Should inventory policy be lean or responsive? Evidence for US public companies[1]

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Abstract: Using financial accounting panel data from the COMPUSTAT database for a representative sample of 722 manufacturing, retailing and wholesaling companies accounting for 30% of US business inventories, we develop a statistical methodology that links managerial decisions related to inventory with accounting returns. We find that superior earnings are associated with the speed of change/responsiveness in inventory management, after controlling for industry- and firm-specific effects. Namely, we find that, in the pooled sample, inventory elasticity with respect to sales, lead times and sales uncertainty is consistently positively associated with both current and forwarded returns on assets. This result provides statistical evidence that public companies that are more responsive in inventory management are, on average, more profitable. Furthermore, we show that higher relative volatility of sales and longer lead times are negatively associated with profitability, due to difficulties in matching supply with demand. Surprisingly, we find no support for the "lean operations" principle: inventory levels alone do not have a significant and negative relation with current or future profitability. Our findings indicate the importance of matching supply with demand when (i) the environment is volatile and (ii) demand is nonstationary, such that responsiveness in inventory management matters more to profitability than do absolute inventory levels.

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1. Introduction

In this paper we are interested in investigating the association between inventory management policies and the financial performance of a firm. Consulting companies provide some limited evidence that firms that excel in supply chain management/lean techniques also enjoy above-average financial returns (D'Avanzo et al. 2004, Anderson et al. 2003). Although several prominent companies have created business value through successful supply chain management (e.g., Dell, Amazon.com, Wal-Mart and Zara; see Cachon and Terwiesch 2005), it is not immediately obvious whether the financial success of these companies can be in full or in part attributed to their ability to manage inventories. Furthermore, the financial success of these and other companies is often attributed to their ability to decrease inventory levels (increase inventory turns). However, it is well known that unreasonably low inventories can be as damaging to a firm's profitability as unreasonably high inventories, and attempts to link absolute inventory levels to the stock price have had limited success (Chen et al. 2005a, 2005b, Lai 2005). Furthermore, there is also empirical evidence (Balakrishnan et al. 1996) demonstrating that the introduction of lean manufacturing/sourcing techniques (such as Just-in-Time, or JIT, systems) does not result in better financial performance, although Hendricks and Singhal (2005) have shown that supply chain disruptions are associated with reductions in both profitability and market capitalization. Thus, the evidence suggesting that inventory management is associated with financial performance is, at best, mixed.

Due to limited understanding of the connection between inventory management and financial performance, few analysts and fund managers use inventories to predict/explain superior accounting returns. A rare exception is David Berman, a hedge fund manager (see Raman et al. 2005) who claims that the financial and stock performance of public retailing companies can be predicted best not merely by looking at the conventional operational metrics such as margins and inventory turns, but rather by analyzing the joint dynamics of inventory and sales. "Wall Street basically ignores inventory.…[T]his gives us one of our edges," Berman states, basing his investment decisions on elaborate inventory analysis and getting into the buy position if changes in sales with respect to changes in inventory indicate a future increase in margins (e.g., “Berman identified this company as a strong buy when he noticed in 2003 that even though sales were flattish, inventory had declined about 20% year over year. To Berman, this boded well for future gross margins”) and getting out of the position in opposite scenarios (e.g., “inventories were now growing at the same pace as sales…and Berman was worried”).

The goal of this paper is to systematically assess the impact of inventory and supply chain management on financial performance across time and segments by using a representative sample of 722 public US companies for the period 1992-2002. In addition to using conventional operational firm-specific variables (inventory levels, margins, lead times), we propose to use several new variables capturing the speed of change (elasticity) of inventory with respect to other variables—lead time, sales, sales uncertainty and gross margin. We propose a two-stage econometric model that separates the impact of inventory/supply chain management on performance from other factors that are typically used to explain accounting returns (e.g., firm- and industry-level effects). We find no evidence either across time or across segments that smaller relative inventory levels (average days of inventory) are associated with better financial performance as measured by the return on assets, ROA. At the same time, firm-level elasticities of inventory with respect to sales, lead times and demand uncertainty that we impute from another econometric model do impact financial performance. Namely, companies that react faster (have greater elasticity) to sales, demand uncertainty and lead time by adjusting inventories do, on average, have higher ROA. This association holds for both current and future ROA. In addition, we conduct year-specific and segment-specific analyses and find that our findings are more consistent across time than across industry segments.

We also find that, consistent with intuitions common to the supply chain literature, companies operating in more volatile environments and with longer lead times have lower profitability. All these results hold while controlling for a set of industry- and firm-level factors such as the competitiveness of a given segment (that impacts the monopolistic power of a company and margins) and overall industry attractiveness (average segment profitability and segment growth). All of these factors are significant and have an expected direction of effects: firms operating in more attractive segments are, on average, more profitable. Finally, we attempt to compute the "data-optimal" levels (i.e., levels that would maximize ROA) for the inventory as well as for inventory elasticities by considering quadratic forms of dependent variables and find almost no evidence of interior (data-feasible) maxima, which we attribute to data aggregation problems.

Our findings indicate the importance of matching supply to demand in volatile environments, whereby one must pay attention not only to the level of the operational variable (inventory), but also to the speed of change in inventory, which can be used as an indication of the quality of management control. The reason is that, in practice, demand exhibits nonstationarity, trends and seasonal effects. Thus, those firms that are able to adjust inventory levels quickly perform better financially. Our empirical results indicate the importance of relaxing assumptions about demand stationarity that are prevalent in the traditional inventory models as well as the importance of endogenizing "responsiveness" in inventory management. We contribute to the literature by analyzing new, non-conventional operational metrics that might better explain variation in profitability across firms thus suggesting ways to improve financial performance. However, we are not trying to predict future performance of companies and instead discuss differences in the cross-sectional and time-series approaches in our analysis.

The rest of the paper is organized as follows. In Section 2 we provide a literature review. In Sections 3 and 4 we describe the sample and variables used in the analysis. In Section 5 we specify the two-step econometric model that allows us to use inventory elasticities along with industry and firm controls to explain financial performance. In Section 6 we discuss the results obtained, and in Section 7 we conclude with the implications of our results and a summary.

2. Literature review

There have been numerous empirical attempts to explain the financial performance of companies in the fields of strategic management/industrial economics, accounting, finance, marketing and management science/operations management. Naturally, each of these areas concentrates on different explanatory variables, and therefore we limit our survey to papers that we perceive as immediately relevant.

We begin with papers in the management science/operations management area. Several studies analyze productivity in manufacturing companies which are a part of our sample. Boyer (1999) attempts to link investments in advanced manufacturing technologies with financial performance in the metalworking industry and finds no cross-sectional association between the two but rather a longitudinal impact of investments on performance. Lieberman et al. (1990) demonstrate that productivity improvements at the world's six major automotive manufacturers have been achieved primarily through more efficient labor utilization, and Lieberman and Demeester (1999) find a strong association between higher productivity and inventory reduction. MacDuffie et al. (1996) find that parts complexity has a persistent negative impact on productivity of automotive assembly plants. In the same context, Fisher and Ittner (1999) find that greater day-to-day variability in option content has a significant adverse effect on productivity and quality. None of these papers focus on inventory management as an explanation for accounting returns.

