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 universe of all inventory-carrying companies in the period from 1994 to 2003, we develop a statistical methodology that links managerial decisions about inventory with accounting returns. We find that, after we control for industry- and firm-specific effects, superior earnings are associated with appropriately defined *responsiveness* in inventory management. Specifically, we define responsiveness as the difference between the percentage change in inventory level (over time) and the percentage change in sales (over time), such that a positive (negative) responsiveness measure implies that inventory is growing (declining) relative to sales. We find evidence both across time and in a cross-section that current ROA (return on assets) and forwarded ROA are asymmetrically associated with inventory responsiveness. Namely, faster inventory growth and a faster decline relative to sales are both associated with lower profitability. Our findings are partially consistent with the intuition of investment analysts and managers, who use a similar measure of responsiveness in practice to predict/assess the financial performance of a company, and they are also consistent with the results of classical inventory models.

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1. Introduction

In this paper we are interested in investigating the association between supply chain 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 attributed, either in full or in part, 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. 2005, 2007, Lai 2005). Furthermore, empirical evidence (Balakrishnan et al. 1996) demonstrates that introducing 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 managers use inventories to predict or explain accounting returns. One rare exception is O'Glove[2] (1987), who argues that, by looking at comparative changes in inventory and sales, one can predict the financial performance of a company. O'Glove provides numerous examples in which, when a company's inventory grew faster than its sales did, its subsequent financial performance was inevitably poor (thus entailing a downward revision of earnings). This early study has a few followers in the investment community: see Moore (2002) and the Motley Fool staff (2006). Another

[2] Thornton O'Glove was the CEO of the Reporting Research Corporation in Englewood Cliffs, New Jersey.

example is David Berman, a hedge fund manager (cited in 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 conventional operational metrics such as margins and inventory turns, but rather by analyzing the joint dynamics of inventory and sales using measures similar to those in O'Glove (1987). In Raman et al (2005), Berman states, "Wall Street basically ignores inventory.…[T]his gives us one of our edges," and bases 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") and getting out of the position in opposing scenarios (e.g., "inventories were now growing at the same pace as sales…and Berman was worried").

Although there appears to be some practical evidence that a measure of the joint dynamics of inventory and sales should be associated with superior financial performance, there is only limited empirical evidence for this effect. This paper aims to systematically assess the impact of inventory management on financial performance in the universe of inventory-carrying public US companies for the period 1994 to 2003 by studying the joint dynamic of inventory and sales. Namely, we use a combination of results from inventory control and motivation from practicing investment analysts to develop our measure of inventory responsiveness, defined as the difference between the percentage change in inventory level (over time) and the percentage change in COGS (over time) so that the positive (negative) responsiveness measure implies that inventory is growing (declining) relative to sales. We argue that companies with superior supply chain management practices should balance inventories with sales. Namely, a firm with perfect demand forecast will have zero inventory responsiveness (sales grows will match inventory growth) while a firm with erroneous demand forecast will have non-zero responsiveness. Therefore, both inventory growth and decline relative to sales are likely to indicate inefficient supply chain management and should be associated with deterioration of both current and future profitability.

We find robust empirical evidence consistent with our hypotheses above. After controlling for firm-specific, industry-specific and time effects, we find that faster inventory growth or decline relative to sales is associated with lower profitability as measured by current and future ROA. We verified that our findings are robust to various specifications of the responsiveness measure (e.g., if changes in inventory/sales are measured relative to the previous year rather than to the previous quarter and if changes in inventory/sales are lagged) as well as to alternative specifications of the dependent variable (return on sales, or ROS, instead of ROA). Our results also hold consistently across time (e.g., for each of four quarters) and across different two-digit standard industry classification (SIC) codes in the COMPUSTAT database. Thus, the key contribution of this paper is to show that supply chain management can be linked to profitability using a simple measure of combined inventory/sales dynamics and in identifying an asymmetry in this relationship. We therefore argue that the same measure of inventory responsiveness can be used to assess the inventory management practices of a company by top management and financial analysts.

The rest of the paper is organized as follows. In Section 2 we provide a literature review. In Section 3 we formulate our hypotheses, and in Section 4 we describe the sample and variables used in the analysis. In Section 5 we specify the econometric model, 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

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

Several studies analyze productivity in manufacturing companies, which are included in 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 the productivity of automotive assembly plants. In the same context, Fisher and Ittner (1999) find that greater day-to-day variability in automotive options has a significant adverse effect on productivity and quality. None of these papers focus on inventory management to explain accounting returns.

Several papers empirically analyze inventories held by public companies. 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 (information technology) 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 after 1980, when JIT practices were adopted. Gaur et al. (2005) explain inventory turnover among public retailing firms using gross margin, capital intensity, and sales surprise and define an alternative measure of inventory turnover. Gaur and Kesavan (2005) further show that firm size and sales growth rate are associated with inventory turnover. Finally, in a study across several industrial segments, Rumyantsev and Netessine (2007) find empirical evidence that firms operating with more uncertain demand, longer accounts payable terms, and higher gross margins have higher inventory levels. Furthermore, larger companies appear to benefit from economies of scale and therefore have relatively less inventory than smaller companies.

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 adopting JIT practices (which, supposedly, decrease inventory) on firms' profitability and find that, on average, there is no statistically significant association between the adoption of JIT practices and ROA. 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 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) to achieve 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-term effects of excess inventories on stock price. 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. Chen et al. (2005, 2007) find decreasing trends for relative inventory (inventory expressed as days of sales) in the manufacturing and wholesaling sectors for the period between 1981 and 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. Several papers in this stream attempt to link inventory levels with financial performance and find little or no connection between the two. Our approach is different: instead of looking at the static level of inventory in a given time period, we consider the co-movements of sales and inventory and argue that if inventory grows faster or declines more slowly than sales, then the company, on average, will be less profitable. This result is obtained while controlling for the relative level of inventory the company holds. As such, our paper is the only one among the subset of literature studying inventories using COMPUSTAT data that utilizes a dynamic measure of inventory management.

