerning demand. The accuracy achieved for these forecasts has consequences for all of the members of the supply chain from retailer to raw materials supplier, and even for companies whose final product is 'make-to-order' (Yelland, 2006). The forecasting problem is difficult due to the interrelated nature of the data series with outliers, level and trend shifts (Fildes and Beard, 1992), to the complexities of the market and general economic environment as well as to the innate optimism of the people who are overoptimistic in their forecasts underestimating future uncertainty significantly (Hogarth and Makridakis, 1981; Makridakis, 1986). Gaur et al. (2005) used the sales surprise ratio (the ratio of actual to anticipated sales) as a measure of the accuracy of forecasts and confirmed its positive impact on inventory turnover ratio. An unexpectedly low actual level of sales, namely a low sales surprise ratio, results in accumulation of unsold inventories, and thus in reducing inventory turns. The authors used the Holt's linear exponential smoothing method to measure anticipated sales because sales' forecasts are not publicly reported.

It is also possible, however, that not all firms achieve a positive sales growth rate. There are firms that face negative sales growth in which case the sensitivity of inventory turnover to the changes of sales growth rate may be different. This issue has been addressed by Gaur and Kesavan (2005) who estimated that the inventory turnover of a firm is more sensitive to sales ratio in the sales contraction region than in the sales expansion region. This assumption can be further supported by retail variety and inventory level decisions. Baumol and Ide (1956) focus on modeling cost–benefit trade-offs in retail variety and argue that the greater the number of items carried by the store, the greater is the likelihood that consumers will purchase something from the assortment.

Using a stochastic version of the above model, Van Ryzin and Mahajan (1999) conclude that when retailers face independent demand, high variety becomes more profitable as sales increase and the store will carry all variants in a sufficiently high volume tending to stock not only more units of each variant but also more variants. Subsequently, in the independent demand case, there are scale economies exploited by stores. Kekre and Srinivasan (1990) find that larger product variety is associated with a larger market share while there is no evidence that larger variety leads to higher costs.

On the contrary, firms that encounter declined (or constant) sales level over time are the most likely to face financing constraints. These firms cannot support growing sales volume because of their inability to invest in fixed assets as well as in working capital. Such firms offset this inability with their intimate knowledge of local markets and the buying flexibility to respond to that information. They are based on regular customers and face low demand variation allowing them to hold low inventory stock. We can conclude that in this case changes in sales ratio bring on bigger changes in inventory turns than in the case of positive growth rate.

Most companies consider inventory level decisions independent of each other which entails that inventory policy is characterized by isolated management approaches. However, market, competitive and environmental factors like seasonality, business cycles, barriers to entry, the bargaining power of vendors, technological changes, prices, the cost of capital and the gross domestic product influence the total inventory investments (see e.g. Blinder, 1981; Blinder and Maccini, 1991; Kahn, 1992; Bils and Kahn, 2000). Those factors may cause systematic differences in inventory turns across retail segments and over time. Hence, a variance decomposition analysis is required to account for time, segment and firm effects.[3]

Based on the arguments mentioned above, although inventory turnover ratio is widely used to evaluate how effectively retailers utilized their investment in inventories, very serious errors can result if inventory turnover figures are accorded greater weight than it deserves in arriving at judgments. Many complex circumstances bear upon policy formulation in the individual firm, and these factors can influence inventory investment. Thus inventory turnover ratio cannot be used routinely or mechanically in judging inventory investment policies; it must be used in conjunction with an analysis of underlying economic and financial aspects. The overall firm strategy determines pricing policy, merchandise variety, assortment and product availability, store size, information technology, location, and the level of customer service. Following the relevant literature, those features can be proxied by gross margin, capital intensity, forecasting accuracy and sales growth which influence inventory levels as well as the cost of goods sold and thus the inventory turns.

[3] This kind of analysis appears in the business strategy literature with representative studies of those of Schmalensee (1985), Rumelt (1991) and McGahan and Porter (1997). McGahan and Porter (2002) improve the robustness of the research methodology and state that industry specific effects and business-specific effects are important in explaining accounting profitability and that industry-specific effect keep on over longer periods. Hawawini et al. (2003) concluded that firm and industry factors have different impact on firms that do not outperform or underperform their peers in the same industry. In the Greek literature, Spanos et al. (2004) provide evidence that firm-specific factors explain greater amount of profit variability than industry factor does. Studies worked on the decomposition of other performance measures like Tobin's q and market share are those of Wernerfelt and Montgomery (1988) and Chang and Singh (2000), respectively. Mauri and Michaels (1998) state that firm effects are more important than industry effects on firm performance but not on core strategies such as technology and marketing. For the purpose of their study they use in addition to return on assets, advertising and R&D intensity measures.

Table 1
Retail sectors and number of firms in the sample.

SIC code	Sector description	Original sample (# of firms)	Final sample (# of firms)
5211	Super markets	93	88
5214	Variety stores	15	10
5222	Meat and meat products retail stores	16	16
5233	Health and personal care stores	38	38
5241	Textile stores	27	23
5242	Apparel stores	164	142
5243	Footwear, leather accessories stores	28	25
5244	Home furniture and equipment stores	83	75
5245	Radio, TV, consumer electronic stores	68	60
5246	Building materials and garden equipment stores	67	63
5251	PC's hardware stores	19	16
TOTAL		**618**	**556**

Table 2
Mean, standard deviation and median of the components of current assets by sector.