The papers most closely related to our study are those that consider the impact of supply chain management, and in particular inventory management, upon firms' financial performance. Balakrishnan et al. (1996) examine the effect of JIT adoption (which, supposedly, decreases inventory) on firms' profitability and find that, on average, there is no statistically significant association between ROA and JIT adoption. However, cross-sectionally, JIT-adopting firms with a diffuse customer base have a superior ROA relative both to adopting firms with a high degree of customer satisfaction and to their matched control firms. Gaur et al. (2002) investigate a relationship between operational and financial performance in retailing and find that different retailers follow different operational strategies (low or high inventory turns) in achieving financial targets. Hendricks and Singhal (2005) show that supply chain disruptions can be quite costly for a company: firms on average experience a 107% drop in their operating income and a 2.32% drop in ROA, and the negative impact of disruptions is long-lasting. Singhal (2005) analyzes the long-run stock price effects of excess inventories. He finds that the stock market partially anticipates excess inventory situations, and the negative effect of excess inventory is significant: mean abnormal returns due to excess inventory are -37.22% in the sample. Lai (2005) provides empirical evidence that (i) the market cannot differentiate between “good” and “bad” inventory, (ii) the market punishes firms when it can tell that inventory decisions are “bad” (e.g., write-offs), and (iii) inventory levels do not statistically explain firm value. Rajagopalan and Malhotra (2001) study trends in inventory levels at US firms over time to test the widely held belief that inventory management has improved due to the introduction of JIT practices and IT system implementations. Using a large sample of firms from the US Census Bureau including both private and public companies, they find that material and work-in-process inventories decreased in the majority of the two-digit SIC industries from 1961 to 1994. Furthermore, in some segments there were greater improvements in the post-1980 period when JIT practices were adopted. Chen et al. (2005a, 2005b) continue this line of work and also find decreasing trends for relative inventory (inventory as days of sales) in manufacturing and wholesaling sectors for the period 1981-2003 and somewhat mixed evidence in the retailing sectors, with a downward trend that started only in 1995. Using an event study, they show that firms with abnormally high inventories have abnormally poor long-term stock returns. They also find that the relationship between Tobin’s q and abnormal inventory (which is a standardized deviation from the sector-wide inventory mean) is absent in the cross-sectional domain. Randall and Ulrich (2001), in a study of the bicycle industry, find that firms that match product variety with supply chain structure perform better than their competitors in a cross-sectional data set. Randall et al. (2005) study factors that persuade Internet retailers to integrate inventory and fulfillment capabilities with virtual storefronts. They find that the probability of bankruptcy is lower when firms align inventory decisions with environmental and strategic factors. Several papers in this stream attempt to link inventory *levels* with financial performance and find little or no connection between the two. We also attempt this approach and find no evidence to suggest that inventory levels are associated with ROA. Instead, we argue that what matters most to financial performance is not the level of inventory, but rather the ability to manage inventories, to respond to changes in the environment.

Finally, there is a stream of papers that analyzes the financial implications of operational decisions other than inventory management. In two papers Brynjolfsson and Hitt (1996, 2002) study the “productivity paradox” of information systems and show that, after properly controlling for the firm-level production function, IS spending has made a substantial and statistically significant impact on firms’ productivity. Frei et al. (1999) identify the links between retail banks’ branch operational processes and their financial performance. Hendricks and Singhal (1997) use an event study to quantify the financial benefits from implementing total quality management systems. They show that over a 10-year period the firms that have won quality awards have outperformed others in terms of operating income. Girotra et al. (2005) estimate the impact of failures in drug development on the market value of pharmaceutical companies. They find that the capacity utilization of development resources and the presence of “backup” projects are two key factors impacting firm value.

In the strategy research domain, McGahan and Porter (1997, 2002) study the performance of US public corporations over the past two decades using COMPUSTAT data. The authors break down factors affecting financial performance into industry, firm, corporate and business effects in the cross-sectional domain. In the time domain they separate permanent and transient effects and study the relative importance of those effects in terms of the incremental explanatory power for the variability of performance. McGahan and Porter (1997) show that year-, industry-, corporate-parent and business-specific effects respectively account for 2 percent, 19 percent, 4 percent and 32 percent of the aggregate variance of accounting profitability. McGahan and Porter (2002) refine the research methodology and test its robustness to conclude again that industry-specific effects and business-specific effects dominate when explaining variability in performance and, moreover, that industry-specific effects persist over longer periods. The authors do not study causality but show that both industry and segment controls as well as time controls should to be used to capture data heterogeneity. We follow this suggestion.

A large stream of research in the accounting/finance domain studies the linkage between managerial accounting and control practices and accounting performance. One example is Fama and French (2000), who study the autoregressive properties of earnings profitability. They show that accounting earnings exhibit mean reversion, with the estimated rate of mean reversion being 38% for US public companies, which is in line with the industrial economics theory of transiently attractive industries. In a related paper Cheng (2005) investigates the determinants of residual income by analyzing the impacts of value-creation (economic rents) and value-recording (conservative accounting) on abnormal return on equity (ROE). He shows that the industry-abnormal ROE increases with industry concentration, industry-level barriers to entry, and industry-conservative accounting factors, and that the difference between the firm- and industry-abnormal ROE increases with market share, firm size, and firm-conservative accounting factors.

3. Data description

We use a representative sample of public US companies obtained from the COMPUSTAT financial database through Wharton Research Data Services. The same sample is employed in Roumiantsev and Netessine (2005). We use data for public companies, because they are obliged to provide operational and financial information following GAAP standards to ensure that investors have access to data regarding their performance dynamics. The choice of public companies precludes our findings from being representative of the whole US economy. However, due to the lack of reliable operational and financial data for private companies, we focus on public companies alone.

We use quarterly data containing 44 time points between 1992 and 2002 for every company in our sample. This period allows us to analyze the most recent data that is less affected by such factors as price inflation and changing industry structure (e.g., due to JIT adoption in the late 1980s and early 1990s). We utilize quarterly rather than annual data to account for seasonal inventory fluctuations within a given year (i.e., demand/inventory shifting across quarters), which has a major impact in many industries. Moreover, quarterly data allows us to obtain more accurate estimates of demand uncertainty than the annual data does. We synchronize quarterly data to use calendar quarters instead of fiscal quarters, since companies have different fiscal periods. Using quarterly data we cannot obtain separate information on different inventory types (raw materials, work in process, finished goods), whereas this information is available in the annual data. We do not perceive this issue to be significant, however, because our goal is to study inventories and their impact on performance at the aggregate company level. Although more frequent (monthly, weekly) data may seem a good alternative to quarterly data, the monthly survey data provided by the US Census are insufficient for our analysis, since it does not track revenues, costs and financial performance.

Working with a panel of data allows us to be certain that the statistical relations we obtain are neither applicable at only a single point of time nor driven by a single company. In our panel, we control for the degree of heterogeneity of various coefficients and have common, segment-specific and firm-specific time and space coefficients. We use both pooled and segment-specific parameters in our tests to obtain coefficients and firm-specific parameters and to ensure that possible biases are captured.

The sample itself was selected as follows. First, we selected at random several two-digit DNUM codes, which are identical to two-digit SIC codes but assigned only to companies that are not widely diversified (defined as having at most four major lines of operations in the COMPUSTAT [North America] User's Guide). Conglomerates such as General Electric with diverse operations were not included in selected DNUM codes, because including widely diversified firms makes segment-specific estimations difficult. We also did not include any service-oriented industries because inventories are less relevant for these companies. We further selected from those DNUM codes all companies that were continuously active between 1992 and 2002. Next, we excluded companies that had fewer than $5M in sales cumulatively over 10 years and those that had zero sales and inventory data for the first three years of data, even if they were otherwise active. The purpose of the filtering process was to ensure that the final sample contained only companies that had been actively operating in retailing, distribution or manufacturing to enable precise estimation of firm-level variables (in particular inventory elasticities). We obtained a final sample of 722 companies including 233 S&P500 companies with 8 segments represented: oil and gas, consumer electronics, wholesale, retail, machinery, computer hardware, food and beverages, and chemicals. To make sure that our sample was representative of the US economy as a whole, we verified that the total inventory in our sample represented 30% of the total US manufacturing and retailing business inventory and, moreover, that it was strongly correlated with the total US inventory (Pearson r=.91, p<0.001).