Finally, there is a stream of papers that analyzes the financial implications of operational decisions beyond inventory management. Brynjolfsson and Hitt (1996, 2002) study the "productivity paradox" of information technology and show that, after properly controlling for the firm-level production function, IT spending has made a substantial and statistically significant impact on firms' productivity. Frei et al. (1999) identify the links between retail banks' branch operation 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. (2007) 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 affecting 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 predominate when explaining variability in performance and, moreover, that industry-specific effects persist over longer periods. The authors do not study causality but show instead that industry, segment, and firm controls as well as time controls should be used to capture data heterogeneity. We follow this suggestion.

A large stream of research in the accounting/finance domain studies the link between managerial accounting and control practices and accounting performance. One example is Fama and French (2000), who study the autoregressive properties of earnings. They show that accounting earnings exhibit mean reversion, with the estimated rate of mean reversion being 38% for US public companies, a finding that 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 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.

Three papers in accounting are particular closely related to our work. Thomas and Zhang (2002) find that the well-known negative relation between accruals and future abnormal returns is mainly explained by inventory changes. The authors do not identify the reason for this relationship but suggest that it may arise from demand shifts. In this paper we formalize the relationship between demand shifts and inventory changes through the notion of inventory responsiveness. Lev and Thiagarajan (1993) and Abarbanell and Bushee (1997) study the ability of "fundamental analysis" to predict the value of corporate securities. One of fundamentals they use is similar to our measure of inventory responsiveness (which they also motivate by observations from O'Glove 1987). Lev and Thiagarajan (1993) find that measurements of inventory responsiveness help to explain earnings with respect to excess returns. Abarbanell and Bushee (1997) find that inventory responsiveness also helps to explain subsequent earnings changes. But our study differs in several ways. First, we do not attempt to predict earnings changes or excess stock returns: our goal is to study profitability (as captured by ROA), because inventory management models focus on maximizing profits. Second, inventory responsiveness is only one of a dozen fundamental signals studied in these two papers, whereas we provide a much more detailed study of inventory responsiveness alone. Using logic from classical inventory theory, we define inventory responsiveness in four different ways. Most important, we provide theoretical reasons to differentiate between positive and negative inventory responsiveness and show that profitability responds differently to these two measures (whereas the related accounting papers above do not have such a result).

Finally, instead of using annual data, we use quarterly data, allowing us to capture seasonal effects, which are vital to inventory management.

3. Hypotheses formulation

Throughout the paper we refer to our findings as "associations" and do not try to test/impose causality, because it is hard to do so using only realizations (sample paths) of variables instead of the true population and the underlying data available for the decision-making process. Our hypotheses rely on the assumption that firms behave rationally and make inventory decisions to maximize expected profits (or to minimize expected costs, as is the case in many classical inventory models). Hence, firms' behavior is manifested in the relationships among operational variables such as inventory and sales, which should be consistent with classical inventory models. The key premise behind our theoretical arguments is that, to achieve financial success, a firm must efficiently manage its inventories to match supply with demand, and any mismatch is costly, resulting in bad financial performance. For example, stock-outs typically lead either to explicit penalties (e.g., monetary compensation to the customer) or to implicit penalties (loss of future and current business). On the other hand, overstocks imply higher costs of carrying inventory, including possible obsolescence and the need for markdowns. Thus, any divergence between sales and inventory indicates supply chain mismanagement, which will be reflected in lower profitability.

Matching supply with demand would be much more straightforward if demand were known with certainty, but in practice there are numerous sources of uncertainty. Therefore, to better match supply with demand, companies use a variety of forecasting techniques combined with proactive supply chain management. The primary challenge, then, is to find an appropriate measure of co-movements for inventory and demand that would adequately reflect a firm's inventory management practices. Our baseline measure of inventory responsiveness is rooted in current practices among investment analysts and managers as well as in classical inventory theory and is defined as follows:

$$XC_t = \frac{I_t - I_{t-1}}{I_{t-1}} - \frac{S_t - S_{t-1}}{S_{t-1}}, \qquad (1)$$

where I_t stands for period *t* inventory and S_t stands for period *t* sales. We now state and discuss the motivation for using this metric and our predictions.

Positive inventory responsiveness ($XC_t>0$).

For reasons that will become obvious shortly, we first discuss the situation in which the inventory responsiveness measure is positive $XC_t>0$, implying that inventory grows faster than sales, or inventory declines more slowly than sales. Much of current investment literature devoted to analyzing inventory points to O'Glove (1987) as a pioneering publication. O'Glove, in chapter 8, argues that inventories constitute a key indicator that the investor needs to look at so as to "predict future downward earnings revisions by Wall Street security analysts" (p. 107). O'Glove's explanation is that "Obviously, higher trending inventories in relation to sales can lead to inventory markdowns, write-offs, etc." (p. 107).[3] O'Glove cites numerous practical examples in which, typically, an increase in a company's sales is accompanied by an even higher increase in inventory (as measured in percentage terms) which, as O'Glove argues, indicates a company's mismanagement of inventory. To cite just one example, Apple Computer inventories increased by 113.9% in the one-year period prior to March 1985, but sales over the same period increased by only 83.9% (see Table 8.4, p. 115). Consistent with O'Glove's prediction, this mismatch was followed by the announcement that expected revenues and earnings would drop in the second quarter of 1985.

Interestingly, O'Glove (1987) focuses almost exclusively on situations in which inventory grows relative to sales and does not discuss what happens in other situations. However, recent follow-ups to his methodology suggest that the same logic applies when inventory declines more slowly than sales, in that this mismatch is a sign of financial trouble. For example, Moore (2002) provides the example of Analog Devices, which posted decreases (measured as percentages) in both sales and inventories in the 2001 to 2002 period, noting that there is "cause for concern" because inventory did not decrease as fast as sales.

[3] O'Glove (1987) also provides reasons to analyze accounts receivable as well as different types of inventories (raw materials, work in process, finished goods). We omit these parts of his arguments which are outside of the scope of the current study.

