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The Relationship Between Abnormal Inventory Growth and Future Earnings for U.S. Public Retailers

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In this paper we examine the relationship between inventory levels and one-year-ahead earnings of retailers using publicly available financial data. We use benchmarking metrics obtained from operations management literature to demonstrate an inverted-U relationship between abnormal inventory growth and one-year-ahead earnings per share for retailers. We also find that equity analysts do not fully incorporate the information contained in retailers' abnormal inventory growth in their earnings forecasts, resulting in systematic biases. Finally, we show that an investment strategy based on abnormal inventory growth yields significant abnormal stock market returns.

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1. Introduction

Retailers pay close attention to inventory growth in their stores, because that can significantly impact their future financial performance. Too much inventory in a store could result in future markdowns whereas too little inventory could result in lower demand in the future because of customer dissatisfaction with poor service. Numerous anecdotes of poor inventory management leading to retailers' decline in financial performance can be found in the business press. However, little empirical evidence exists on the relationship between retailers' current inventory levels and their future financial performance.

In fact, evidence is growing that even Wall Street investors may have trouble understanding the relationship between inventory levels and retailers' future financial performance. Kesavan et al. (2010) found that even though inventory contains useful information to predict sales for retailers, Wall Street analysts fail to incorporate this information into their sales forecasts. Hendricks and Singhal (2009), who examined excess-inventory announcements of firms from multiple industry sectors, including retail, found that these announcements are associated with negative stock market reactions in a vast majority of cases. Because excess inventory is reported only when such inventory problems become large enough, their results suggest that stock market investors failed to anticipate these announcements even though they had access to past inventory levels of the firms, which could have enabled them to predict such announcements.

In this paper, we are interested in examining the relationship between inventory and one-year-ahead earnings per share. We choose earnings per share because of the following reasons. First, earnings per share is an important financial metric for firms, and their forecasts form a key input to investment decisions. Givoly and Lakonishok (1984, p. 40) found that "earnings per share emerges from various studies as the single most important accounting variable in the eyes of investors and the one that possesses the greatest information content of any array of accounting variables." Second, current evidence on the relationship between inventory and one-year-ahead earnings for retailers is weak. Accounting literature examining this question has yielded a mixed response. Abarbanell and Bushee (1997) did not find evidence of this relationship for retailers, but Bernard and Noel (1991) did. Even Bernard and Noel (1991), who found that inventory predicts earnings for retailers, assumed a linear relationship between inventory and earnings, and found evidence for the same. Because earnings are one measure of a firm's profitability, one might expect the relationship to be an inverted U, based on the operations management literature. This raises the additional question of whether the inverted-U relationship that forms the building block of inventory models at the SKU level is lost at the firm level.

Several challenges arise in testing the relationship between inventory and earnings at the firm level. First, raw inventory level cannot be used to determine the relationship because it is correlated with number of stores, sales, etc. For example, a retailer's inventory could grow either because of increasing amounts of aging inventory or as a result of new stores opening. Whereas the former scenario would be associated with lower earnings in the future, the latter would not. So, an appropriate method for normalizing inventory is required before we test the relationship between inventory and earnings. Second, retailers' could make inventory decisions based on private information. For example, service-level information is not publicly available. It is therefore difficult to figure out whether a retailer's inventory level is high because the business is carrying excess inventory or because it is providing a high level of service. The former would be a negative signal of future earnings, whereas the latter might not.

In this paper, we use the expectation model from Kesavan et al. (2010) to obtain the expected inventory growth. This expectation model subsumes many factors identified in the operations management literature as driving retailers' inventory levels. Then we calculate abnormal inventory growth (AIG) as the deviation of actual inventory growth from expected inventory growth and use it as the benchmarking metric to investigate the relationship between inventory and one-year-ahead earnings. We investigate the economic significance of information contained in abnormal inventory growth by examining whether equity analysts' earnings forecasts incorporate it, and test whether an investment strategy based on abnormal inventory growth would yield significant abnormal returns.

Our analysis uses quarterly and annual financial data, along with comparable store sales, total number of stores, and earnings per share for a large cross-section of U.S. retailers listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), or NASDAQ from Standard and Poor's Compustat database. Equity analysts' earnings forecasts are collected from the Institutional Brokers Estimates System (I/B/E/S). Stock returns inclusive of dividends are obtained from the Center for Research in Security Prices (CRSP). The fiscal years 1999–2009 constitute our study period.