The obvious disadvantage of using COMPUSTAT as a source of information for testing hypotheses about the impact of inventory management upon financial performance is that financial accounting may only crudely reflect actual processes within a company. For example, at the industry level one can use Consumer Price Indexes to express everything in constant dollar terms, an approach that is not applicable for firm-level data. However, the US economy has had a low level of inflation over the past decade (below 1% quarterly), so this should not cause significant variations in the data. We used ratios (to sales) to normalize for prices, which is the correct approach if the input-output price ratio does not change over time (i.e., if margins are stable). To verify this stability we checked the correlation between sales (expressed in output prices) and cost of goods sold (expressed in input prices), which turned out to be 92%, meaning that margins are indeed relatively stable over time compared to sales and inventory fluctuations.

Table 1a provides a summary description of the sample. Companies in our sample hold $396M of inventory on average and have on average $527M of quarterly sales, expressed in input prices, whereas an S&P500 company on average holds $690M of inventory and on average has $800M of quarterly sales. From Table 1a we also see that companies vary in size across segments, with companies being larger on average in the oil and gas and the retail segments. S&P500 companies appear leaner on average (with a smaller inventory-to-cost-of-goods-sold ratio). We also see that relative inventory levels vary by segment: the chemical, computer hardware and electronics segments have the largest relative inventory levels (1.40, 1.25 and 1.22 correspondingly for quarterly relative inventory levels), while the oil and gas segment appears to be the leanest, with an average relative inventory ratio of only 0.42.

4. Description of variables

We use three subscripts to account for time-specific (*t=1,…,44*), company-specific (*i=1,…,722*) and segment-specific (*s=1,…,8*) effects. For the *dependent variable*, we use the return on assets (denoted ROA_{its}) as a measure of financial performance. ROA is calculated as (Net Income + Interest Expense Net of Income Tax Savings)/Average Total Assets, which, according to Stickney and Weil (1999), "attempts to measure the success of a firm in creating and selling goods and services to customers, activities that fall primarily within the responsibility of production and marketing personnel" (p. 278). There are several other measures of financial performance that are available: return on equity (ROE), operating income (percentage EBITDA), absolute or percentage economic value added (EVA) from the accounting side (based on historical performance), financial returns (simple or compounded) and, finally, market-to-book ratio (Tobin's q) from the financial markets side (expected long-term performance). However, we choose to focus on ROA, for several reasons. We choose ROA over ROE, since we are not interested in the capital structure effects that are implicitly captured by ROE (Frei et at. 1999). We choose ROA over EBITDA, because ROA is more often used to measure financial performance of companies (Stickney and Weil 1999). We choose ROA over EVA to avoid scaling problems (higher absolute EVA can merely be a function of company size) and to avoid using the cost of capital proxies that are hard to estimate accurately. Finally, we concentrate on ROA rather than on measures linked to the financial markets, because financial markets are subject to many external factors that are difficult to control for. We analyze both the current ROA as well as the one- and two-quarter-forwarded ROA denoted by $ROAF1_{its}$ and $ROAF2_{its}$ respectively. To analyze autoregressive properties of ROA, we use DeltaROA, DeltaROAF1 and DeltaROAF2 which respectively denote percentage changes in ROA, ROAF1 and ROAF2 from quarter to quarter.

For *explanatory variables* we use time/industry dummies (segment dummies *s* for each of the 8 industry segments, quarterly dummies q_t and yearly dummies *year* to control for time-specific effects), industry controls, firm controls, operational variables and operational elasticities. All dependent variables are relative, to minimize scale effects and compare results across firms. For the sake of simplicity, we omit panel indexes while describing variables.

Industry controls. We control for the average segment profitability as measured by segment average ROA (denoted as SegmentROA). Furthermore, we control for the annual segment sales growth to avoid transitory seasonal effects. This sales growth is denoted by the SegmentGrowth variable and is calculated as the percentage of change in annual sales for the total segment. Finally, we control for the segment concentration as measured by the sum of squared market shares (the Herfindahl-Hirschman Index) within a four-digit DNUM code (denoted as Concentration). All these controls have proven important (see McGahan and Porter 1997 and Cheng 2005) in explaining cross-sections of firms' profitability.

Firm controls. We control for firm size, sales growth and sales volatility. We use the logarithm of cost of goods sold (LogCOGS) as a proxy for firm size. The logarithm function is employed to eliminate scaling effects: other variables are relative and vary within a specific range, whereas absolute firm sales or COGS vary substantially. The firm-level sales dynamics are captured by the sales growth (SalesGrowth), which measures quarter-over-quarter relative sales changes. These two controls were found to be significant in explaining firms' inventories in Roumiantsev and Netessine (2005), and they should also directly affect financial performance. Finally, we classify firms as volatile (denoted by a dummy variable Volatile) if in a given time period the coefficient of variation for the historical sales for a firm (calculated using a four-quarter moving window) is above the median coefficient of variation for the firms in the same segment. Using this variable we would like to check if relatively high volatility of sales causes problems for a firm's financial performance. The coefficient of variation is calculated as SigmaSales/COGS where SigmaSales is a proxy for demand uncertainty. To calculate SigmaSales, we assume that our sales data can be decomposed in an additive way into trend, seasonal and noise components. Additive techniques are by far the most common and are used by the US Census as well as by other statistical agencies. Additive decomposition implies that sales variance is determined by the variance of noise only. To estimate noise, we run individual regressions with a fifth-degree polynomial capturing trend and with seasonal (quarterly) dummies denoted by q_t, and we take residuals as demand noise. We do this for all 772 firms in our panel, and thereafter we estimate the variance of residuals, again using a four-quarter moving window as follows:

$$\text{Sales}_t = \text{ActualSales}_t - a_1 t - a_2 t^2 - a_3 t^3 - a_4 t^4 - a_5 t^5 - a_6 - b_1 q_1 - b_2 q_2 - b_3 q_3,$$

$$\text{SigmaSales}_t = \sqrt{\frac{\sum_{i=0}^{3}\left(\text{Sales}_{t-i} - \sum_{i=0}^{3}\text{Sales}_{t-i}/4\right)^2}{4}}, t = 3, \ldots, 44.$$

The same measure of demand uncertainty is used in Roumiantsev and Netessine (2005).

Operational variables. We use three proxies to measure the value chain for a firm: sourcing, producing, and selling. Justification for these three proxies comes from financial accounting definitions. Production cycle time is defined as the average days of inventory outstanding; sourcing lead time for inputs is defined as the average days of accounts payable outstanding; and cash collection (or output delivery time, or days of sales outstanding) is defined as the average days of accounts receivable outstanding (see Stickney and Weil 1999). Together, these measures define a cash conversion cycle, the average time it takes a dollar of investment to buy inputs, produce, sell outputs, and collect cash. Although these measures are only proxies for the physical production cycle and lead times, they provide the right direction of logic: accounts payable are credited to the firm in question, then inputs are shipped to it and are typically debited, then inputs are received and cash paid for them. Hence, financial transactions are correlated with times of shipment and delivery of inputs, and therefore are correlated with lags in production: the greater the lag between the firm's receipt of inputs and its generation of products, the less responsive it is to a changing market environment in terms of its ability to adjust inventories quickly. The recognition of shipments/payments is linked to a company's policy of recognizing revenues/expenses and is known to vary by company to some extent. However, since we study public companies that are closely monitored by investors and the Securities and Exchange Commission, in most cases these companies will have practices that are relatively consistent, if not in the aggregate then within the industry segment.