While the arguments above apply to any company carrying inventory, the David Berman case (Raman et al. 2005) uses the same performance metric exclusively in the context of retailing. However, Berman's argument seems more nuanced: he differentiates between higher sales due merely to putting more inventory in the store and higher sales due to some more fundamental change (e.g., stocking more attractive products). The former, according to Berman, is only a short-term effect whereas the latter should lead to long-term growth in profits. Raman et al. (2005) provide several examples of companies for which increases in inventory (as measured in percentages relative to sales changes) resulted in poor financial performance. For example, the Bombay Company announced in November 2003 that sales were up 19% whereas inventories were up 50% year over year, leading to a significant decline in stock price.

Thus far these arguments support the conclusion that a higher positive measure of inventory responsiveness XC_t should be associated with lower profitability. We find support for this argument in inventory management literature as well, if we look at inventory responsiveness as a proxy for demand forecast accuracy and/or as a proxy for supply chain flexibility. Namely, firms typically stock inventories to anticipate demand and attempt to forecast demand as accurately as possible (Cachon and Terwiesch 2005). Imagine, however, that the firm makes an error (e.g., due to a lack of sophisticated forecasting tools or due to a lack of visibility into the supply chain, or both) and its forecast is too optimistic. In this case the firm will pre-position inventories but, because of this forecasting error, its sales will grow or decline more slowly than inventory does. In this case the higher inventory responsiveness measure will indicate the high cost of carrying inventory and possibly the obsolescence of the inventory. As a result, higher $XC_t>0$ will signal a lower ability to predict demand and to match supply with demand, and therefore should translate into inferior financial performance.

A parallel argument can be made that the measure of inventory responsiveness $XC_t>0$ indicates the firm's ability to adjust inventory quickly to respond to changes in demand or the demand forecast. For example, suppose that the firm over-forecasts demand, but nevertheless has an efficient/responsive supply chain that can cope with quick changes in demand patterns (see, e.g., Fisher and Raman 1996 and examples of companies like Dell and Zara in Cachon and Terwiesch 2005). Such a company would be able to cope quickly with updates in the demand forecast by adjusting its inventory appropriately and hence will not demonstrate a large positive inventory responsiveness, $XC_t>0$. On the other hand, a company with a less efficient supply chain would not be able to cope with such swings in the demand forecast and would therefore end up with excess inventory and suffer financially. Based on all of these arguments, we propose the following hypothesis:

Hypothesis 1. *When XC_t is positive, a higher measure of responsiveness in inventory management (as captured by higher XC_t) is associated with worse financial performance.*

Negative inventory responsiveness ($XC_t<0$).

A negative inventory responsiveness measure $XC_t<0$ indicates that the firm's sales increased but its inventory increased less than its sales, or possibly that inventory decreased but sales decreased less than inventory. The investment literature is relatively mute in this situation. For example, we could not find any examples of such a circumstances in O'Glove (1987) or Moore (2002). Accounting papers (Lev and Thiagarajan 1993 and Abarbanell and Bushee 1997) do not differentiate between positive and negative inventory responsiveness and therefore seem to argue that, regardless of whether $XC_t>0$ or $XC_t<0$, higher inventory responsiveness should be associated with lower financial performance. Likewise, the David Berman case (Raman et al. 2005) argues that the more negative the inventory responsiveness, the better the company's prospects. For example, Berman identified Saucony as a strong buy in 2003 because, even though sales were flattish, inventories declined 20%.

Interestingly, we found that some prominent companies use the same indicator to benchmark their performance internally. For example, in a 2004 10K financial statement Wal-Mart introduced the following performance metric: "Inventory growth at a rate less than half of sales growth is a key measure of our efficiency." Later, in a 2006 10K financial statement this performance metric was revised to drop the word "half," which was clearly an unrealistic goal. In an interview in the *Wall Street Journal*, the chief financial officer of Wal-Mart commented that "If you look back at the last six or eight quarters, we have not met that objective" (Hudson and Zimmerman 2006). This view seems to indicate that higher $XC_t<0$ should be associated with lower financial performance. Based on this evidence from accounting literature and current practices among financial analysts and company managers, we formulate the following hypothesis:

Hypothesis 2a. *When XC_t is negative, a higher measure of responsiveness in inventory management (as captured by higher XC_t) is associated with worse financial performance.*

However, we also offer an alternative view of negative inventory responsiveness that uses inventory theory arguments. Suppose, similar to the arguments above for positive inventory responsiveness, that the firm attempts to predict demand and makes a mistake by under-forecasting. In other words, demand turns out to be much higher than expected. The reason might be, once again, that the firm is not sophisticated enough in forecasting or information sharing. As a result, the firm's inventories for some products are depleted, and it cannot satisfy all demand. Clearly, such an event will result in a negative measure of inventory responsiveness: sales may increase, but inventory will increase less than sales, or inventory may decrease but with sales decreasing even less. In either case, the firm is likely to suffer financially because of the mismatch between demand and supply: having out-of-stock items may lead to lost sales, often with explicit penalties (e.g., in business-to-business settings, the firm may be contractually bound to supply a predetermined quantity). In other cases the penalties might be implicit: e.g., customer dissatisfaction due to stock-outs may lead to lower sales and/or missed opportunities to sell complementary products.

Once again, firms that possess efficient and flexible supply chains should be able to react quickly to such demand underestimations and procure the necessary products promptly, thus avoiding the negative inventory responsiveness measure $XC_t<0$, whereas inefficient firms will display significant inventory decreases relative to sales. Based on these arguments, we postulate an alternative hypothesis:

Hypothesis 2b. *When XC_t is negative, a higher measure of responsiveness in inventory management (as captured by higher XC_t) is associated with better financial performance.*

4. Data and variables description

We use the COMPUSTAT North America quarterly database accessed through Wharton Research Data Services (WRDS) to test our hypotheses. We analyze all publicly held US companies using their quarterly financial statements for the period 1994 to 2003. These date cutoffs are not entirely arbitrary; we chose them so as to ensure that we would study the most recent data, which is less affected by changing industry structures, while limiting the time period under consideration so as to minimize panel attrition. The choice of public companies naturally limits the universality of our findings, but there is little financial data for private companies. An additional caveat is that reporting practices vary from company to company, and therefore care should be taken in interpreting findings that rely on publicly available information. For example, different companies may include different expenses when reporting the cost of goods sold, and financial statements are often restated after the fact. Unfortunately, this is the best data that is currently available to the financial community and the public and therefore is widely used.