Our paper reports the following findings. First, we demonstrate an inverted-U relationship between abnormal inventory growth and one-year-ahead earnings. Our results are robust to the metric used to measure abnormal inventory growth. Second, we find that equity analysts do not fully incorporate information contained in past inventory, resulting in systematic bias in their earnings forecasts; this bias is predicted by the previous year's AIG. Third, we find that an investment strategy based on AIG yields significant abnormal returns.

Our paper is closest to Kesavan et al. (2010), who found that incorporating inventory and margin information significantly improves sales forecasts for U.S. public retailers. Further, they found that analysts do not fully incorporate this information, resulting in predictable biases in their sales forecasts. We build on the findings of Kesavan et al. (2010) by showing that inventory also contains information useful to predict earnings in the retail industry. Because earnings are a function of sales and expenses, we run multiple tests to show that inventory predicts earnings not only because it predicts sales, but also because it predicts expenses for a retailer. Similarly, we show that bias arises in analysts' earnings forecasts not only because analysts ignore information in inventory useful to predict sales, as shown by Kesavan et al. (2010), but also because they failed to consider the impact of inventory on expenses. Finally, we analyze stock market data for retailers, which were not considered in Kesavan et al. (2010).

Our paper contributes to the operations management literature in the following ways. First, operations management researchers' interest is growing in firm-level inventory (Gaur et al. 2005, Gaur and Kesavan 2009, Rumyantsev and Netessine 2007a, Rajagopalan 2010). Many such papers are motivated to develop new benchmarking metrics that are useful to gauge inventory performance at the firm level. Our paper complements this line of research by demonstrating that such benchmarking metrics possess incremental information, not present in simpler metrics of inventory performance that have shown to predict returns in the accounting and finance literature, and can serve as a basis for investment strategies. In addition, research on firm-level inventory has sought to examine whether insights from the analytical models also hold at the firm level. Rumyantsev and Netessine (2007a), for example, argued for the importance of performing such tests to demonstrate to high-level managers who deal with firm-level inventory that they may benefit from understanding classical inventory models. Ours is the first paper to demonstrate that the inverted-U relationship between inventory and profitability, which forms the building block of SKU-level literature, holds at the firm level as well.

This paper is organized as follows. In §2, we discuss the operations management literature and accounting literature that relate to our work. In §3, we discuss existing theory in operations management to argue why changes in inventory levels could be considered a signal of future earnings; §4 outlines our research setup, and §5 describes the methodology we adopt to calculate abnormal inventory growth. We report in §6 results showing the relationship between abnormal inventory growth and one-year-ahead earnings, and §7 investigates the economic significance of ignoring information contained in abnormal inventory growth. We conclude by specifying limitations and directions for future research in §8.

2. Literature Review

The development of benchmarking metrics for firm-level inventory performance has been attracting significant interest. Gaur et al. (2005) studied inventory turns and developed a metric, *adjusted inventory turns*, to compare inventory productivity across firms. Rumyantsev and Netessine (2007a) showed that increasing demand uncertainty, lead times, and margins, and decreasing economies of scale are associated with increasing inventory levels. In another paper, Rumyantsev and Netessine (2007b) define inventory responsiveness as the difference between percentage change in inventory level and percentage change in sales and show that it is associated asymmetrically with current and future return on assets. Chen et al. (2007) benchmarked inventory performance using a metric called *abnormal days-of-inventory*, or *AbI*, which is defined relative to the segment's average days of inventory. Rajagopalan (2010) combined primary and secondary data to show that product variety, along with other factors such as gross margin and economies of scale, affects the firm-level inventory carried by retailers. Our work builds on this literature by using two of the metrics to test the relationship between inventory and future earnings.

Some evidence links firms' inventory performance to their stock market performance. Chen et al. (2007) found correlation between inventory changes and abnormal stock market returns. Hendricks and Singhal (2005) showed that announcement of supply chain glitches, which commonly cause inventory problems, are associated with a negative reaction in the stock market. Our paper adds to this literature by showing that inventory-based benchmarking metrics may serve as a basis for investments in the stock market because Wall Street analysts and investors fail to fully incorporate information in past inventory levels in their forecasts and investment decisions, respectively.