SIC code	Inventories to total assets		Inventories to current assets		Cash and cash equivalents to current assets		Accounts receivables to current assets		Obs.
	Mean (s.d.)	Median	Mean (s.d.)	Median	Mean (s.d.)	Median	Mean (s.d.)	Median	
5211	0.337 (0.174)	0.338	0.519 (0.231)	0.532	0.303 (0.224)	0.255	0.178 (0.191)	0.106	528
5214	0.385 (0.172)	0.405	0.533 (0.247)	0.605	0.315 (0.285)	0.216	0.152 (0.099)	0.135	60
5222	0.105 (0.162)	0.045	0.140 (0.202)	0.063	0.438 (0.317)	0.428	0.422 (0.297)	0.380	96
5233	0.541 (0.207)	0.529	0.673 (0.196)	0.690	0.087 (0.170)	0.035	0.240 (0.116)	0.186	228
5241	0.541 (0.201)	0.529	0.673 (0.206)	0.690	0.087 (0.112)	0.035	0.240 (0.174)	0.186	138
5242	0.446 (0.239)	0.417	0.573 (0.242)	0.577	0.209 (0.207)	0.131	0.219 (0.199)	0.155	852
5243	0.416 (0.198)	0.360	0.573 (0.234)	0.612	0.193 (0.152)	0.151	0.234 (0.229)	0.137	150
5244	0.351 (0.200)	0.311	0.458 (0.227)	0.418	0.194 (0.192)	0.112	0.347 (0.223)	0.305	450
5245	0.358 (0.194)	0.312	0.438 (0.221)	0.383	0.191 (0.151)	0.152	0.371 (0.207)	0.372	360
5246	0.406 (0.216)	0.380	0.513 (0.237)	0.506	0.126 (0.153)	0.070	0.360 (0.216)	0.365	378
5251	0.152 (0.112)	0.142	0.168 (0.117)	0.162	0.294 (0.245)	0.213	0.538 (0.226)	0.557	96
All	**0.389 (0.222)**	**0.357**	**0.510 (0.250)**	**0.506**	**0.216 (0.208)**	**0.141**	**0.274 (0.223)**	**0.217**	**3336**

In this paper, we build upon the methodology of Gaur et al. (2005) to investigate the determinants of inventory turnover at the firm level. Both operational drivers and microeconomic characteristics are examined such as gross margin, capital intensity, forecasting accuracy and sales growth. Having estimated the impact of these factors on inventory turns, an expected trade-off curve is obtained which can be used to evaluate the inventory performance. If a firm's inventory turnover ratio is lower than expected (for specific values of the above factors), then the firm should investigate the causes of such ineffectivity and rectify its inventory productivity. Thus, the model can be useful for operation and financial management in decision making process providing a benchmark against which to measure firms' inventory performance.

Moreover, decomposing the total variance of inventory turns and estimating the proportion of variance that is due to differences between years within firms, across firms and across retail segments, we provide a more satisfying treatment of inventory behaviour within the retail industry. Diagnosing the sources of variation can offer information about the drivers of inventory heterogeneity at the firm level. We note that studies in strategic management examine the total variance in the rate of return and not in the operating performance measures like inventory turns as we do in this paper.

Finally, it should be noted that prior research focused only on publicly listed firms, despite the fact that private retail firms hold a large proportion of total retail inventories even in large economies. Because we study both private and publicly listed retail companies, our analysis should yield more representative results for inventory turnover performance in retailing.

3. Data description—definition of variables

In this study we use financial data for Greek retail firms operating over the years 2000–2005, drawn from annual income statements and balance sheets. Firms in the retail industry are classified into 11 sectors according to the standard industry classification code. The entire dataset contains 618 firms, out of which we had to exclude those firms that, for several reasons (mergers, acquisitions, bankruptcy, etc) had missing data or negative gross margin over the six-year period. Thus, we obtained a balanced panel dataset of 556 firms, and a number of 3336 observations as shown in Table 1. Considering that our models are log linear, variables with zero value cannot be used in logarithms as well as in denominators. Thus, every variable with zero value is replaced by the smallest nonzero value that appears in the sample. However, such transformations create outliers. Because outlier observations may cause problems in estimation, particularly when using ratios, we follow the method of winsorization of the data. Thus, for every variable, the 1% at both tails of their distribution is replaced (see, e.g. Gompers et al., 2005) by the highest (lowest) value that is not removed[4].

Table 2 presents summary statistics of inventories and other components as a share to total and current assets. For Greek retailers, inventories represent on average 38% of total assets and

[4] Other data problems include the "earnings management", "exaggeration" of inventory level when inventories serve as collateral of debt in order to affect creditors, etc. Unfortunately, we cannot deal with such problems and hope that accounting bias is negligible.

Table 3
Descriptive statistics for capital intensity, gross margin, and inventory turnover ratio.

SIC code	Capital intensity (*ci*)		Gross margin (*gm*)		Inventory turnover ratio (*it*)	
	Mean (s.d.)	Median	Mean (s.d.)	Median	Mean (s.d.)	Median
5211	0.474 (0.228)	0.478	0.175 (0.058)	0.178	9.245 (12.412)	6.604
5214	0.359 (0.152)	0.352	0.231 (0.104)	0.250	9.344 (17.707)	3.418
5222	0.643 (0.307)	0.750	0.171 (0.055)	0.163	93.605 (110.586)	46.150
5233	0.276 (0.213)	0.229	0.288 (0.146)	0.286	2.457 (1.219)	2.231
5241	0.232 (0.187)	0.197	0.409 (0.105)	0.401	1.166 (0.908)	0.867
5242	0.323 (0.257)	0.279	0.354 (0.117)	0.357	2.820 (4.476)	1.700
5243	0.335 (0.213)	0.342	0.339 (0.122)	0.333	2.419 (1.647)	2.077
5244	0.363 (0.250)	0.319	0.374 (0.118)	0.369	3.673 (4.613)	2.265
5245	0.291 (0.226)	0.246	0.246 (0.137)	0.216	3.309 (3.928)	2.694
5246	0.312 (0.261)	0.253	0.245 (0.109)	0.241	3.724 (5.237)	2.223
5251	0.330 (0.229)	0.271	0.257 (0.159)	0.221	13.785 (16.180)	8.927
All	0.351 (0.254)	0.316	0.291 (0.136)	0.274	7.041 (25.085)	2.569

51% of current assets. Of the remaining 49% of current assets, cash and cash equivalents represent 22% and accounts receivables represent 27%.