We use days of accounts payable (AP) as a proxy for the sourcing lead time (see extensive discussion in Roumiantsev and Netessine 2005, which indicates that AP terms in our sample are not dominated by industry practices and AP does not correlate with the company size), which we define as $\text{LeadTime}_{its} = 365/\left(4\times\text{COGS}_{its} / \text{AP}_{its}\right)$. We use days of inventory (denoted DaysofInv) to measure how lean the company is, given its size. We use days of accounts receivable (denoted DaysofAR and defined analogously to LeadTime) to measure the speed of collecting cash. With respect to all three variables, we expect that companies that source/collect cash faster and operate more leanly (as suggested by operations management theory) should have better financial performance. Proxies that we use are subject to aggregation (especially aggregation across products), but we believe that firm-level data on inventory and accounts payable and receivable levels does provide a summary of the operational activities of a company, and a company is typically judged based on these aggregate numbers.

Operational elasticities. Using the econometric model of Roumiantsev and Netessine (2005), we obtain elasticities (from a multiplicative model) of firm-level inventories with respect to:

1) sales changes (as measured by COGS), denoted as FitCOGS,
2) lead time changes (as measured by LeadTime, as defined above), denoted as FitLeadTime,
3) demand uncertainty (as measured by SigmaSales, as defined above), denoted as FitSigma, and
4) gross margin (measured as a relative gross margin), denoted as FitMargin.

Statistically, these elasticities represent a percentage change in the inventory level associated with a one-percent change in one of these variables for a given company in a given quarter. We believe that these imputed elasticities provide an important measure of the company's ability to control its supply chain by adjusting inventory quickly, which plays a key role in the nonstationary environment. Thus, these elasticities implicitly capture the quality of management and control practices in a firm and serve as proxies for the organizational measures that are non-observable to us. Roumiantsev and Netessine (2005) demonstrate that all of these elasticities are statistically significant when explaining firms' inventories, and their signs are consistent with predictions following from classical inventory models, namely that higher mean demand, demand uncertainty, lead times and gross margins are all associated with higher inventory levels.

Table 1c provides a description of the variables we are exploiting in the study. Mean ROA is negative for most segments—on average, firms are losing money. Sales growth for all sectors is around 2% per quarter. Firms in the oil and gas and wholesale segments appear to be leaner on average—companies in these segments hold only 36-38 days of sales in inventory, whereas chemical companies have the highest inventories: around 127 days of sales. Payment terms vary the most in the computer hardware sector, which has a coefficient of variation of days of accounts receivable almost 10 times higher than other sectors. Such preliminary observations point out the heterogeneity of operational and accounting variables across industries that impose different conditions on the ways companies operate and make inventory decisions. From Table 1b we see that there are no significant correlations among firm-level variables.

5. Model specification and research design

We propose a two-step econometric model to link empirically inventory/supply chain management to financial performance while controlling for firm, industry and time effects. First, we impute operational elasticities from the model utilized in Roumiantsev and Netessine (2005) to estimate FitCOGS, FitLeadTime, FitMargin and FitSigma as follows:

$$\text{Model I:}\begin{cases}\log\left(\text{Inv}_{\text{its}}\right)=a_{it}+b_{it}^{1}\log\left(\text{COGS}_{\text{its}}\right)+b_{it}^{2}\log\left(\text{GrossMargin}_{\text{its}}\right)+b_{it}^{3}\log\left(\text{LeadTime}_{\text{its}}\right)\\ \qquad +b_{it}^{4}\log\left(\text{SigmaSales}_{\text{its}}\right)+b_{it}^{5}\log\left(\text{TBillRate}_{\text{t}}\right)+b_{it}^{7}\log\left(\text{PositiveSalesSurprise}_{\text{its}}\right)\\ \qquad +b_{it}^{8}\log\left(\text{SalesGrowth}_{\text{its}}\right)+c_{it}^{1}q_{1}+c_{it}^{2}q_{2}+c_{it}^{3}q_{3}+\varepsilon_{its},\end{cases}$$

$$\widehat{\text{FitCOGS}}_{\text{its}}=b_{it}^{1},\ \widehat{\text{FitMargin}}_{\text{its}}=b_{it}^{2},\ \widehat{\text{FitLeadTime}}_{\text{its}}=b_{it}^{3},\ \widehat{\text{FitSigma}}_{\text{its}}=b_{it}^{4},$$

$$t=1,\ldots,44\text{ - time index, } i=1,\ldots,722\text{ - company index, } s=1,\ldots,8\text{ - segment index.}$$

In addition to the variables described above, TBillRate is a proxy for the proxy for inventory holding cost (three-month T-bill rate[2]) and PositiveSalesSurprise takes a value of 1 if the realized demand is higher than forecasted and takes a value of 0 otherwise.

We run Model I separately for two periods, 1992-1996 and 1997-2002, to obtain non-static, firm-specific values for inventory elasticities. Ideally, we would like to obtain estimates for inventory elasticities for each quarter but, since there are only 44 time data points for each firm, we can estimate at most a few levels of elasticities over time, because each estimation requires at least as many data points as there are parameters for identification and double or triple this number to obtain robust statistical results. We believe that at least 20 observations are needed to calculate each elasticity and therefore we are limited to two estimates. Another possibility is to make estimates based on a moving 20-quarter window. However, in this case we would lose the first five years of data entirely. Next, we estimate the association between our independent variables and ROA:

$$\text{Model II}\begin{cases} \text{ROA}_{\text{its}} = a_s + b_s^1\text{SegmentROA}_{\text{ts}} + b_s^2\text{AnnualSalesGrowth}_{\text{ts}} + b_s^3\text{Concentration}_{\text{ts}} + \\ \qquad + b_s^4\text{Log}(\text{COGS}_{\text{its}}) + b_s^5\text{SalesGrowth}_{\text{its}} + b_s^6\text{Volatile}_{\text{its}} + \\ \qquad + b_s^7\text{LeadTime}_{\text{its}} + b_s^8\text{DaysofInv}_{\text{its}} + b_s^9\text{DaysofAR}_{\text{its}} + \\ \qquad + b_s^{10}\widehat{\text{FitCOGS}}_{\text{its}} + b_s^{11}\widehat{\text{FitSigma}}_{\text{its}} + b_s^{12}\widehat{\text{FitMargin}}_{\text{its}} + b_s^{13}\widehat{\text{FitLeadTime}}_{\text{its}} + \\ \qquad + d_1q_1 + d_2q_2 + d_3q_3 + d_4 year + \varepsilon_{its} \end{cases}$$

$$t = 1,\ldots,44\text{ - time index},\ i = 1,\ldots,722\text{ - company index},\ s = 1,\ldots,8\text{ - segment index.}$$

Note that we include an explicit time trend as well as seasonality effects in Model II, because financial performance can be affected by unobserved effects through the time dimension. We do not include an explicit time trend in Model I, because in the inventory management theory time trends should affect sales and sales forecasts in the first place, and companies should react by adjusting their inventory policies.

We run Model II in the pooled sample both for current ROA and forwarded (by one and two quarters) ROA. Furthermore, we run ROA regressions with and without quadratic terms for operational

[2] In Roumiantsev and Netessine (2005) we also use Weighted Average Cost of Capital (which is firm-specific) as another proxy for inventory holding cost. Both of these proxies result in similar estimates.

variables and operational elasticities in order to find potentially optimal levels of operational independent variables (levels that maximize ROA in the sampled data). An argument can be made that functional forms other than the quadratic should be used (e.g., multiplicative, piecewise linear and nonlinear spline estimations), but we believe that, given our aggregate panel, the data is too noisy for complex nonlinear analysis, which is not going to be parsimonious. The limitations of our approach to studying data-imputed optimal parameters are that (i) it is possible to say that a dependent variable Y is data-maximizing of the independent variable X only if the coefficient for Y is positive and the coefficient for Y^2 is negative, and (ii) the optimal parameter may be outside the feasible range and therefore there is not going to be an interior optimum. Thus, we also conduct descriptive segment-specific analysis for quartiles of dependent variables. We calculate quartiles for a specific sector and a specific point of time and break down empirical distributions for dependent variables into four quartiles ([0%,25%], [25%,50%], [50%,75%] and [75%,100%]) that maximize mean ROA.