Next, we briefly review the accounting literature that relates to our work. Accounting literature offers mixed evidence of the predictive power of inventory over earnings in the retail sector. Bernard and Noel (1991) found that inventory predicts earnings in the retail industry, but Abarbanell and Bushee (1997) did not. Our paper differs from both these papers in methodology as well as contribution. Both Bernard and Noel (1991) and Abarbanell and Bushee (1997) used a simple expectation model of inventory growth based on sales growth. We use a sophisticated expectation model based on operations management literature that considers not only sales growth, but also changes in gross margin, store growth, days-payables, and capital investment. Furthermore, the accounting literature typically has assumed a linear relationship between inventory and future earnings. We are motivated by theoretical literature in operations management to test an inverted-U relationship between inventory and one-year-ahead earnings, and find evidence to support this relationship.

Sloan (1996), a seminal paper in the accounting literature, showed that the stock market misprices *accruals*, defined as changes in working capital. In other words, hedge portfolios formed based on accruals generate significant abnormal stock returns. This was called the *accruals anomaly*, as the stock market fails to process publicly available information, causing stocks to be mispriced. Thomas and Zhang (2002) decomposed accruals into components and showed that most of accruals' predictive power is generated by its inventory component. This finding has been confirmed in many papers, including Chan et al. (2001) and Zach (2003). A further insight is provided by Allen et al. (2011), who used hand-collected data on inventory write-downs to show that firms with extreme positive changes in inventory, as measured by Thomas and Zhang (2002), have a disproportionately higher incidence of such write-downs. Our results offer a further insight compared to Thomas and Zhang (2002) by showing that the abnormal component of inventory growth, not the normal component, generates abnormal returns. We find that AIG contains incremental information, not subsumed in simpler metrics of inventory performance, that is useful to make investment decisions in the retail sector. Thus, we show that a benchmarking metric for inventory performance derived from the operations management literature can serve as a basis for investment strategy.

3. Can Abnormal Inventory Growth Signal Future Earnings?

Earnings are a summary measure of a firm's financial performance, widely used to value shares and determine executive compensation. They are a function of revenue, cost of goods sold, interest expenses, income tax, insurance, etc. The contemporaneous impact of inventory growth on earnings is well known. The most recognized component of this impact is the holding cost of inventory, which affects both the capital cost of money tied up in inventory and the physical cost of having inventory (warehouse space costs, storage taxes, insurance, rework, breakage, spoilage, etc.). In addition, indirect costs associated with an inventory increase impact a retailer's earnings as well. These include the risks of lower gross margins and inventory write-offs due to stale inventory. The relationship between inventory growth and future earnings, however, is unclear.

Inventory growth may be understood as two components. The "normal" component is due to change in the firm's economic activities. For example, a retailer may open or close stores, resulting in an increase or decrease in inventory levels throughout its chain. Operations management literature has documented many other factors that could account for normal changes in retailers' inventory levels. These factors include gross margin, capital intensity, and sales surprise (Gaur et al. 2005); sales growth and size (Gaur and Kesavan 2009); demand uncertainty and lead time (Rumyantsev and Netessine 2007a); competition (Olivares and Cachon 2009); and product variety (Rajagopalan 2010). The second component of inventory growth is "abnormal" growth in inventory, which cannot be explained by other concomitant changes.

We argue that the relationship between inventory growth and future earnings arises because of the *abnormal* inventory growth component. A positive abnormal inventory growth indicates that the retailer's inventory grew more than expected during that time period (or less, for *negative* abnormal inventory growth). Next, we argue the implications, separately, of positive abnormal inventory growth and negative abnormal inventory growth for one-year-ahead earnings.

3.1. Implications of Positive Abnormal Inventory Growth for Future Earnings

Positive abnormal inventory growth for a retailer could indicate the retailer's inventory levels are bloated and may need to be discounted for clearance. The theoretical literature shows the optimal price trajectory decreasing with stocking quantity (Gallego and van Ryzin 1994, Smith and Achabal 1998). Thus, an increase in abnormal inventory growth would signal lower gross margin and consequently lower future earnings. In some cases, retailers may decide to write down inventory instead of discounting items to clear the merchandise. For example, Ferguson and Koenigsberg (2007) stated that Bloomingdale's Department Store salvages about 9% ($72 million) of its women's apparel by selling it to discount retailers for pennies on the dollar in order to make space for new inventory. Such inventory write-downs also reduce earnings.