We have selected only companies with inventory-related operational activities and exclude the services, construction, and transportation segments. The Department of Commerce assigns four-digit SIC (Standard Industry Classification) codes to each firm. We include firms in minerals and mining (SIC 1000-1499), manufacturing (SIC 2000-3999), and wholesale and retail (SIC 5000-5999) in our sample. We further focus only on companies with strictly positive data on quarterly sales (the “data2” field in the COMPUSTAT files), inventories (“data37”), COGS (“data30”), operating income before depreciation EBITDA (“data21”) and total assets (“data44”). See Thomas and Zhang (2002) for a similar methodology. We further exclude companies that have merged, have been acquired, or have become inactive because studying the often great effects of these events on the financials of companies is beyond the scope of this paper. Finally, we require that a company has at least 20 time series data points (out of a maximum 40 in this timeframe) to ensure that firms with longer data series do not skew the statistical results. Our final sample contains more than 60,000 firm-quarter observations. We did not delete missing data after constructing the final sample but instead relied on the statistical procedures “xtreg” and “xtregar” in STATA that handle partially complete panel data automatically by disregarding all observations that have missing values for the dependent variable or missing values for any of the independent variables (the so-called "listwise deletion" method which is statistically appropriate as long as values are randomly missing).

We use quarterly data to be able to assess joint dynamics of inventories and sales. In particular, different industries operate under a variety of seasonal cycles caused by internal (e.g., capacity) and external (e.g., demand) factors, and seasonality plays important and varying roles in supply chain management decisions. These seasonal patterns are suppressed in the annual data: in fact, using annual COMPUSTAT data we found that, at the annual level, inventory and sales are pretty much synchronized, and therefore tracking inventory responsiveness (changes in inventory) becomes less informative. (We do not report our results using annual data in this paper.) Thus, we found that using quarterly rather than annual data is critical when assessing the ways firms adjust their operations and inventories to match sales dynamics. On the other hand, quarterly COMPUSTAT data is known to be of worse quality (e.g., it is restated more often) than the annual data, which potentially can affect our results. It would be ideal to use monthly data, but public firms do not report their monthly profitability numbers. Both quarterly and annual data may also be subject to earnings management by the company (see Thomas and Zhang 2002), and therefore any results should be interpreted with caution. Working with a panel of data allows us to ensure that the statistical relations we obtain are neither applicable at only a single point of time (the cross-sectional aspect of the analysis) nor driven by a single company (the time series aspect of analysis).

We use three subscripts to account for time-specific (*t*), firm-specific (*i*), and segment-specific (*s*) effects similar to those seen in Rumyantsev and Netessine (2007) and Gaur et al. (2005). A "segment" is defined as all companies within the two-digit SIC code. We provide summary statistics of variables used in the paper in Table 1. As a primary *dependent variable* in our study we use operating return on assets (ROA_{its}), defined as the ratio of operating income before depreciation to total assets. We choose ROA because it is the most frequently used measure of operating performance (see Barber and Lyon 1996 for a review of this and other operating performance measures). Several other measures of financial performance are available: return on sales (ROS), 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, the 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 al. 1999). We choose ROA over EBITDA, because ROA is more often used to measure the financial performance of companies (Stickney and Weil 1999). We choose ROA over EVA to avoid scaling problems (because higher absolute EVA can merely reflect 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. The average ROA in our sample is 0.031. We report results for both the current ROA_{its} as well as the one-quarter-forwarded ROA ($ROAF_{its}$) to confirm the consistency of cross-sectional findings. To ensure the robustness of our results, we used ROS (return on sales, the ratio of net income before interest and tax to sales) as another proxy for profitability, and our results remained qualitatively unchanged. (Results for ROS are not reported in the paper.)

For *explanatory variables* we use (i) time controls, (ii) industry controls, (iii) firm controls, and (iv) the inventory metrics. This approach and these variable choices are consistent with McGahan and Porter (2002) and Barber and Lyon (1996). All independent variables except for the proxy of the firm size are relative so as to minimize scale and price effects and to enable us to compare results across different firms.

Time controls. We introduce yearly dummies to control for possible trends in profitability over time due to industry cycles. For example, if both ROA and inventory decreased over time, the regression without time controls would indicate a spurious positive correlation. The use of yearly dummies is consistent with McGahan and Porter (2002). Moreover, we introduce quarterly dummies to control for possible seasonality effects that are present in many industries (e.g., retail). Most related studies use annual rather than quarterly data and therefore do not control for quarterly effects. We found that quarterly dummies do not affect any of the results, and therefore we omit them when reporting our results to reduce clutter in tables.

Industry controls. We control for the average segment profitability as measured by segment average gross margin (denoted by SM_{its}) to ensure that a firm's profitability is measured relative to the average profitability in its industry. Average segment profitability is 0.67 in our sample, a relatively high number that is explained by the presence in the sample of several high-margin segments such as the pharmaceutical, medical equipment, and high-tech production industries. Furthermore, we control for annual segment sales growth (denoted by SG_{its}) to account for transitory seasonal effects: some industries might be going through growth/decline stages, and the profitability of companies within the industry can change accordingly. SG_{its} is calculated as the percentage change in the annual sales for the entire segment. Average segment growth in our sample is 0.05. These controls have proven to be important in previous research (see Cheng 2005).