We estimate Models I and II using both panel (fixed and random effects) estimations to capture individual heterogeneity and OLS cross-sectional estimations. Recall that imputed operational elasticities are quasi-static in time. Clearly, such infrequent estimation of elasticities limits the panel data usage. Formally, one can still proceed with panel data analysis, but it should be understood in advance that time-series within firm variation is not going to be captured well. However, we believe that this is not a major limitation in our study, since we are interested in the cross-sectional behavior and in comparing and explaining profitability across firms (unlike, for example, Fama and French 2000, who look at autoregressive properties of earnings). Although we conduct both panel and cross-sectional analysis, when reporting results we concentrate on cross-sectional results for specific time periods given the quasi-static data limitations described above.

We try to compare OLS and fixed effects results to delineate the impact of the firm-level effects that might not be captured by an OLS estimation. One can argue that the OLS results are going to be unbiased and consistent with fixed effects if there is a proper number of relevant industry and firm-level controls in the econometric model. The need for comparison comes from the quasi-static nature of our inventory elasticity estimates. Thus, we need to concentrate on the cross-sectional properties, and, for specific periods of time (in a year by year estimation), we have to estimate only cross-sectional regressions.

6. Results

Table 2 provides regression results for the pooled sample using both OLS estimation with robust standard errors and fixed effects specification (random effects specification is rejected, using Hausman's test). Overall, the results of these two approaches are consistent, although OLS regression produces a larger number of statistically significant estimates. All regressions are significant at least at the 1% level so we do not report overall F and p values unless results are not significant.

Among *industry controls*, a segment's ROA is consistently significant and positive in explaining current profitability and is also significant in explaining future profitability in the OLS regression. Segment growth impacts only a firm's future profitability, indicating the lag in achieving benefits from market growth. Segment concentration is negatively associated with ROA (both current and forwarded), and its impact is more significant in the OLS regression. These observations are in line with the findings of McGahan and Porter (1997, 2002).

Firm controls indicate that larger firms, on average, have higher current and future profitability. However, this finding might be due to the double survivorship bias: we consider a sample of companies that are still in operation and are public. A company's sales growth does not appear to be associated with financial performance. However, demand volatility (captured by the dummy variable Volatile) has a consistent negative association with both current and future profitability. This finding seems to indicate that companies suffer financially from their inability to match supply with demand in a volatile environment. We note that the higher volatility of sales in our model is largely a function of seasonal changes, since we utilize a four-quarter moving window to create a proxy for sales uncertainty.

With respect to *operational variables*, we do not see a consistent association between inventory levels or accounts receivable and ROA. For the inventory level, we find that no OLS regressions show statistically significant results, while the fixed effects model shows that current ROA is positively associated with inventory, which contradicts the standard assertion in operations management theory that lean companies should perform better financially. These findings are in line with those of Chen et al. (2005a, 2005b), Lai (2005) and Balakrishnan et al. (1996), who find limited evidence of an association between inventory levels and financial performance. Furthermore, we find that longer lead times have a consistent negative association with ROA, which is statistically significant in all OLS estimations. This finding is in line with the reasoning from operations management literature that shorter lead times translate into faster sourcing, which helps a company to react to changes in the environment. We note that, interestingly, a prevailing suggestion in the accounting literature that it is good (from the definition of accounts payable, see Stickney and Weil 1999) to postpone payment to suppliers as long as possible. Our results suggest that the negative operational effect of longer lead times on financial performance outweighs the positive accounting effect.

Operational elasticities show remarkable consistency and significance in explaining current and future profitability. First, we see that inventory elasticity to sales and to demand uncertainty is consistently positively associated with both current and future ROA and is significant in all regressions. Surprisingly, inventory elasticity to gross margin changes is negatively associated with ROA, the result that is significant in all OLS regressions. This counterintuitive result might be a consequence of the interplay between the gross margin and inventory. For example, companies often artificially lower margins (use discounting) to decrease inflated inventories. Such practice may result in high inventory elasticity with respect to the gross margin but it may not be associated with higher profitability if heavy discounting is caused by excessive inventories. Finally, inventory elasticity to lead time changes is positively associated with ROA and is statistically significant in two OLS regressions. A higher degree of inventory elasticity with respect to a specific parameter is equivalent to the ability of a company to make larger changes in inventory levels over a given period (the quarter, in our study) and, therefore, to be more responsive in its inventory management. These statistical results indicate that, over time, public companies in our sample with more responsive inventory management systems (i.e., those that react faster to changes in the economic environment) have been more profitable on average.

We further verify the robustness of our findings by running a cross-sectional OLS regression for specific time periods using the current ROA as a dependent variable, as shown in Table 3. (Fixed effects regression results in qualitatively similar findings and hence is omitted.) We see, once again, that average segment ROA is statistically significant in almost all years, whereas the impact of the annual segment growth and segment concentration varies year by year. Larger firms and firms with larger sales growth are, once again, consistently more profitable. Furthermore, firms operating in more volatile environments are consistently less profitable. Neither the relative inventory level nor accounts receivable has a statistically significant effect, but longer lead times have a significant (in most years) and negative association with ROA. Results for operational elasticities hold for most of the years: inventory elasticity to sales and to demand uncertainty are both positive and significant in most time periods, inventory elasticity to lead time is positive and significant in some years, whereas inventory elasticity to the gross margin is again mostly negative but almost never significant. We note that the explanatory power of results is higher for individual years than for the pooled sample which is in line with the fact that quasi-static imputed inventory elasticities can explain only cross-sectional (between firms) and not time series (within firms) variations.

Next, we estimate OLS regressions for the period 1997-2002 within each of 8 segments in the sample using current ROA as a dependent variable (see Table 4). Interestingly, most of our results are not homogeneous across segments. The explanatory power of independent variables varies greatly, ranging from only 3% for the wholesale segment to 28% for the machinery segment. In only one segment—machinery—do we see that high inventory levels are negatively associated with ROA (which may be because of large gains due to JIT methods), whereas in retailing and electronics the association is significant and positive. Our result for the retailing sector can be compared with the corresponding result in Gaur et al. (2002), who find a negative relationship between gross margins and inventory turns for retailing companies, whereas we find the same relationship between ROA and inventories. With a couple of exceptions, company size is positively related to ROA, and the volatility of firm's environment is negatively related to ROA. The ability to source faster has a statistically significant impact on ROA only in the electronics and retailing segments. Overall, there is mixed evidence regarding the impact of inventory elasticities on profitability across segments.

Our results indicate that the sample is more heterogeneous across segments than across time. Namely, the results obtained for the pooled sample hold across time (for both current and forwarded ROA) but hold less consistently across segments. This finding should be compared with the finding of Roumiantsev and Netessine (2005) that inventory behavior is consistent both in the pooled sample and across segments. Therefore, we suggest that more detailed segment-specific analysis be performed on a less aggregated data sample so as to discover the operational factors that improve financial performance.