Bloated inventory levels could also cause cash-flow constraints for retailers, because of a longer cash-conversion cycle. Carpenter et al. (1998) found that firms' inventory investment decreases when they face cash-flow constraints. Thus, retailers with bloated inventory levels might delay introducing new products to their stores. Difficulties introducing new products—the "life blood" of retailing—may depress demand, reducing earnings as well.

Finally, a retailer's bloated inventory levels could be symptomatic of operational issues that may continue into the future, resulting in higher costs due to supply–demand mismatches. Fisher (1997) stated that excess inventory at a retailer indicates supply–demand mismatches and is associated with poor operational performance. Excess inventory could also result from supply chain glitches that can cause operational performance to deteriorate (Hendricks and Singhal 2005). Hendricks and Singhal (2005) also note that operational performance might not recover to its earlier levels even several years after the supply chain glitch. Hence, positive abnormal inventory growth could signal operational issues at a retailer that could lead to lower future earnings.

On the other hand, positive abnormal inventory growth could result from managers' private information about higher future demand or increase in service levels. Managers may have access to little-known information about higher future demand, and might decide to increase their inventory investment in anticipation. Positive abnormal inventory growth thus could serve to signal higher future earnings, in such cases. It is also possible that positive abnormal inventory growth is the result of managers' decision to increase product availability in their chain. This could result in an increase in service level leading to higher customer satisfaction. Increased customer satisfaction has been found to lead to higher rates of customer retention and increased revenue (Ittner and Larcker 1998) and higher profitability (Anderson et al. 2004) in several settings.

In the aggregate sample, we expect positive abnormal inventory growth to be driven by bloated inventory levels as well as other unobservable factors. Thus, positive abnormal inventory growth may be a signal of higher earnings for some retailers and lower earnings for others. Therefore, the nature of relationship between positive abnormal inventory growth and one-year-ahead earnings would depend on the dominating factor in an aggregate sample.

3.2. Implications of Negative Abnormal Inventory Growth for Future Earnings

Next we present implications for future earnings of negative abnormal inventory growth—which, for a retailer, implies that its inventory grew less than expected. This could be the result of operational improvements at the retailer, resulting in leaner inventories. If a retailer were able to make its inventory leaner, several financial benefits to the retailer could accrue. First, lean inventories could lead to reductions in expenses such as inventory holding costs and markdown-related expenses, as well as increased revenues because of retailers' ability to react more quickly to changes in demand, to offer fresher merchandise to customers (Fisher 1997). The reduction in expenses as well as increased revenues leads to higher earnings. Hence, if negative abnormal inventory growth has been driven by leaner inventory, we can expect higher future earnings.

On the other hand, negative abnormal inventory growth might also result from retailers' cutting back on inventory in anticipation of lower future demand. In such cases, negative abnormal inventory growth would reflect management's private information about lower future demand, signaling lower earnings. In some cases, negative abnormal inventory growth may result from supply chain glitches that affect product replenishment or managerial action that resulted in cutting down of too much inventory. This could result in lost sales causing customers to switch to competitors for their future purchases. Several researchers in operations management have developed analytical models of fill-rate strategies when customers switch to competitors as a result of out-of-stocks (Bernstein and Federgruen 2004, Dana 2001, Gaur and Park 2007). Thus, negative abnormal inventory growth could signal lower future earnings.

In summary, the relationship between abnormal inventory growth and one-year-ahead earnings depends on which effects dominate to result in positive or negative abnormal inventory growth. This relationship would be an inverted U if positive abnormal inventory growth is associated with lower earnings due to bloated inventory level, or if negative inventory growth is associated with lower earnings due to management's private information of lower future demand or lost sales. Whether or not the relationship is an inverted U is an empirical question that we address in this paper.

4. Research Setup

The next two sections summarize relevant variables and data sets.

4.1. Definition of Variables

The following notations are used in this paper. For retailer i in fiscal year t, we denote SR_{it} as total sales revenue; $COGS_{it}$ as the cost of sales; SGA_{it} as selling, general, and administrative expenses; $LIFO_{it}$ as the last-in, first-out (LIFO) reserve; $RENT_{it1}, RENT_{it2}, \ldots, RENT_{it5}$ as rental commitments for the next five years; $EBXI_{it}$ as income before extraordinary items; CFO_{it} as operating cash flows; TA_{it} as total assets; and N_{it} as the total number of stores open for firm i at the end of fiscal year t. These are obtained from the Compustat Annual Database. For firm i in fiscal year t and quarter q, we denote PPE_{itq} as the net property, plant, and equipment; AP_{itq} as accounts payable; and I_{itq} as the ending inventory. These are obtained from the Compustat Quarterly Database.