Using the data described earlier, the following variables were calculated for the estimation purposes of this study. The econometric models are specified in the next section.

Inventory turnover ratio (*it*) at year *t*, is defined as the ratio *of cost of goods sold* (*CGS*) minus *depreciation* (*Depr*) to *inventories* (*Inv*) at year *t*:

$$it_{sit} = \frac{CGS_{sit} - Depr_{sit}}{Inv_{sit}}$$

From an accounting perspective the relation between inventory level and the cost of goods sold can be illustrated as follows. Beginning-of-period inventories plus net purchases constitute goods available[5] for sale. The costs of these goods' inventories are initially recorded on the balance sheet. As a firm operates and sells the inventories, these costs are removed from the balance sheet and flow into the income statement as cost of goods sold. Hence, the cost of goods available for sale is allocated between balance sheet (as a future expense) and income statement (as already realized cost). At the end of the fiscal year the flow of the costs is "terminated" – for accounting reasons – so that both the cost of goods sold and the end-of-period inventories can be determined.

Gross margin (*gm*) is defined as the ratio of sales minus cost of goods sold at year *t* to sales at year *t*:

$$gm_{sit} = \frac{Sales_{sit} - CGS_{sit}}{Sales_{sit}}$$

Capital intensity (*ci*) is defined as the ratio of net fixed assets (*NFA*) to the sum of inventories (*Inv*) and net fixed assets (*NFA*) at year *t*:

$$ci_{sit} = \frac{NFA_{sit}}{NFA_{sit} + Inv_{sit}}$$

Table 3 presents descriptive statistics for *ci*, *gm* and *it* by sector. Inventory turnover ratio ranges from 1.16 (*textile stores*) to 93.6 (*Meat and meat products retail stores*). Exceptionally high values of inventory turnover ratio were observed for the third sector because of the nature of the inventories.

Another important explanatory variable for inventory turnover is *sales surprise* (*ss*). This index is defined as the ratio of actual sales to anticipated sales. In order to calculate the denominator, considering that sales' forecasts are not publicly reported, we estimate sales' forecast from historical data using Holt's linear exponential smoothing method. The sales forecast for year *t* is

[5] Consider the case of commercial firms.

Table 4
Correlation coefficients matrix (total number of observations for 2002–2005 period).

	it	*gm*	*ci*	*sgr*	*ss*
it	1.000				
gm	−0.234	1.000			
ci	0.356	−0.011	1.000		
sgr	0.004	0.000	0.032	1.000	
ss	−0.011	0.078	0.029	0.219	1.000

$$sales\ \mathrm{forecast}_{it} = L_{i,t-1} + T_{i,t-1}$$

where

$$L_{it} = a_i Sales_{it} + (1-a_i)(L_{i,t-1} + T_{i,t-1})$$

$$T_{it} = \gamma_i (L_{it} - L_{i,t-1}) + (1-\gamma_i) T_{i,t-1}$$

and $a, \gamma\{a, \gamma \in [0,1]\}$ are constant weights. For each firm we define the values of a_i and γ_i that provide the best and unbiased forecasts. Thus, sales surprise (*ss*) is obtained as follows:

$$ss_{sit} = \frac{sales_{sit}}{sales\ forecast_{sit}}$$

However, sales forecasts may not correspond to the ones estimated by managers. This can happen because our estimates rely on historical data, while managers form their forecasts on information not available to us. Hence, besides using *ss* as an explanatory variable in our models, we have estimated the same models by replacing *ss* with *sales growth rate* (as a proxy to sales surprise ratio), defined as

$$sales\ \ growth\ \ rate_{sit} = \frac{sales_{sit} - sales_{si,t-1}}{sales_{si,t-1}}$$

In order to avoid having negative values we modify the *sales growth rate* variable as follows:

$$sgr_{sit} = 1 + \frac{sales_{sit} - sales_{si,t-1}}{sales_{si,t-1}} = \frac{sales_{sit}}{sales_{si,t-1}}$$

To test for the impact of changes in sales growth rate to inventory turns in sales-declined region as well as in sales-increased region, we introduce another variable, named *censgr*, which takes the following values:

$$censgr_{sit} = \left| \begin{array}{ll} 0, & \text{if} \quad \log sgr_{sit} < 0 \\ \log sgr_{sit}, & \text{if} \quad \log sgr_{sit} > 0 \end{array} \right.$$

Thus, if in addition to *sgr*, we include the *censgr* variable in the model, we can distinguish two regions of sales growth ratio (*sgr*)

1. sales-declined region, where $\log sgr_{sit} < 0 \Rightarrow sgr_{it} < 1 \Rightarrow sales_{sit} < sales_{si,t-1}$
2. sales-increased region, where $\log sgr_{sit} > 0 \Rightarrow sgr_{it} > 1 \Rightarrow sales_{sit} > sales_{si,t-1}$

Finally, Table 4 shows the correlation matrix of the model's variables.