Overall significance of pooled regressions (5% on average) might appear low and therefore we compare our results with similar studies in accounting and finance that attempt to explain earnings and profitability. Following Fama and French (1995, 2000) who study autoregressive properties of earnings, we conduct a fixed effect estimation of the AR(2) model for relative changes in ROA. Namely, we attempt to explain DeltaROAF2 (relative change in ROAF2) by DeltaROAF1 (relative change in ROAF1) and by DeltaROA (relative change in ROA). This approach is based on the finding of Fama and French (2000) that earnings are mean reverting over time: a firm that has abnormally high earnings in a period is more likely to have a decrease in earnings over time. Table 6 summarizes results of both pooled and segment-specific fixed effect estimations of the autoregressive model. The key observation from the table is that, aside from the high overall goodness-of-fit, AR(2) model has almost no explanatory power for the between-firms (cross-sectional) variation (R^2=0%) while it has high explanatory power for the within-firm variation (R^2=30%). Table 6 also confirms that earnings are exhibiting mean reversion (all coefficients are negative) and this pattern is consistent across segments. Comparison of Tables 6 and Table 2 shows that, for the fixed effects estimation, the situation is reversed: the between-firms variation is explained at the 25% goodness-of-fit level while the within-firm goodness-of-fit in Table 2 is low (1-2%) which drives down the overall explanatory power of the model (5%). However, these explanatory levels are on par with results in accounting and finance literature (Fama and French 1995, 2000, Cheng 2002) where high overall adjusted R^2 is typically achieved either by explicitly including fixed effects as dummies into the analysis (e.g., McGahan and Porter 1997, 2002) or by introducing lags of dependent variable and analyzing the autoregressive properties of ROA (e.g., Fama and French 1995, 2000). Tables 2 and 6 demonstrate that cross-sectional and time-series approaches to ROA analysis differ. When forecasting future earnings, the time-series aspect is crucial. However, we do not attempt to forecast earnings and hence we do not use lagged dependent variables in our analysis since they help explain the within-firm variation in ROA but are of little help (given the variance structure in our data) in explaining the between-firm variation even though they do help in achieving higher overall adjusted R^2.

We have also performed the analysis with quadratic forms for each variable but found only two occasions of interior solutions that maximize ROA in the feasible data range. First, the optimal level of inventory elasticity to sales uncertainty in 1998 is 2.95. Second, the optimal level of inventory elasticity to lead time for machinery segment for the 1997-2002 period is 0.098. All other occasions in which ROA was maximized were beyond data-feasible ranges. Since interior maxima are very rare, we can neither generalize these findings nor make practical recommendations based on them. We hypothesize that, because of the data aggregation, quadratic forms are unlikely to find interior maxima, since linear OLS regression is typically more robust to data outliers while quadratic terms are mostly affected by these same outliers. Clearly, our sample contains many outliers, since we estimate elasticities across firms, and coefficients of variation for estimated elasticities are very high, as can be seen from Table 1c. Perhaps the quadratic form approach can be more useful when analyzing a specific segment with more detailed information about firms.

Finally, we conduct an exploratory analysis of quartiles of firm-level dependent variables that result in the maximum mean ROA across segments. We summarize these findings in Table 1d. We conducted the same analysis with respect to both mean and median current and forwarded ROA, but results were qualitatively similar. Overall, companies with inventory levels in the 2nd and 3rd quartiles (25-75%) of the empirical distribution have the highest mean ROA. This result is consistent with the finding of Chen et al. (2005a, 2005b) that companies that perform well financially have "average" inventory levels. Moreover, companies with shorter lead times (the 1st and 2nd quartiles) have the highest ROA. With respect to inventory elasticities, being faster is associated with being better off financially: companies that react quickly to changes in sales, uncertainty, margins and lead times by adjusting inventory accordingly (i.e., companies that have inventory elasticities in the 3rd and 4th quartiles) have, on average, the highest ROA.

To illustrate our findings with specific examples, we consider two large retailing companies, Wal-Mart and Kmart. Wal-Mart is a highly profitable company and is widely considered a leader in supply chain management, whereas Kmart is less distinguished in terms of both profitability and supply chain management. We calculated the relative (quartile) positions of these companies in terms of inventories, inventory elasticities, and ROA, and these results appear in Table 5. Wal-Mart has achieved strong financial performance (3rd and 4th quartiles ROA) without being the leanest in the retail category: it falls into the 2nd quartile in terms of inventory. However, it has been very successful in responding quickly to environmental variables, which places Wal-Mart in the top quartile in terms of inventory elasticity with respect to sales. Kmart, on the other hand, is not a top performer financially (in the 1st through 3rd quartile ROA), but it is not the worst in terms of inventory turns, either: in most years it fit into the 2nd or 3rd quartiles, comparable to Wal-Mart. However, Kmart is sluggish in terms of the speed of inventory management: inventory elasticity to sales is close to the median (2nd quartile). This example illustrates that the speed of inventory management is more important in explaining financial performance than inventory levels alone.

7. Summary

In this paper we propose that several operational factors are associated with financial performance of public companies in the US and confirm this proposition using a sample of companies that operated during the period 1992-2002. The importance of the systematic analysis of the relationship between operational factors and financial performance is dictated by the lack of literature studying this issue. Although a few studies consider the link between inventory and financial performance, their results are mixed: there appears to be no simple relationship between the relative size of inventories and financial performance. To our knowledge, our study is the first to systematically analyze the relationship between companies' inventory management policies/operational environment (as captured by the relative inventory level, lead time, demand uncertainty and inventory elasticities, with respect to several environmental variables) and accounting returns as reflected by ROA. Our analysis is both cross-sectional at fixed points in time and longitudinal within 8 industry segments.

In the pooled sample, we find that, even after controlling for industry effects (average segment profitability, segment growth and concentration), there are important firm-level effects related to a company's ability to match supply with demand. Consistent with the common wisdom in the operations literature (see Cachon and Terwiesch 2005), firms operating in an environment with relatively more volatile demand consistently under-perform their peers in terms of both current and future ROA. On the sourcing side, longer lead times (as measures by the average days of accounts payable outstanding) are consistently negatively associated with both current and future ROA. This finding is again in line with predictions from inventory models (Cachon and Terwiesch 2005) as well as with anecdotal evidence suggesting that successful companies achieve better financial performance through fast sourcing (e.g., Zara, Dell).

Using a two-stage econometric model, we impute firm-level inventory elasticities with respect to sales, demand uncertainty, lead time and gross margin. This is done using results from Roumiantsev and Netessine (2005) suggesting that these factors are all important in explaining inventory behavior for an entire company. Our belief is that these elasticities can be used as proxies for the company's ability to adjust inventories in response to changes in the environment, and hence they are indicative of the quality of management control over inventories. We also believe that these elasticities are more relevant measures of the operational excellence of firms than just the relative inventory level, given the reality of nonstationary demands for products and the constant need for adjusting the supply.

Overall, our results are consistent with these beliefs. In the pooled sample, we have found that a greater elasticity of inventory with respect to changes in sales, sales uncertainty, and lead times is positively associated with both current and future ROA: firms that are "faster" or more responsive in their inventory management also perform better financially, on average. Contrary to our expectation, our results suggest that higher elasticity of inventory to gross margins is negatively associated with ROA. Somewhat surprisingly, we found no consistent association between inventory levels (days of inventory) and ROA. This result is in line with the work of Balakrishnan et al. (1996), Lai (2005) and Chen et al. (2005a, 2005b), who, in different samples, found that JIT implementation is not associated with financial performance and that high Tobin's q or stock performance does not have a significant statistical association with low inventory levels. Hence, we argue that a better measure of a company's operational strategy is not how lean it is, but how responsive.

Our findings in the pooled sample hold quite consistently across time but less so across individual segments. We attribute this difference to the data aggregation problems; more detailed data is needed to analyze specific business segments. It very well might be that the taxonomy of Fisher (1997) applies here, so that it is more important for some companies to be responsive and for others to be lean. Discerning these differences is a promising area of future research. We do not succeed in finding ROA-maximizing levels of operational variables using quadratic forms. Namely, except for two occasions, we fail to find interior optima in the sample. We attribute this negative result to the fact that quadratic terms are sensitive to outliers that come mainly from firm-level elasticity estimations that are highly variable. However, a descriptive statistics approach to finding implicit ROA-maximizing values of operational variables supports our statistical findings: relative inventory levels that maximize ROA are typically in the 2nd or 3rd quartile (so these companies are not necessarily lean), whereas inventory elasticities that maximize ROA are in the 3rd or 4th quartile (so these companies are responsive).