Next, we explain the adjustments we make to variables. The use of first-in, first-out versus last-in, first-out methods for valuing inventory produces an artificial difference in the reported ending inventory and cost of sales. Hence, to ensure that all retailers have similar inventory valuations, we add back the LIFO reserve to the ending inventory and subtract the annual change in LIFO reserve from the cost of sales. Similarly, the value of PPE could vary depending on the values of capitalized leases and operating leases held by the retailer. Hence, we first compute the present value of rental commitments for the next five years using $RENT_{it1}, RENT_{it2}, \ldots, RENT_{it5}$ and then add that to the PPE to adjust uniformly for operating leases held by a given retailer. Here, we use a discount rate of $d = 8\%$ per year to compute the present value and verify our results with $d = 10\%$. We normalize some of the above variables by the number of retail stores in order to avoid correlations that could arise because of scale effects caused by an increase or decrease in the size of a firm. Consistent with recent accounting literature, we define accruals as the difference between earnings and operating cash flows (Hribar and Collins 2002). Refer to Table 1 for the relevant data fields in the Compustat database. Using

Table 1 Data Fields for Variables (Retailer i, Fiscal Year t, Quarter q)

Variable name	Definition	Field name in Compustat database
AP_{itq}	Accounts payable	APQ
I_{itq}	Ending inventory	INVTQ
PPE_{itq}	Net property, plant, and equipment	PPENTQ
$COGS_{it}$	Cost of sales	COGS
CFO_{i}	Operating cash flows[a]	OANCF-XIDOC
$Comps_{it}$	Comparable store sales growth	RTLCS
$EBXI_{it}$	Income before extraordinary items	IBC
$LIFO_{it}$	LIFO reserve	LIFR
N_{it}	Number of stores	RTLNSE
P_{it}	Closing stock price	PRCC_F
$RENT_{it,1\ldots5}$	Rental commitments	MRC1…5
SGA_{it}	Selling, general, and administrative expenses	XSGA
TA_{it}	Total assets	AT

[a]Operating cash flows from continuing operations are obtained as difference of total cash of operations and cash flow of discontinued operations and extraordinary items (Hribar and Collins 2002). This is consistent with our dependent variable that is derived from earnings per share before extraordinary items and discontinued operations. Additional data variables required for testing bias in analysts' forecasts and stock market returns are provided below their respective tables.

these data and adjustments, we calculate the following variables for each firm i in fiscal year t and fiscal quarter q:

Average cost-of-sales per store: $CS_{it} = [COGS_{it} - LIFO_{it} + LIFO_{it-1}]/N_{it}$;

Average inventory per store: $IS_{it} = [\frac{1}{4}\sum_{q=1}^{4} I_{itq} + LIFO_{it}]/N_{it}$;

Gross margin: $GM_{it} = SR_{it}/[COGS_{it} - LIFO_{it} + LIFO_{it-1}]$;

Average SGA per store: $SGAS_{it} = [SGA_{it}]/N_{it}$;

Average capital investment per store: $CAPS_{it} = [\frac{1}{4}\sum_{q=1}^{4} PPE_{itq} + \sum_{r=1}^{5}(RENT_{itr}/(1+d)^r)]/N_{it}$;

Store growth: $G_{it} = [N_{it}]/N_{it-1}$;

Accounts payable to inventory ratio: $PI_{it} = [\sum_{q=1}^{4} AP_{itq}/4[(\sum_{q=1}^{4} I_{itq}/4) + LIFO_{it}]$;

Accruals: $Acc_{it} = [(EBXI_{it} - CFO_{it})]/TA_{it-1}$.

The variables obtained after taking the logarithm are denoted by their respective lowercase letters, i.e., cs_{it}, is_{it}, gm_{it}, $sgas_{it}$, $caps_{it}$, g_{it}, and pi_{it}. In addition, we refer to comparable store sales as $Comps_{it}$, actual earnings per share excluding extraordinary items and discontinued operations as EPS_{it}, and closing share price as P_{it}. All three values are obtained from the Compustat Annual Database. Finally, we collected data on individual sell side analysts' earnings and sales forecast error from I/B/E/S and stock market returns from CRSP.