4. Econometric analysis

To investigate the inventory turnover behaviour in this paper, we specify a log linear model based on the results of recent studies analyzed in Section 2. Thus, the model takes the following form:

$$\log it_{sit} = F_i + c_t + b_{1,s}\log gm_{sit} + b_{2,s}\log ci_{sit} + b_{3,s}\log ss_{sit} + u_{sit} \quad (1)$$

where index i refers to the firm, s refers to the sector where the firm belongs and t measures time. Thus, the dependent variable $\log it_{sit}$ denotes the log of inventory turnover of firm i in sector s at year t. The independent variables, $\log gm$, $\log ci$ and $\log ss$, denote the log of gross margin, capital intensity and sales surprise, respectively. The error term u_{sit} captures idiosyncratic disturbances that vary over time as well as across firms. F_i denotes the firm-specific effects, which are unobservable effects, constant over time but varying across firms; e.g. differences in managerial efficiency or in accounting methods among firms. The term c_t denotes the period-fixed effects, which are unobservable effects constant across firms but varying over time; e.g. interest rates and prices. The introduction of firm-specific and period effects takes care of the "omitted variable" problems which may result in inconsistent estimates of the coefficients. Finally, parameters b_s denote the coefficients to be estimated and may be allowed to vary among sectors.

We estimate model (1) assuming differences among sectors. In doing so we introduce 11 dummy variables and also, interact them with each one of the explanatory variables. To test whether these differences are statistically significant we compare model (1) with the following model which is a pooled regression:

$$\log it_{sit} = F_i + c_t + b_1\log gm_{sit} + b_2\log ci_{sit} + b_3\log ss_{sit} + u_{sit} \quad (2)$$

An F-test is performed to test the null hypothesis of parameter equality for each of the explanatory variables.

In addition, to avoid any multicollinearity problems between ci and gm, which are the functions of inventory level and cost of goods sold, respectively, and so is the dependent variable it, we re-estimate models (1) and (2) by using the level of inventories inv as dependent variable. We also introduce as independent variable the cgs (cost of goods sold) to control for scale effects

$$\log Inv_{sit} = F_i + c_t + b_{1,s}\log gm_{sit} + b_{2,s}\log ci_{sit} + b_{3,s}\log ss_{sit} + b_{4,s}\log cgs_{sit} + u_{sit} \quad (3)$$

Finally, we estimate models (1) and (2) by using alternative forecasting methods to estimate the sales surprise variable. Such a variable is the sgr instead of ss, which may take care of the differences between forecasting methods estimated from the model and those produced by the managers.

To test the inventory turnover reaction to sales changes when firms operate in "sales-declined region" as well as in "sales-increased region" we estimate the following model:

$$\log it_{sit} = F_i + C_t + b_1\log gm_{sit} + b_2\log ci_{sit} + b_3\log sgr_{sit} + b_4\, censgr_{sit} + u_{sit} \quad (4)$$

where sgr and $censgr$ were defined in the previous section.

Due to the nature of our dataset it is very likely that the independent variables are correlated with the firm-specific effects. Thus, fixed effects estimation is more appropriate than random effects estimation because if the true model has individual-specific effects correlated with the regressors, then a random effect process yields inconsistent estimates (Mundlak, 1978).

To test whether fixed effects are present we employ a Hausman test (Hausman, 1978). A large value of the Hausman test statistic was estimated (Chi-sq stat=50.33, p-value=0.00) leading to the rejection of the null hypothesis that the firm-specific effects are uncorrelated with the independent variables and to the conclusion that fixed effects are present.

Conclusions that the true model is *two-way fixed effects* can be amplified by testing the significance of the unobserved effects. We perform an F-test of the null hypothesis (H_0) that all the coefficients of cross-section dummies are jointly equal to zero (see Table 5—Model 2). With an F-statistic of 34.8 (with 555° and 2217° of freedom), we reject the H_0 at the 0.1% level ($p < 0.001$).

Similarly, we reject the null (F-statistic of 7.8 with 4 and 2217 degrees of freedom) that all the coefficients of time-dummies are jointly equal to zero as well as all the coefficients of both dummies (time and cross-sectional) are jointly equal to zero (F-statistic of 34.62 with 559 and 2217 degrees of freedom).

At Table 6 we present F-tests for equality between coefficients for each of the explanatory variables across sectors. The null hypothesis of no differences across sectors is rejected for all three variables.

We estimate all models assuming different residual variance for each firm. Moreover, residual variance between firms and different periods is assumed to be zero

$$E(u_i u_i^{/}/X_i) = \sigma_i^2 I_T$$

$$E(u_{ik} u_{jt}^{/}/X_i) = 0$$

for all i, k, j and t with $i \neq j$ and $k \neq t$, where X_i contains all the explanatory variables as well as the relevant cross-section (F_i) and period effects (C_t).

Hence, feasible generalized least squares (FGLS) estimation for this specification is the proper method, allowing for cross section heteroskedasticity.

Variance decomposition analysis relies on the model below

$$\log it_{sit} = a + F_i + C_t + H_s + u_{sit} \quad (5)$$

where H_s denotes segment-specific effects and α the overall mean of $\log it$.

Following the relevant literature, we estimate Eq. (5) by using variance components analysis (see e.g. Searle et al., 1992) treating F_i,

Table 5
Tests of significance of cross-section and period-fixed effects.

MODEL (2)			
Effects test	**Statistic**	***df***	**Prob.**
Cross-section F	34.85	(555,2217)	0.00
Cross-section Chi-square	6323.18	555	0.00
Period F	7.80	(4,2217)	0.00
Period Chi-square	38.86	4	0.00
Cross-section/Period F	34.63	(559,2217)	0.00
Cross-section/Period Chi-square	6325.41	559	0.00

Table 6
Equality tests of explanatory variables across sectors.