Our study suggests that the importance of matching supply with demand should not be underestimated and that it is not enough merely to look at the inventory levels in judging a firm's performance, because doing so can prove misleading. Moreover, it is well known that relative inventory levels are prone to manipulation by managers: e.g., by delaying acceptance of shipments from suppliers (and artificially lengthening lead times), the manager can temporarily decrease inventories. We would like to suggest that it is harder to manipulate inventory elasticities that may provide a fuller picture of the situation. By analyzing a firm's response to the environment in terms of inventory adjustments, boards of directors might be able to better evaluate the management of a company (see Ittner and Larcker 1998 for a survey of nonfinancial performance measures). Furthermore, by conducting similar analyses, investors like David Berman might be able to better predict the financial performance of companies so as to make better investment decisions. However, more research is needed to link inventory elasticities to stock performance as well as to show causality with respect to other financial measures.

As in our earlier work (Roumiantsev and Netessine 2005), our findings suggest that insights from classical operations models have applicability beyond single-item inventory management. Additionally, our empirical results suggest that responsiveness in inventory management should be endogenized into inventory models, especially those that do not assume that demand is stationary. For example, a company's speed of sourcing is rarely (if ever) a decision variable in extant inventory models, although in practice companies can and do control this variable.

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Table 1a. Sample description (quarterly data in $M, 1992-2002).

Segment	Segment name	# of companies	Mean Inventory	Mean COGS	Mean Inv/COGS	COV, Inv/COGS	Percentiles, Inv/COGS Ratio 25%	50%	75%
1	oil and gas	86	559	1343	0.42	5.48	0.08	0.23	0.39
2	electronics	190	168	173	1.22	2.51	0.47	0.89	1.40
3	wholesale	61	254	502	0.39	1.23	0.04	0.29	0.55
4	retail	95	968	1057	1.02	1.02	0.38	0.67	1.50
5	machinery	22	578	573	1.11	0.82	0.59	0.91	1.46
6	computer hardware	117	141	181	1.25	4.38	0.37	0.84	1.36
7	food and beverages	35	736	872	0.64	1.11	0.23	0.51	0.86
8	chemicals	116	388	314	1.40	1.70	0.38	1.01	1.76
Non S&P500		489	246	390	1.08	3.30	0.15	0.83	1.36
S&P500		233	690	800	0.91	1.35	0.27	0.71	1.15
Total:		722	396	527	1.03	2.94	0.25	0.74	1.29

Table 1b. Correlation among firm-level variables.

	LogCOGS	SalesGrowth	Volatile	DaysofInv	LeadTime	DaysofAR	FitCOGS	FItSigma	FitMargin	FitLeadTime
LogCOGS	1.0000									
SalesGrowth	-0.0094	1.0000								
Volatile	-0.1899	0.0112	1.0000							
DaysofInv	-0.1851	0.0091	0.1040	1.0000						
LeadTime	0.0770	0.0847	0.0085	0.0342	1.0000					
DaysofAR	-0.0352	-0.0004	0.0220	0.1115	0.0127	1.0000				
FitCOGS	0.0003	-0.0043	0.0052	0.0025	-0.0234	0.0015	1.0000			
FitSigma	-0.0063	0.0048	-0.0003	0.0176	0.0164	0.0128	-0.7883	1.0000		
FitMargin	0.0278	0.0103	-0.0096	0.0240	-0.0036	-0.0015	0.0210	-0.0088	1.0000	
FitLeadTime	-0.0716	-0.0021	0.0190	0.0026	-0.0153	0.0155	0.1200	0.0227	-0.0030	1.0000

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Table 1c. Summary statistics by segment – means and standard deviations of firm-level variables (quarterly data, 1992-2002).

	oil and gas	electronics	wholesale	retail	machinery	computer hardware	food and beverages	chemicals	Total
ROA	-0.0005 (0.0679)	-0.0154 (0.1455)	-0.0209 (0.7673)	0.0070 (0.0320)	0.0083 (0.0221)	-0.0333 (0.2385)	0.0086 (0.0355)	-0.0198 (0.5284)	-0.0128 (0.3318)
SalesGrowth	2.6365 (29.4538)	2.7451 (76.9199)	1.7592 (19.9669)	1.5990 (7.9370)	1.9013 (10.7368)	1.2605 (19.6968)	1.4771 (15.4689)	1.8368 (46.6698)	2.0329 (46.3951)
DaysofInv	38.3398 (210.1707)	111.3926 (279.6832)	36.3542 (43.8790)	93.2657 (95.0071)	102.1163 (83.8190)	114.1177 (500.3014)	58.7668 (65.1010)	127.9086 (217.4883)	94.2022 (276.8944)
LeadTime	315.9634 (1812.659)	116.9781 (386.7988)	119.873 (383.7867)	152.9212 (472.5366)	295.7437 (2567.882)	119.2681 (351.09)	192.8454 (1686.694)	209.0238 (1232.901)	170.5957 (1044.831)
DaysofAR	59.2243 (133.4247)	59.5665 (119.336)	55.8985 (503.1597)	16.6987 (85.8453)	92.5699 (79.9292)	123.9394 (2532.981)	28.0502 (21.3697)	52.7933 (119.7057)	62.3831 (1032.566)
FitCOGS	-3.7004 (30.9696)	-0.1807 (14.6560)	1.5092 (11.7883)	0.2739 (29.6512)	4.1236 (22.3543)	3.7830 (29.2718)	-2.2735 (31.1021)	3.8931 (56.3793)	0.9254 (31.9225)
FitSigma	1.5551 (17.7685)	-0.4924 (11.9206)	0.0081 (8.1991)	-0.0519 (14.3979)	-0.9644 (11.4538)	-0.9558 (17.0044)	1.1234 (15.1808)	-1.8658 (28.6473)	-0.3790 (17.4215)
FitMargin	0.0522 (1.1832)	0.1541 (1.7527)	0.0756 (1.6195)	0.1711 (1.0078)	-0.1762 (0.7153)	-0.1886 (1.0816)	-0.0121 (0.9322)	0.2735 (1.8824)	0.0832 (1.4729)
FitLeadTime	0.1098 (0.3953)	0.1565 (0.9655)	0.0875 (0.2994)	0.0253 (0.1917)	0.0978 (0.1808)	0.1318 (0.3151)	0.0047 (0.1705)	-0.1329 (2.7057)	0.06801 (1.2193)

Table1d. Quartiles with maximum mean ROA (total number of quartiles = 4).

	oil and gas	electronics	wholesale	retail	machinery	computer hardware	food and beverages	chemicals	overall
DaysofInv	3	2	3	3	2	2	2	3	3
LeadTime	2	2	1	1	1	2	2	2	2
DaysofAR	3	2	2	2	2	2	3	3	2
FitCOGS	1	4	4	3	3	4	4	4	4
FitSigma	3	3	3	4	3	3	4	3	3
FitMargin	4	1	4	3	1	4	4	3	4
FitLeadTime	1	3	3	3	3	4	3	3	3

Table 2. 1992-2002 pooled OLS and fixed effects regressions for ROA and forwarded ROA.