Firm controls. We control for firm size and sales growth. We use the logarithm of cost of sales ($LogS_{its}$) as a proxy for firm size because larger firms tend to have larger profits (see Barber and Lyon 1996). The logarithm function is employed to control for scaling effects: other variables are relative and vary within a specific range, whereas firm sales is an absolute number and varies substantially. The average logarithm of sales in our sample is 4.28. Firm-level sales dynamics are captured by the sales growth variable (denoted by G_{its}), which measures quarter-over-quarter relative sales changes. We control for it because previous research finds a link between profitability and firm growth (Fairfield and Yohn 2001). Moreover, since our measure of responsiveness indirectly involves sales growth, we want to ensure that the effects we capture are not merely due to sales growth/decline. The average individual company's sales growth is 0.035 in our sample.

Inventory metrics. First, we control for a firm's inventory investment using the ratio of inventory to the cost of goods sold, which is denoted by I_{its}. Along with inventory turnover, this is a standard measure of inventory investment (see Gaur et al. 2005, Gaur and Kesavan 2005, Rumyantsev and Netessine 2007). We control for inventory investment for several reasons. First, we need to be certain that the relationship between our measure of inventory responsiveness and our dependent variable ROA_{its} is not due to the fact that inventory is a part of a firm's assets and hence enters both the ROA calculation and the inventory responsiveness metric. Hence, we want to control for any mathematical relationship between ROA_{its} and I_{its}. Second, we want to be certain that the relationship between profitability and responsiveness is not simply driven by inefficient firms stocking too much inventory, as previous research suggests (Chen et al. 2005, 2007). The average firm in our sample has an inventory-to-COGS quarterly ratio of 1.05.

Finally, we capture the joint behavior of inventory and sales using the inventory responsiveness measure XC_{its} introduced earlier. However, the time periods *t* and *t-1* in (1) can be selected in a variety of ways because I_{its} is only a proxy for how much inventory the firm carries—it reflects only end-of-period inventory holdings. To ensure that our measure of responsiveness is robust, we study four different specifications for the responsiveness variable (see Table 2 for summary statistics by quarter).

1) We denote by XC_{its} current period inventory change minus current period COGS change:

$$XC_{its} = \frac{I_{its} - I_{i,t-1,s}}{I_{i,t-1,s}} - \frac{S_{its} - S_{i,t-1,s}}{S_{i,t-1,s}}. \qquad (2)$$

This is the same definition that we used in equation (1) above. For an average firm in our sample, XC_{its} = 0.06.

2) An argument can be made that inventory I_{its} reflects only the end-of-period inventory level, which is the amount of inventory available for the subsequent period *(t+1)*. Thus, inventory changes in the current period should be compared with sales changes in the subsequent (rather than the current) period. Moreover, inventory decisions in the current period may reflect expectations of sales in the subsequent period rather than reflect (or be in addition to) inventory management in the current period (as also suggested by inventory models that look at the expected rather than realized sales levels). To account for this reasoning, we introduce the variable $XLEAD_{its}$ to capture current period inventory change minus the next period COGS change**:**

$$XLEAD_{its} = \frac{I_{its} - I_{i,t-1,s}}{I_{i,t-1,s}} - \frac{S_{i,t+1,s} - S_{its}}{S_{its}}. \tag{3}$$

For an average firm in our sample, $XLEAD_{its}$ = 0.008.

3) Another way to look at the inventory investment I_{its} is to say that in the short term (the current quarter) the firm forecasts demand and often makes mistakes in forecasting that do not necessarily indicate inventory mismanagement. Rather, they indicate an accidental random realization of demand which may or may not be reflected in the firm's financial performance. However, over a longer term (the subsequent quarter) any forecasting errors should be corrected and inventory should be adjusted accordingly but with a delay (which corresponds to the notion of static expectations when adjustments are made with lags). To account for this possibility, we denote by $XLAG_{its}$ the current period inventory change minus the previous period COGS change:

$$XLAG_{its} = \frac{I_{i,t+1,s} - I_{its}}{I_{its}} - \frac{S_{its} - S_{i,t-1,s}}{S_{i,t-1,s}}. \tag{4}$$

For an average firm in our sample, $XLAG_{its}$ = -0.008.

4) Finally, an argument can be made that, due to seasonality in many industries, it is most appropriate to measure co-movements of inventory and sales relative to the same quarter of the previous year to compare similar periods of operation. This is the approach that O'Glove (1987) often takes. Hence, we denote by XH_{its} year-over-year inventory change minus year-over-year sales changes**:**

$$XH_{its} = \frac{I_{its} - I_{i,t-5,s}}{I_{i,t-5,s}} - \frac{S_{its} - S_{i,t-5,s}}{S_{i,t-5,s}}. \tag{5}$$

For an average firm in our sample, XH_{its} = -0.02.

Since our Hypotheses 1 and 2b predict non-symmetric relationships between measures of responsiveness and profitability, we further define the following variables that capture positive and negative observations for each of four responsiveness measures as follows:

$$XCplus_{its} = XC_{its} \times 1_{(XC \geq 0)}, \;\; XCminus_{its} = XC_{its} \times 1_{(XC < 0)},$$

and other variables are defined analogously. For example, for an average firm in our sample, $\text{XCplus}_{\text{its}}$ = .108 and $\text{XCminus}_{\text{its}}$ = -.102. For comparative purposes, in Table 2 we list average values for the eight inventory responsiveness variables by quarter. Note that, due to higher demand, average inventory levels are lower in the fourth quarter.

Tables 3.1 and 3.2 describe the correlation properties of the sample. We only include basic variables (without "plus" or "minus") in Table 3.1 because of the large number of such variables, but we verified that results do not change appreciatively if we include variables with "plus" or "minus." Note that the correlation matrix in Table 3.1 is quite sparse, indicating that we should not experience collinearity problems and therefore all estimates should be quite robust. The largest correlation coefficients are observed among different responsiveness measures which we do not intend to include in the regression simultaneously. Additionally, in Table 3.2 we present correlation coefficients among "plus" and "minus" responsiveness measures and we again report that there are no strong correlations between the same variable with "plus" and "minus" notations.