Model (1)	***F*-statistic**	***df***	**Probability**
log(*ss*)	24.806	(10, 2188)	0.00
log(*gm*)	12.029	(10, 2188)	0.00
log(*ci*)	18.787	(10, 2188)	0.00

C_t and H_s as random effects rather than fixed effects. This is because if all the individual effects are treated as fixed and different there is no way to obtain meaningful estimates without an enormous number of observations. The econometric problem is to estimate only the intercept (α) and four variances (including the variance of u_{sit}) on these effects and not the relationships between the depended and the explanatory variables. With this specification we expect that the effects are not correlated with the levels of the effects. Thus, we view time, firm and segment-specific effects as random variables while still allowing them to differ from firm to firm, from time to time and from segment to segment.

5. Results

Estimation results are presented in Tables 7–10 below. Parts A and B of Table 7 include the estimates obtained from the first two models. The most important of them are as follows:

5.1. Inventory turnover is negatively correlated with gross margin

The coefficient of *gm* in model (1) is found negative in 10 out of 11 sectors. Out of the negative ones, eight are statistically significant ($p<0.001$), while the positive one is statistically insignificant. The observed negative relation between gross margin and inventory turnover implies that (at least in the same segment) retailers trade off gross margin for inventory turns to achieve similar return on inventory investment (the product of gross margin and inventory turnover). If inventory turnover ratio is lower than the targeted given the level of gross margin, then management should be alarmed with this inefficiency.

As mentioned in the literature review, the coefficient of gross margin in our models may also account for the impact of operational and financial characteristics that are shaped by the industry structure such as product variety, price, the length of product life cycle, the selecting target market, the organizational structure, the information and distribution systems to support the strategic direction, asset and capital structure and the combination of them. Therefore, it is likely that the coefficient of gross margin differs between sectors (see equality tests at Table 6). The negative elasticities of gross margin are bounded by -0.7% (*PC's Hardware stores*) and -83.8% (*Textile stores*) corresponding to a between sectors relative variation of 12.42% (see Table 7). Using only the gross margin as explanatory variable in the model, we cannot separate the impact of those (unobservable) factors which lead to individual heterogeneity across retail sectors.

5.2. Inventory turnover is positively correlated with capital intensity

The coefficient of *ci* in model (1) is found positive in 10 out of 11 sectors. All positive coefficients, except one, are statistically significant ($p<0.001$) while the negative one is statistically insignificant. The coefficient of *ci* for the super market sector is relatively higher than those for the other sectors (see Table 7) indicating the importance of the investments in information technology in that sector; supermarkets may experience improved product availability associated with the reduction of stockouts while they can carry less backup inventory to stay in stock. Thus, inventory levels are lower, and with a lower inventory investment, inventory turnover is higher.

5.3. Inventory turnover is positively correlated with sales surprise

The coefficient of *ss* in model (1) is found positive for 9 out of 11 sectors. Out of the positive ones, 8 are statistically significant ($p<0.002$) while one of the two negative parameters is

Table 7
Coefficient estimates of models (1) and (2)

A. Model (1): Dependent Variable log *it*									
SIC Code	**Log *gm***			**Log *ci***			**Log *ss***		
	Coef.	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**
5211	−0.572	0.036	0.000	0.383	0.039	0.000	−0.319	0.069	0.000
5214	−0.512	0.211	0.015	0.435	0.072	0.000	1.359	0.139	0.000
5222	0.277	0.145	0.056	0.015	0.009	0.092	1.232	0.187	0.000
5233	−0.396	0.087	0.000	0.041	0.005	0.000	−0.046	0.028	0.101
5241	−0.838	0.066	0.000	0.207	0.026	0.000	0.453	0.053	0.000
5242	−0.654	0.044	0.000	0.096	0.024	0.000	0.112	0.089	0.205
5243	−0.398	0.047	0.000	−0.006	0.008	0.424	0.152	0.049	0.002
5244	−0.479	0.063	0.000	0.119	0.007	0.000	0.603	0.050	0.000
5245	−0.583	0.054	0.000	0.088	0.011	0.000	0.425	0.075	0.000
5246	−0.311	0.046	0.000	0.078	0.008	0.000	0.707	0.089	0.000
5251	−0.007	0.110	0.951	0.183	0.056	0.001	0.798	0.112	0.000
A. Model (2): Pooled	**−0.485**	**0.023**	**0.000**	**0.069**	**0.004**	**0.000**	**0.223**	**0.047**	**0.000**
B. Model (1): Dependent Variable log *it*									
SIC Code	**Log *gm***			**Log *ci***			**Log *sgr***		
	Coef.	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**
5211	−0.536	0.023	0.000	0.404	0.033	0.000	−0.107	0.058	0.064
5214	−0.692	0.138	0.000	0.425	0.032	0.000	0.834	0.072	0.000
5222	−0.015	0.147	0.918	−0.021	0.013	0.113	0.453	0.131	0.001
5233	−0.405	0.095	0.000	0.042	0.005	0.000	0.020	0.010	0.039
5241	−0.843	0.041	0.000	0.073	0.011	0.000	0.332	0.041	0.000
5242	−0.617	0.026	0.000	0.098	0.017	0.000	0.463	0.040	0.000
5243	−0.383	0.038	0.000	−0.006	0.008	0.493	0.165	0.018	0.000
5244	−0.421	0.087	0.000	0.093	0.010	0.000	0.529	0.035	0.000
5245	−0.563	0.028	0.000	0.143	0.007	0.000	0.486	0.056	0.000
5246	−0.376	0.007	0.000	0.076	0.011	0.000	0.399	0.022	0.000
5251	0.014	0.110	0.900	0.183	0.054	0.001	0.174	0.077	0.025
B. Model (2): Pooled	**−0.466**	**0.021**	**0.000**	**0.073**	**0.005**	**0.000**	**0.356**	**0.025**	**0.000**