Estimation method	OLS	fixed effects	OLS	fixed effects	OLS	fixed effects
Dependent variable	ROA		ROAF1		ROAF2	
SegmentROA	0.3324***	0.3241***	0.0818***	0.0447	0.0545***	0.0279
SegmentGrowth	-0.0001	0.0011	0.0098***	0.0120**	0.0100***	0.0127***
Concentration	-0.0390***	-0.0003	-0.0350***	0.0301	-0.0953*	-0.0832***
LogCOGS	0.0092***	0.0103***	0.0083***	0.0119***	0.0080***	0.0068***
SalesGrowth	0.0000	0.0000	0.0002***	0.0000	0.0000	-0.0000
Volatile	-0.0268***	-0.0111***	-0.0178***	-0.0000	-0.0222***	-0.0097***
DaysofInv	0.0000	0.0005***	0.0000	0.0000	0.0000	0.0000
LeadTime	-0.0007***	-0.0000	-0.0000***	-0.0000	-0.0004***	-0.0000
DaysofAR	-0.0000	-0.0000	0.0000	0.0000	-0.0000	-0.0000
FitCOGS	0.0019**	0.0015*	0.0017***	0.0016***	0.0022***	0.0020***
FitSigma	0.0037***	0.0031*	0.0034***	0.0032***	0.0043***	0.0040***
FitMargin	-0.0014***	-0.0005***	-0.0012***	-0.0000	-0.0015***	-0.0013
FitLeadTime	0.0031***	0.0000	0.0016***	0.0000	0.0001	0.0001
q1	0.0167***	0.0167***	-0.0183***	-0.0176***	-0.0018	-0.0021
q2	0.0157***	0.0156***	0.0012	0.0018	-0.0227***	-0.0228***
q3	0.0149***	0.0146***	0.0021	0.0020	-0.0019	-0.0023
Year	-0.0023***	-0.0025***	-0.0028***	-0.0032***	-0.0025***	-0.0026***
Constant	4.6336***	5.0513***	5.5978***	6.3602***	5.0902***	5.2146***
Within firm R^2		1%		1%		2%
Between firms R^2		25%		24%		25%
Adjusted R^2	5%	5%	5%	5%	5%	5%

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

Table 3. Cross-sectional OLS regressions with robust standard errors (dependent variable: ROA).

ROA	1997-2002	1997	1998	1999	2000	2001	2002
SegmentROA	0.3011**	0.5427***	0.6615***	0.0528**	1.0001	0.7364***	0.0870
SegmentGrowth	0.0007	-0.0092	0.0281	-0.0300***	0.0366**	-0.0269	-0.0278
Concentration	-0.0485**	0.0761**	-0.0605	-0.0479	-0.0432	-0.0519	-0.0762
LogCOGS	0.0103***	0.0073***	0.0063***	0.0076***	0.0130***	0.0115***	0.0112***
SalesGrowth	0.0002**	0.0000	0.0001	0.0006***	0.0009	0.0006**	0.0002**
Volatile	-0.0304***	-0.0202***	-0.0226***	-0.0125***	-0.0548***	-0.0326***	-0.0389***
DaysofInv	0.0000	0.0000	0.0000	-0.0000	0.0000	0.0000	0.0000
LeadTime	-0.0006***	-0.0000***	-0.0000	-0.0002***	-0.0000	-0.0001**	-0.0000
DaysofAR	-0.0000	-0.0002***	-0.0001	-0.0000	0.0000	0.0000	0.0001
FitCOGS	0.0039***	0.0049***	0.0066***	0.0040***	0.0024***	0.0033	-0.0020
FitSigma	0.0076***	0.0097***	0.0130***	0.0080	0.0044**	0.0062	-0.0042
FitMargin	-0.0007	-0.0022	0.0007	-0.0002	-0.0009	-0.0031	-0.0042**
FitLeadTime	0.0132***	0.0094	0.0154**	-0.0051	-0.0033	0.0171	0.0421*
q1	0.0215***	0.0100***	0.0126**	0.0059	0.0096	0.0125	0.0222***
q2	0.0195***	0.0095**	0.0128**	0.0112***	0.0067	0.0089	0.0143
q3	0.0189***	0.0097**	0.0094	0.0044	0.0066	0.0118	0.0157***
Constant	7.0506***	-0.0260***	-0.0187	-0.0202**	-0.0493***	-0.0473**	-0.0622***
Adjusted R^2	5%	20%	28%	17%	4%	9%	5%

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

Table 4. Segment-specific OLS regressions with robust standard errors, 1997-2002.

ROA	oil and gas	electronics	wholesale	retail	machinery	computers	food & bev.	chemicals
LogCOGS	0.0018***	0.0117***	0.0296	0.0044***	-0.0023***	0.0140***	0.0051***	0.0100***
SalesGrowth	0.0000	0.0003***	0.0005	-0.0006	-0.0001***	-0.0002	-0.0004	-0.0003***
Volatile	-0.0227***	-0.0312***	-0.0489	0.0039**	-0.0073***	-0.0469***	-0.0072**	-0.0328***
DaysofInv	0.0000	0.0000***	0.0006	0.0003*	-0.0001***	0.0002	-0.0009	0.0009
LeadTime	0.0000	-0.0000***	-0.0002	0.0000	0.0000	-0.0001***	0.0000	-0.0000
DaysofAR	0.0002	-0.0002**	0.0004	-0.0001***	-0.0000	-0.0000	0.0006	0.0002
FitCOGS	-0.0020*	0.0015	0.0120***	0.0030	-0.0006	0.0016	-0.0089***	0.0013
FitSigma	-0.0044*	0.0039	0.0246***	0.0040	-0.0004	0.0031	-0.0183***	0.0031
FitMargin	-0.0001	-0.0025**	0.0166	0.0130	0.0290***	0.0023	-0.0161***	0.0072***
FitLeadTime	0.0016	-0.0127	0.0261	0.0031	0.0257***	0.0605	-0.0200	0.0351
q1	-0.0015	0.0044	0.0534	0.0023	0.0020	0.0087	0.0021	0.0269***
q2	-0.0020	0.0042	0.0450	0.0020	-0.0006	0.0028	0.0041	0.0278***
q3	-0.0024	0.0027	0.0308	0.0021	0.0009	0.0061	0.0034	0.0325***
Year	-0.0010	-0.0015	-0.0238	-0.0004	0.0003	-0.0001	-0.0004	-0.0056
Constant	2.1263	3.1378	47.4282	0.8096	-0.7262	0.3395	0.8853	11.2680
Adjusted R^2	19%	15%	3%	9%	28%	6%	16%	6%

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

Table 5. Retail examples of dynamics of inventory, inventory elasticity and ROA

Wal-Mart

Year	Days of Inv	Inventory Quartile	FitCOGS	FitCOGS Quartile	ROA Quartile
1997	54	2	3.4143	4	3
1998	48	2	3.4144	4	4
1999	45	2	3.4145	4	3
2000	44	2	3.4146	4	3
2001	41	2	3.4147	4	3
2002	44	2	3.4148	4	3

Kmart

Year	Days of Inv	Inventory Quartile	FitCOGS	FitCOGS Quartile	ROA Quartile
1997	77	3	-2.2804	2	2
1998	75	3	-2.2805	2	3
1999	76	3	-2.2806	2	3
2000	65	3	-2.2807	2	3
2001	57	2	-2.2808	2	1
2002	58	2	-2.2809	2	1

Table 6. Autoregressive properties of changes in ROA.

DeltaROAF2	oil and gas	electronics	wholesale	retail	machinery	computers	food & bev.	chemicals	total
DeltaROAF1	-0.568*** (0.016)	-0.625*** (0.010)	-0.647*** (0.019)	-0.658*** (0.015)	-0.565*** (0.031)	-0.613*** (0.009)	-0.618*** (0.025)	-0.197*** (0.007)	-0.562*** (0.005)
DeltaROA	-0.278*** (0.016)	-0.346*** (0.010)	-0.328*** (0.019)	-0.294*** (0.015)	-0.334*** (0.031)	-0.305*** (0.009)	-0.264*** (0.025)	-0.296*** (0.006)	-0.287*** (0.005)
Constant	0.000 (0.001)	0.002 (0.001)	0.000 (0.018)	-0.000 (0.0005)	-0.000 (0.0006)	0.003 (0.002)	0.000 (0.0009)	0.003 (0.002)	0.001 (0.001)
Within firm R^2	26%	31%	31%	32%	27%	47%	29%	37%	30%
Between firms R^2	7%	11%	13%	15%	14%	13%	7%	6%	0%
Adjusted R^2	26%	31%	31%	32%	27%	47%	29%	37%	30%

Note: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.