5. Model specification and research design

We use the following econometric model to link a firm's financial performance with measures of inventory responsiveness while controlling for time, industry and firm effects.

$$\begin{aligned}\text{ROA}_{\text{its}} &= a_i + b^1\text{SM}_{\text{ts}} + b^2\text{SG}_{\text{ts}} + b^3\text{LogS}_{\text{its}} + b^4\text{G}_{\text{its}} + b^5\text{I}_{\text{its}} \\ &\quad + b^6\text{XCplus}_{\text{its}} + b^7\text{XCminus}_{\text{its}} + d_1q_1 + d_2q_2 + d_3q_3 + d_4 year + \varepsilon_{its}.\end{aligned} \tag{6}$$

In this model a_i represents the additive firm fixed effects; b^1 to b^7 are regression coefficients for independent variables described above; and d_1 to d_4 are coefficients for time controls. Finally, ε_{its} is a random disturbance term for a firm/segment/time period combination which additively includes firm-specific and time-specific effects along with random noise to ensure that unobserved variables in the panel such as management quality, marketing decisions, etc., are controlled for, thus helping us to avoid biased estimators (Greene 1997). We model firm-specific and time-specific effects using both random and fixed-effect models. When reporting final results we estimate using fixed-effects coefficients, because the Hausman test (Greene 1997) rejects the hypothesis that random-effects estimators are efficient and because the large size of our sample indicates the need for fixed effects in the research design.

We begin by testing the cross-sectional properties of the sample using model (6). We then test the robustness of model (6) in the time dimension by using one-quarter-forwarded ROA (ROAF) as a dependent variable. We further estimate model (6) using each of four pairs of inventory responsiveness variables. We tested model (6) using alternative specifications to ensure the robustness of our findings. First, we used ROS rather than ROA as a dependent variable. Further, we used two-quarters-forwarded ROA, and performed median regressions to ensure that our results are not driven by potential data outliers. Results of all these alternative specifications were qualitatively similar both in signs and magnitudes of coefficients. We also run model (6) separately for individual two-digit SIC segments and found the model to be significant overall with consistent results. Finally, to test for the consistency of our results across time and to control for potential seasonal effects we estimated model (6) for each of the four quarters individually and found the results to be consistent and robust. Given the volume of results we generated, we report details of only the most important results. Other results are summarized where relevant.

6. Results

We use panel data modules “xtreg” and “xtregar” in STATA to perform our analysis. The STATA package provides embedded tools to analyze panel data (including the ability to analyze information with missing data points) and to estimate fixed and random effects with a possible autoregressive structure. We provide statistical results of estimating models (6) for ROA and ROAF in Table 4. We note that the overall goodness of fit (adjusted R^2) is around 17-18% for both current and forwarded ROA models. The F-statistic for all models is highly significant ($p<.0001$), and most coefficients are significant at the 1% level unless indicated otherwise.

First, we observe that the direction of industry and firm-level controls is consistent with previous research findings. Namely, firms in higher-margin industries have, on average, higher current and future profitability, where industry sales growth rate is negatively associated with current-period ROA and positively associated with one-period forwarded ROA. Larger and faster growing firms are, on average, more profitable. These observations are in line with the findings of previous research. See, for instance, McGahan and Porter (1997, 2002). It also appears that there is a negative trend in profitability over time.

Second, we see that the amount of inventory held by the firm is consistently negatively associated with ROA. The unit increase in inventory turns is associated, on average, with a decrease in current period ROA by 0.016-0.018 and a decrease in ROAF by 0.011-0.013. This may imply that firms with large (small) inventories are, correspondingly, less (more) profitable. Similarly, Chen et al. (2005) find that stock prices of firms with excessive inventories perform worse than stock prices of firms with average or low inventories, and Singhal (2005) finds that inventory write-downs have a significant negative effect on stock returns. However, since ROA is a decreasing function of a firm's assets which include inventories, we cannot be sure that the observed relationship is not simply the mathematical relationship between ROA and inventory. Determining this would depend on the amount of inventory that the company holds relative to other assets.

Third, we observe the consistent association between the introduced proxies of inventory responsiveness and profitability. Namely, as we report in Table 4, there is a consistent negative association between all positive inventory responsiveness variables (XCplus, XLAGplus, XLEADplus and XHplus) and both current and forwarded ROA: all eight coefficients are negative and statistically significant. Thus, there is strong support for Hypothesis 1. At the same time, there is a consistent positive association between negative inventory responsiveness variables (measured by XCminus, XLAGminus, XLEADminus and XHminus) and current ROA. The relationship with forwarded ROA is somewhat spotty, with two coefficients being negative (rather than positive) and statistically significant. Thus, we find strong support for Hypothesis 2b for current ROA but not for forwarded ROA, while there is no support for Hypothesis 2a for current ROA and only marginal support for forwarded ROA.

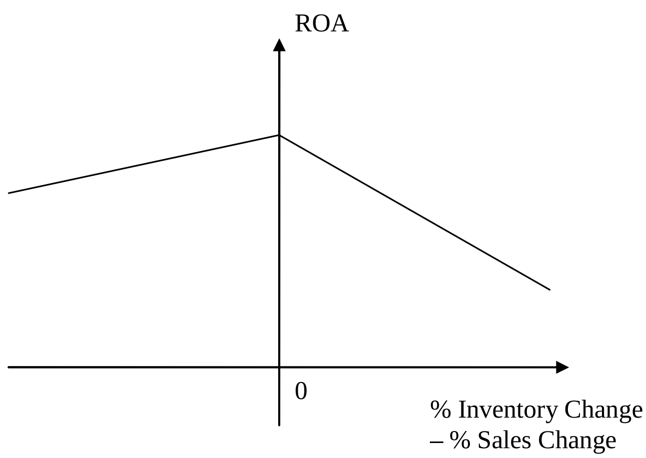
We note that the coefficient for XCplus is -0.008 and the coefficient for XCminus is 0.002 for the current period, and all coefficients are generally of the same order of magnitude. If we focus on XCplus and XCminus proxies for inventory responsiveness, it appears that ROA is about four times more sensitive to inventory increases relative to sales (positive responsiveness) than to inventory declines (negative responsiveness). Moreover, we verified that the two coefficients for positive and negative responsiveness are statistically significantly different across all four proxies for responsiveness—the null hypothesis that they are the same is rejected with the alternative hypothesis being that $b^7 > b^6$. In other words, inefficient inventory management due to demand under-forecasting (excess inventory growth as compared to sales growth) seems to be more strongly associated with reduced profitability than is inefficient inventory management due to demand over-forecasting. The possible reason might be the asymmetry between underage and overage costs, which in turn can cause different profitability outcomes in cases of under-forecasting and over-forecasting. Another possible reason might be that it is generally easier for firms to respond to demand over-forecasting (e.g., by reducing or delaying future orders) than it is to respond to demand under-forecasting (e.g., because suppliers might have limited capacity).