Table 8
Coefficient estimates of model (3)

A. Dependent Variable: log *Inv*												
SIC Code	**Log *gm***			**Log *ci***			**Log sgr**			**Log cgs**		
	Coef.	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**
5211	0.497	0.034	0.000	−0.463	0.056	0.000	0.208	0.030	0.000	0.939	0.055	0.000
5214	0.144	0.233	0.538	−0.692	0.071	0.000	−0.504	0.093	0.000	0.519	0.085	0.000
5222	−0.579	0.199	0.004	−0.010	0.003	0.001	−0.352	0.242	0.146	0.095	0.044	0.030
5233	0.372	0.033	0.000	−0.027	0.003	0.000	0.207	0.050	0.000	0.589	0.069	0.000
5241	0.507	0.059	0.000	−0.105	0.027	0.000	−0.093	0.036	0.009	0.511	0.043	0.000
5242	0.435	0.028	0.000	−0.093	0.020	0.000	−0.220	0.028	0.000	0.708	0.076	0.000
5243	0.360	0.014	0.000	0.005	0.005	0.348	0.121	0.032	0.000	0.486	0.026	0.000
5244	0.306	0.038	0.000	−0.031	0.009	0.001	−0.151	0.031	0.000	0.380	0.041	0.000
5245	0.275	0.026	0.000	−0.116	0.013	0.000	−0.017	0.047	0.713	0.301	0.019	0.000
5246	0.189	0.022	0.000	−0.086	0.009	0.000	−0.021	0.010	0.034	0.170	0.019	0.000
5251	−0.198	0.156	0.206	−0.177	0.074	0.017	0.415	0.180	0.021	0.293	0.354	0.408
B. Dependent Variable: log *Inv*												
SIC Code	**Log *gm***			**Log ci**			**Log ss**			**Log cgs**		
	Coef.	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**	**Coef.**	**Std. Er.**	***p*-Value**
5211	0.452	0.034	0.000	−0.403	0.043	0.000	0.641	0.079	0.000	0.646	0.042	0.000
5214	0.298	0.173	0.085	−0.624	0.065	0.000	−0.961	0.160	0.000	0.689	0.090	0.000
5222	−0.594	0.091	0.000	−0.018	0.001	0.000	−0.850	0.198	0.000	0.520	0.142	0.000
5233	0.309	0.022	0.000	−0.015	0.002	0.000	0.349	0.025	0.000	0.513	0.028	0.000
5241	0.482	0.068	0.000	−0.145	0.040	0.000	−0.302	0.075	0.000	0.496	0.056	0.000
5242	0.374	0.019	0.000	−0.092	0.014	0.000	0.231	0.050	0.000	0.564	0.041	0.000
5243	0.382	0.027	0.000	0.005	0.006	0.352	0.050	0.068	0.462	0.512	0.021	0.000
5244	0.298	0.018	0.000	−0.039	0.005	0.000	−0.141	0.012	0.000	0.371	0.026	0.000
5245	0.270	0.020	0.000	−0.113	0.011	0.000	−0.112	0.058	0.052	0.306	0.022	0.000
5246	0.185	0.022	0.000	−0.082	0.007	0.000	−0.053	0.027	0.046	0.193	0.027	0.000
5251	−0.130	0.204	0.526	−0.154	0.068	0.025	−0.451	0.269	0.094	0.576	0.397	0.147

Table 9
Coefficient estimates of model (4).

Dependent variable: **log *it***				
Independent variables	**Coefficient**	**Std. error**	***t*-Statistic**	**Prob.**
log *gm*	−0.469	0.021	−22.886	0.00
log *ci*	0.076	0.005	14.248	0.00
censgr	−0.202	0.040	−5.090	0.00
log *sgr*	0.464	0.025	18.352	0.00

Table 10
Variance component estimates of model (5).

Dependent variable: log *it*			
Independent variables	**Coefficient**	**Std. error**	**$P>\|z\|$**
Intercept	1.229	0.279	0.000
Variance components **Source of variation**	**Estimates**		**Std. error**
Variance between years	0.003		0.002
Variance across segments	1.105		0.509
Variance across firms	0.621		0.039
Residuals variance	0.175		0.005
Proportion of total variance explained			
Variance between years	0.16%		
Variance across segments	58.03%		
Variance across firms	32.61%		
Residuals variance	9.21%		

statistically significant. If a retailer overforecasts, resulting in an overbought situation where sales surprise ratio is low slowing down inventory turns, the store runs promotions or marks merchandise down in price until the overstocked condition is corrected. The need to mark down merchandise leads directly to lower gross margins leading to a further reduction in inventory turns. If management underbuys, a situation where sales surprise ratio is high speeding up inventory turns, it can either expedite a new order or try to substitute other merchandise. The important point for the retailer, however, is that despite these 'buffers', inaccurate forecasts impose additional burdens in the form of out-of-pocket and opportunity costs, customer goodwill and poor performance at merchandising levels (Geurts and Kelly, 1986).

In the pooled regression (part A, Model 2 of Table 7) the coefficient of *gm* is found negative and statistically significant. In the case of *ci*, a positive and statistically significant impact is estimated. Finally, the impact of *ss* on inventory turnover is found positive and statistically significant. When we use the *sgr* instead of *ss* in models (1) and (2), results are slightly different (part B of Table 7). The overall prediction accuracy for model 2 is 94.10%.