4.2. Data Description

We start with the entire population of U.S. retailers that reported at least one year of financial information during the period 1999–2009. Our sample begins from 1999 since this was the first year when Compustat started providing data on the total number of stores in a retail chain. The U.S. Department of Commerce classifies retailers into eight categories, identified by a two-digit Standard Industrial Classification (SIC) code, as follows: lumber and other building materials dealers (SIC 52); general merchandise stores (SIC 53); food stores (SIC 54); eating and drinking places (SIC 55); apparel and accessory stores (SIC 56); home furnishing stores (SIC 57); automotive dealers and service stations (SIC 58); and miscellaneous retail (SIC 59).

We exclude retailers in the categories eating and drinking places and automotive dealers and service stations from our study, because they contain a significant service component to their business. There were 657 retailers that reported at least one year of data to the U.S. Securities and Exchange Commission (SEC) for these years. We find that 208 retailers did not report any store information. To enable us to perform a longitudinal analysis, we consider only retailers that had at least five years of consecutive data. After removing several observations that lacked data for variables required in our analysis, we find that 351 of the 449 were left for further analysis. Further, we eliminated foreign retailers listed as American Depository Receipt (ADR) in the U.S. stock exchanges, and also removed jewelry firms from the miscellaneous retail sector, as their inventory levels could be driven by commodity prices and other macroeconomic conditions not captured by our model.

Inventory changes could also happen because of changes in foreign exchange rates, mergers and acquisitions (M&A), and discontinued operations. For some companies, these changes could be substantial. Following Hribar and Collins (2002), we remove firm-years from our sample in which a retailer was involved in a merger or acquisition using the Compustat annual footnote code. Next, we use the variables *discontinued operations* (Compustat variable name: *DO*) and *foreign exchange income* (*loss*) (Compustat variable name: *FCA*) to identify firm-years when retailers' financial performance was impacted by discontinued operations and changes in foreign exchange rates. We find that 34.6% and 26.8% of our observations have the variables for discontinued operations and foreign exchange income (loss) populated, respectively. To preserve sample size, we do not drop all of these observations. We find that the values of *DO* and *FCA* have a wide range and depend on the relative firm size. Hence, we normalize *DO* by total revenue and *FCA* by net income, and drop any observations that are more than three standard deviations away from the mean, because we expect that these observations are likely to be cases in which inventory could have undergone substantial changes due to discontinued operations and changes in foreign exchange rates. Finally, some retailers may combine part of their selling, general, and administrative expenses with cost of goods sold; we identify 11 such firm-year observations in the period 1999–2009 using the data code *xsga_dc* (which is populated as "4" in such cases), and drop them from our analysis. We combine SIC 52 and SIC 57 because SIC 52 has a smaller number of firms and is closest in match to SIC 57. After removing observations with missing data and making the above adjustments, the resulting data set had 308 retailers across five retail segments, namely, apparel and accessory stores, food stores, general merchandise stores, home and lumber, and miscellaneous retail stores. This resulted in 1,662 observations for the period 1999–2009.

We divide the 11-year sample period roughly into two equal parts such that the period from 2004 to 2009 serves as our test sample for analyzing the relationship between abnormal inventory growth and one-year-ahead earnings. This subsample contains 128 retailers and 560 firm-year observations. To determine the economic significance of our results, we conduct further analysis with analysts' forecasts and stock market data. We found individual analysts' earnings

Table 2 Description of Initial, Final, and Test Data Sets by Retail Sectors, 1999–2009

Retail sector	Two-digit SIC code	Examples of firms	No. of firms	No. of firms that reported at least five years of data	Overall sample 1999–2009 No. of firms	Overall sample 1999–2009 No. of obs.	Test sample I 2004–2009 No. of firms	Test sample I 2004–2009 No. of obs.	Test sample II 2004–2009 No. of firms	Test sample II 2004–2009 No. of obs.
Lumber and other building materials	52	Home Depot, Lowe's, National Home Centers	27	17	56	305	22	92	20	89
Home furnishing stores	57	Williams-Sonoma, Jennifer Convertibles	67	42						
General merchandise stores	53	Costco, Dollar General, Walmart	76	49	45	259	19	93	22	79
Food stores	54	Safeway, Dairy Mart convenience stores, Shaws	91	54	48	245	15	64	9	49
Apparel and accessory stores	56	Men's Wearhouse, Harolds, Children's Place	90	72	66	409	44	191	42	135
Miscellaneous retail	59	Toys R Us, Officemax, Walgreens	306	117	93	444	28	120	20	83
Total			657	351	308	1,662	128	560	113	435

Notes. Columns 4 and 5 are based on the population of retailers in 1999–2009. This population was used to generate the overall sample for the same time period. Test sample I was used to test the relationship between AIG and one-year-ahead earnings. Test sample II was used to test the economic significance of AIG using analysts' forecasts and stock market returns data.

per share (EPS) forecasts for 435 of the 560 observations from I/B/E/S, and obtained stock market returns data for these 435 observations from CRSP. We provide further details on these data in §7.