Finally, as one of our robustness checks, we tested model (6) for individual calendar quarters to ensure that our results are not specific to a particular time of the year (e.g., a seasonal increase in sales in quarter 4). In Table 5 we provide quarterly estimates using XCplus and XCminus as explanatory variables and using ROAF as a dependent variable: our results are very robust and in each of four quarters the coefficient for XCplus is negative and the coefficient for XCminus is positive. (Results using current ROA are very similar.) We note again that coefficients for XCplus are larger than coefficients for XCminus (which is consistent with Table 4) for all quarters, as again verified by a t-test. Thus, Hypotheses 1 and 2b are strongly supported within each of four quarters for both current and forwarded ROA, while Hypothesis 2a is rejected.

7. Summary and managerial implications

Extant literature attempts to link the supply chain management and financial performance of a firm using static metrics of supply chain performance (e.g., inventory turns at a given point in time or announcements of supply chain disruptions). In this paper we propose an inherently dynamic metric of supply chain performance, which we call inventory responsiveness. Inventory responsiveness measures quarter-over-quarter or year-over-year changes in inventories relative to changes in sales. The main virtue of this metric is its simplicity: it is easy to calculate and easy to explain to practicing managers and investment analysts. Intuitively, we argue that when inventory and sales diverge (inventory either grows or declines relative to sales), the firm is probably mismanaging its supply chain, and we expect it to perform poorly. We cite evidence that this or similar metrics of inventory responsiveness are often used by companies, financial analysts, and fund managers. Moreover, the intuition behind the metric of inventory responsiveness is consistent with predictions of a variety of classical inventory models, although it differs somewhat from fundamental metrics used in accounting literature, which do not differentiate between positive and negative inventory responsiveness.

We find a very robust statistical association between our proposed measures of inventory responsiveness and profitability as measured by ROA, forwarded ROA, and ROS. Our key result can be concisely summarized in Figure 1. When inventory increases relative to sales, a firm's profitability declines, and when inventory decreases relative to sales, a firm's profitability declines as well. Generally, we find that profitability is much more sensitive to the positive inventory responsiveness metric than to the negative one. This result is very robust: it holds for individual quarters throughout the year as well as for individual two-digit industries.



As a first step in linking financial performance with supply chain management, we selected a very simple yet powerful metric capturing co-movements of inventories and sales. Indeed, Rumyantsev and Netessine (2007) demonstrate that sales dynamics explain 70% of inventory fluctuations, whereas the explanatory power of other variables (e.g., margins, sales uncertainty, etc.) is weaker. Nevertheless, future studies could analyze whether co-movements of inventories and, say, margins, have a similar impact on financial performance. Moreover, while we focused on a firm's profitability, investors are often more concerned with the stock performance of a public company. Chen et al. (2005, 2007) found some evidence that companies with excess inventories under-perform the market, and it would be interesting to see whether our inventory responsiveness metric can be used to reliably predict stock performance as shown by David Berman (Raman et al. 2005). Finally, future research can look deeper into suggestions by O'Glove (1987), who goes beyond inventory and points to accounts receivable as a major indicator of profitability. Another technique that O'Glove uses is to segregate inventory into three components and to consider their joint co-movements relative to sales. This is yet another promising direction for future research.

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Table 1. Summary statistics for the sample.

Variable	N	Mean	St. Dev.	25%	Median	75%
ROA	64030	0.031	0.036	0.016	0.032	0.049
SM	64030	0.672	0.645	0.284	0.486	0.832
SG	62120	0.051	0.297	-0.061	0.025	0.119
LogS	64030	4.280	2.031	2.730	4.246	5.683
G	52059	0.035	0.339	-0.039	0.071	0.179
I	64030	1.051	0.746	0.531	0.885	1.383
XC	62005	0.060	0.402	-0.126	-0.003	0.124
XCplus	62005	0.108	0.241	0.000	0.000	0.125
XCminus	62005	-0.102	0.287	-0.126	-0.003	0.000
XLEAD	60078	0.008	0.411	-0.102	-0.004	0.098
XLEADplus	60078	0.092	0.243	0.000	0.000	0.099
XLEADminus	60078	-0.084	0.308	-0.102	-0.004	0.000
XLAG	60083	-0.008	0.449	-0.130	-0.006	0.116
XLAGplus	60083	0.103	0.253	0.000	0.000	0.117
XLAGminus	60083	-0.112	0.339	-0.131	-0.006	0.000
XH	52059	-0.020	0.500	-0.130	-0.008	0.112
XHplus	52059	0.100	0.244	0.000	0.000	0.113
XHminus	52059	-0.121	0.409	-0.134	-0.008	0.000

Table 2. Mean statistics for inventory variables by quarter.