Parts A and B of Table 8 below contain the estimation results of model (3). Interpretation of coefficients of *gm*, *ci*, *ss* and *sgr* is similar to that of models (1) and (2). The results do not differentiate much, while the new independent variable introduced, log *cgs*, is statistically significant in all sectors except the last one.

Table 9 includes the estimates of model (4). The estimated coefficient of log *sgr* shows the impact of sales' growth rate on inventory turn in sales-declined region. The coefficient is positive and statistically significant. Its value, 0.46, indicates that *it* tends to change, ceteris paribus, by 0.46% for a 1% change in *sgr*. The sum of the values of log *sgr* and *censgr* which is 0.26 shows the impact of sales' growth rate on inventory turn in sales-increased region. Its value indicates that *it* tends to change, ceteris paribus, by 0.26% for a 1% change in *sgr*. The average value of log *sgr* is

Table 11
Estimates of model (8).

Dependent variable	Coefficient of *t*	Std. error	*t*-Statistic	*P*-value	Durbin–Watson stat
log *gm*	0.026	0.001	26.598	0.00	1.734
log *ci*	0.008	0.002	5.312	0.00	1.161
log *it*	−0.034	0.002	−18.162	0.00	1.565

obtained if we omit the variable *censgr* from the model and it is about 0.35 (see part B of Table 7).

Based on these results we can conclude that *inventory turnover is more sensitive to the changes in sales growth rate when firms operate in the sales-declined region than in the sales-increased region*. In the case where a firm operates in sales-declined region, one approach to maintain acceptable inventory turnover is to reduce the number of merchandise categories, the number of stock-keeping-units or the number of items within a unit (to reduce the inventories' "breadth" and "depth"). But if customers cannot find what they prefer they will shop elsewhere and sales volume can further decrease. Sales reduction leads to poor cash inflows. As a result, the firm cannot take advantage of quantity discounts and economies of scope and scale, increasing the cost of goods sold, and thus, decreasing inventory turnover even further.

In Table 10 we present estimates of model (5). As mentioned in the previous section, this model provides estimates of variance components that partition variance into between years within firms, across firms and across industries. In the first part of Table 10 we present the estimations of variance components and in the second one the proportion of the total variance explained by them. The above results suggest that both industry and firm effects are significant. The proportion of the total variance that is due to differences across segments is 58.03% while the variability across firms accounts for 32.61% of the total variance. A small amount of the total variance (0.16%) is due to year-to-year changes within firms.

Summarizing, differences in the inventory turnover relate to economic factors shaped by industry effects, as well as to internal strategic choices. However, according to the results we presented and discussed earlier, one of the determinants of inventory turns is gross margin. This variable, observed at the firm level, may capture industry (through the "market structure" mechanism) or firm-specific effects. Hence, we must be careful about what such effects mean. If gross margin and capital intensity (the other key determinant of inventory turns) are industryspecific (beyond the control of a firm's management), then segment-wise effects dominate the firm-specific ones. Therefore, without an explicit assumption about the origin of the variation of gross margin and capital intensity and even of sales growth, the results of the variance decomposition analysis of inventory turns need to be interpreted with caution. Nevertheless, the above findings can be useful for further investigation of the sources of inventory heterogeneity, i.e. industry factors or firm considerations.

6. Time trends of inventory productivity indices

Since the time-dimension of our dataset is only six years, we cannot study long-run trends. Nevertheless, we can get an estimate of the time trends by using the entire sample of firms and the following random growth model[6]:

$$\log IT_{sit} = F_i + h_i t + b_1 \log gm_{sit} + b_2 \log ci_{sit} + b_3 \log ss_{sit} + u_{sit} \tag{6}$$

where h_i denotes time trends in the inventory turns for each firm i after controlling for the correlation with the explanatory variables. By writing in first differences, the term F_i is eliminated and since $\Delta t = 1$, becomes

$$\Delta \log IT_{sit} = h_i + b_1 \Delta \log gm_{sit} + b_2 \Delta \log ci_{sit} + b_3 \Delta \log ss_{sit} + \varepsilon_{sit} \tag{6a}$$

where $\varepsilon_{sit} = \Delta u_{sit}$. Applying the fixed-effects method to we get the estimates of h_i. Out of 556 firms, 328 were found with a negative *sign* (197 of them statistically significant with $p < 0.0001$). That is, about 60% of the firms have shown a decrease in inventory turns after controlling for the impact of the other explanatory variables. The rest 228 showed an increase (125 of them having a positive and statistically significant effect). Moreover, we estimate time trends in the inventory turns for each firm i, without taking into account the correlation with the explanatory variables, by fitting the following model:

$$\log IT_{sit} = F_i + h_i t + u_{sit} \tag{7}$$

We find that the estimate of h_i is positive for 275 firms and negative for 281 firms. Finally, we estimate the overall trend of *it*, *gm* and *ci*

$$\log y_{sit} = F_i + ht + u_{sit} \tag{8}$$

where y stands for *it*, *gm* and *ci*. F_i is the intercept of each firm and h the common slope of time variable across all firms measuring the rate of change annually.

Table 11 shows that, during the period 2002–2005, there was a statistically significant decline in inventory turns by 3.4% annually, an increase in gross margin by 2.6%, as well as a small, though statistically significant, increase in capital intensity by 0.8%.