Quarter	1	2	3	4
I	1.078	1.058	1.064	1.007
XC	0.075	-0.022	0.017	-0.039
XCplus	0.158	0.082	0.103	0.093
XCminus	-0.082	-0.104	-0.086	-0.133
XLEAD	0.046	-0.015	0.008	-0.004
XLEADplus	0.127	0.075	0.085	0.084
XLEADminus	-0.081	-0.090	-0.077	-0.088
XLAG	-0.028	0.049	-0.025	-0.027
XLAGplus	0.098	0.141	0.084	0.093
XLAGminus	-0.125	-0.092	-0.109	-0.120
XH	-0.021	-0.018	-0.025	-0.019
XHplus	0.101	0.104	0.097	0.100
XHminus	-0.122	-0.122	-0.122	-0.119

Table 3.1. Correlation matrix (all correlations are significant at the 1% level).

	ROA	SM	SG	LogS	G	I	XC	XLEAD	XLAG	XH
ROA	1.000									
SM	0.195	1.000								
SG	-0.182	-0.003	1.000							
LogS	0.279	-0.095	-0.061	1.000						
G	0.237	-0.059	-0.031	0.112	1.000					
I	-0.179	0.319	0.165	-0.250	-0.156	1.000				
XC	-0.108	0.055	0.249	-0.039	-0.142	0.218	1.000			
XLEAD	-0.064	0.042	0.087	-0.020	-0.103	0.167	0.401	1.000		
XLAG	-0.047	0.026	0.258	-0.020	-0.134	0.142	0.371	-0.121	1.000	
XH	-0.019	0.051	0.051	-0.012	-0.327	0.192	0.355	0.399	0.312	1.000

Table 3.2. Correlation matrix for inventory responsiveness variables (all correlations are significant at the 1% level).

	XCplus	XCminus	XLEADplus	XLEADminus	XLAGplus	XLAGminus	XHplus	XHminus
XCplus	1.000							
XCminus	0.189	1.000						
XLEADplus	0.720	-0.001	1.000					
XLEADminus	0.077	0.230	0.138	1.000				
XLAGplus	0.182	0.076	0.049	-0.091	1.000			
XLAGminus	-0.138	0.682	-0.353	0.088	0.175	1.000		
XHplus	0.310	0.064	0.327	0.043	0.293	0.028	1.000	
XHminus	0.044	0.388	0.006	0.479	0.015	0.360	0.123	1.000

Table 4. Results of the pooled regression for ROA and ROAF.

Variable	ROA	ROA	ROA	ROA		ROAF	ROAF	ROAF	ROAF
SM (segment margin)	0.047*** (0.001)	.047*** (.0005)	0.047*** (0.0004)	.047*** (.0005)		.014*** (.0005)	.014*** (.0005)	.013*** (.0005)	.013*** (.0005)
SG (segment growth)	-0.013*** (0.0003)	-.012*** (.0003)	-0.012*** (0.0003)	-.012*** (.0003)		.047*** (.0003)	.047*** (.0003)	.047*** (.0003)	.047*** (.0003)
LogS (log of sales)	.016*** (.0003)	.017*** (.0003)	.017*** (0.0003)	.017*** (.0003)		.014*** (.0003)	.014*** (.0003)	.015*** (.0003)	.015*** (.0003)
G (firm growth)	.004*** (.0003)	.004*** (.0003)	.004*** (0.0003)	.006*** (.0005)		.007*** (.0003)	.007*** (.0003)	.007*** (.0003)	.008*** (.0005)
I (relative inventory)	-.016*** (.0004)	-.016*** (.0003)	-.017*** (0.0003)	-.018*** (.0003)		-.011*** (.0003)	-.011*** (.0003)	-.013*** (.0003)	-.013*** (.0003)
Xcplus	-.008*** (.0004)					-.006*** (.0005)			
XCminus	.002*** (.0002)					-.0006*** (.0004)			
XLEADplus		-.009*** (.0005)					-.006*** (.0005)		
XLEADminus		.0012*** (.0003)					-.001*** (.0004)		
XLAGplus			-.001*** (.0003)					-.002*** (.0004)	
XLAGminus			.004*** (.0004)					.003*** (.0003)	
XHplus				-.002** (.0008)					-.001* (.0007)
XHminus				.003** (.001)					-.0002 (.0003)
Year	-.0008*** (.000)	-.001*** (.0000)	-.0008*** (.0000)	-.0008*** (.0000)		-.0005*** (.0000)	-.0006*** (.0000)	-.001*** (.0000)	-.0006*** (.0000)
Constant	-.040*** (.0006)	-.040*** (.0006)	-.041*** (.0006)	-.040*** (.0006)		-.020*** (.0010)	-.020*** (.0009)	-.020*** (.001)	-.020*** (.0010)
Between R^2	38%	38%	38%	37%		25%	26%	25%	24%
Within R^2	19%	19%	19%	19%		19%	19%	19%	18%
Overall R^2	18%	19%	18%	17%		16%	17%	16%	16%

*** and * denote statistical significance at the 1% and 10% level, respectively. Quarterly dummies not shown.

Table 5. Results of the pooled regression for ROAF by quarter.

Quarter	1	2	3	4
SM (segment margin)	.025*** (.0009)	.028*** (.0009)	.028*** (.001)	.024*** (.0009)
SG (segment growth)	.043*** (.001)	.047*** (.0012)	.032*** (.001)	.037*** (.001)
LogS (log of sales)	.015*** (.0007)	.015*** (.0007)	.015*** (.0008)	.014*** (.0008)
G (firm growth)	.008*** (.0007)	.005*** (.0007)	.006*** (.0007)	.006*** (.0007)
I (relative inventory)	-.016*** (.0006)	-.018*** (.0007)	-.017*** (.008)	-.018*** (.0008)
XCplus	-.002*** (.001)	-.007*** (.0015)	-.005*** (.0017)	-.001* (.0005)
XCminus	.001* (.0006)	.001*** (.0002)	.001*** (.0008)	.002** (.001)
Year	-.0006*** (.0000)	-.0006*** (.0000)	-.0006*** (.0000)	-.0006*** (.0000)
Constant	-.024*** (.003)	-.0223*** (.0033)	-.024*** (.0037)	-.017*** (.0038)
Between R^2	27%	29%	22%	25%
Within R^2	18%	19%	18%	18%
Overall R^2	16%	19%	16%	17%

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