7. Implementation of models in inventory management and limitations

Estimated models allow determining the behaviour of inventory turnover subject to the values of gross margin, capital intensity and sales surprise ratio. Besides those factors are of even greater importance, unobserved firm and time-specific effects can be estimated. Since the time effects (c_t) are constant across firms, firm-specific ones (*Fi*) represent the managerial effectiveness of each firm. In our sample, 285 firms are presented with negative F_i. Firms with low F_i can be considered "ineffective", because, other factors besides the explanatory variables (*gm*, *ci* and *ss*) affect inventory turnover so that it is lower than that of their competitors. Thus, changes in inventory turnover cannot be directly interpreted as managerial improvement or weakening.

Gaur et al. (2005) suggest the adjusted inventory turnover, denoted as *AIT*, as a more accurate metric for benchmarking inventory performance of retailers. Its value is computed as

$$\log AIT_{sit} = \log it_{sit} - b_1 \log gm_{sit} - b_2 \log ci - b_3 \log ss_{sit}$$
$$\Rightarrow AIT_{sit} = \exp(C_t + F_i + u_{sit})$$

[6] See, e.g. Wooldridge (2002).

Table 12
Classification of mean values of RoA by values of exp (F_i).

Classification by e^{FE}	$e^{FE}<0.5$	$0.5<e^{FE}<0.7$	$0.7<e^{FE}<1.05$	$1.05<e^{FE}<2.0$	$2.0<e^{FE}$	All
Obs by year	150	67	112	97	130	556
Year	**Return on assets (*RoA*) (%)**					
2001	1.84	3.98	5.09	7.16	7.34	4.97
2002	1.81	3.75	4.82	10.82	10.47	6.25
2003	1.43	4.52	5.40	9.77	10.68	6.22
2004	0.43	3.11	3.98	7.76	7.87	4.49
2005	−0.52	2.22	3.36	5.99	6.30	3.32

where all variables are defined in the previous sections. Therefore, the comparison of *AIT* between firms may indicate which firm is more or less effective than its peers.[7]

Besides, efficient inventory management may contribute to corporate profitability. Short term financial management literature provides evidence that a reduction in the inventory conversion period (thus an increase in inventory turns) which is a component of the cash conversion cycle (CCC)[8] is associated with higher levels of firm's profitability (Jose et al., 1996). Koumanakos (2008), analyzing a large sample of Greek firms in a cross-sectional econometric study, concludes that the higher the level of inventories preserved by a firm, the lower its rate of return. However, it is true that it is not easy to show a direct connection between inventory management and the firm's performance (Vastag and Whybark, 2005; Cannon, 2008), although there is some evidence for a positive relationship in the longrun (Chen et al., 2005). Considering that *AIT* is a more representative measure of inventory performance than inventory turnover the use of *AIT* in the analysis of the relations between profitability and inventory management would lead to a more comprehensive conclusions. In Table 12 we classify the firms of our dataset by value of exp (*firm-specific effects*), which is the main component of *AIT*, and list the means of a profitability measure, the return on assets (*RoA*) by year.

The results in Table 12 suggest a strong association between *profitability* and *operating efficiency*. Hence, our models could be applied in future research investigating the linkages between operating performance and profitability of firms. Moreover, with the confirmation of the hypothesis of different inventory turnover sensitivity in sales' changes, managers should pay more attention to inventory management when a firm operates in sales-declined region.

Variance decomposition analysis helps us to identify the sources of variation in a firm's inventory turnover. The finding that along with firm individual characteristics, industry specific effects make significant contribution to the variation of inventory turnover suggests that retail segments differ systematically in terms of the required inventory investments and the associated costs.

This study presents several drawbacks one of which is related to short time dimension of our data. Moreover, our choice to use balanced panel can potentially lead to selection and survival bias. However, when we used various subperiods, the results we obtained did not differ from what we have already presented, leading to the conclusion that such bias does not influence our estimates. Another limitation concerns the aggregate effects of the explanatory variables which may differ at a more disaggregated level. For instance, in the case of capital intensity, the effect of various types of investments in fixed assets may not be homogeneous. This is however a common problem present in most econometric models.

[7] Efficiency is determined using stochastic frontier econometric techniques (see e.g. Schmidt, 1985; Bauer, 1990).

[8] CCC is an additive measure of the number of days funds are committed to inventories (=365/inventory turnover) and receivables less the number of days payments are deferred to suppliers (see Gitman, 1974; Richards and Laughlin (1980)).

8. Conclusion—directions for further research

This study is an attempt to investigate the determinants of inventory turnover ratio. It was conducted on a sample of financial data for 566 Greek retail firms for the period 2000–2005. By employing panel data techniques it was found that inventory turnover ratio is negatively correlated with gross margin and positively correlated with capital intensity and a measure of sales surprise. Moreover, the inventory turnover reaction to sales changes was also studied when firms operate in "sales-declined region" as well as in "sales-increased region". It was estimated that changes in sales ratio bring on bigger changes in the former case than in the latter one. Partitioning the total variance of inventory turns into its components, we found that a substantial amount of the variability is due to segment-wise effects. However, to address accurately the impacts of firm and segment effects on inventory turns, further empirical and theoretical research is required about the origins of the differences in the determinants of inventory turnover.

These results are useful in identifying methods and applications to improve inventory performance among firms and over time. Therefore, our study may contribute to further research on the microeconomic characteristics of inventory turnover and its application in performance analysis and managerial decision making. Possible extensions of the model include the use of a longer time series dataset and the introduction of variables that improve the explanatory power of the model. Indicatively we suggest the introduction of variables like investments in buildings and in information systems, the level of interest-rates and the prices of products, the length of product life as well as the size of stores and warehouses. Such improvements will make the results from the inventories research more reliable and applicable in the areas of operation and financial management.

It is finally pointed out that although our evidence comes from the retailing industry, the methodology could be as well applied for the investigation of inventory performance in the manufacturing industry.

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