The number of retailers in each segment and distribution of retailers are given in Table 2. Summary statistics for all variables used in our analysis are displayed in Table 3.

5. Methodology

We use the expectation model of growth in inventory per store from Kesavan et al. (2010) to measure AIG for retailers. We use this model because it subsumes many of the factors identified in past research, and it was found to be useful in the context of sales forecasting. This growth model is derived from an underlying model of the inventory per store for retailers. Kesavan et al. (2010) use a log–log specification to model inventory per store for a retailer in a given fiscal year as depending on firm-fixed effect (J_i), inventory per store in the previous fiscal year ($IS_{i,t-1}$), contemporaneous and lagged cost-of-goods-sold per store (CS_{it}, $CS_{i,t-1}$), gross margin (GM_{it}), lagged accounts payable to inventory ratio ($PI_{i,t-1}$), store growth (G_{it}), and lagged capital investment per store ($CAPS_{i,t-1}$) for that retailer. Using lowercase letters to denote the logarithm of these variables, the logged inventory per store for retailer i in fiscal year t is given as

$$is_{it} = J_i + \boldsymbol{\beta}_2 \mathbf{x}'_{it} + \eta_{it}, \tag{1a}$$

where $\mathbf{x}'_{it}$ is a column vector of all right-hand side explanatory variables; $\mathbf{x}'_{\mathrm{it}} = (1, cs_{it}, gm_{it}, cs_{it-1}, is_{it-1}, pi_{it-1}, g_{it}, caps_{it-1})'$; and $\boldsymbol{\beta}_2$ is the row vector of

Table 3 Definitions and Summary Statistics of Variables for 2004–2009

Definitions	Variables	Mean	Standard deviation	Min	Max
Average cost-of-sales per store ($M)	CS_{it}	7.865	12.139	0.067	115.267
Average inventory per store ($M)	IS_{it}	1.191	2.447	0.018	19.107
Gross margin	GM_{it}	1.578	0.259	1.113	2.632
Average SGA per store ($M)	$SGAS_{it}$	1.950	2.583	0.67	21.834
Store growth	G_{it}	1.076	0.162	0.612	1.972
Accounts-payable-to-inventory ratio	PI_{it}	0.528	0.344	0.141	3.773
Accruals	Acc_{it}	0.006	0.345	−0.255	0.171
Comparable store sales growth (%)	$Comps_{it}$	2.521	5.210	−14.691	17.092
Change in gross margin	ΔGM_{it}	−0.005	0.035	−0.175	0.091
Earnings per share ($)	EPS_{it}	0.963	1.151	−4.77	4.91
Prior period closing price ($)	P_{it-1}	20.21	12.31	1.75	51.49
Change in earnings per share ($)	ΔEPS_{it}	−0.038	0.781	−2.98	3.156
Change in earnings per share/price	$\Delta EPS1_{it}$	0.004	0.128	−0.866	1.054
Price by earnings ratio (P/E)	PE_{it}	15.92	27.02	−128.33	175.67

Note. Descriptive statistics are based on sample size = 560 observations.

the corresponding coefficients, $\boldsymbol{\beta}_2 = (\beta_{20}, \beta_{21}, \beta_{22}, \beta_{23}, \beta_{24}, \beta_{25}, \beta_{26}, \beta_{27})'$.

This underlying levels model is then first differenced to obtain the following growth model:

$$\Delta is_{it} = \Delta \mathbf{x}'_{it}\boldsymbol{\beta}_2 + \Delta\eta_{it}. \tag{1b}$$

Here Δ denotes the change in logged variable in fiscal year t from fiscal year $t-1$.

One may treat all coefficients $\boldsymbol{\beta}_2$ in the above regression as being firm specific, i.e., allowing the sensitivity of inventory per store to different factors such as cogs per store, gross margin, capital investment per store, etc., to vary from retailer to retailer. However, to estimate such a model, we would need a long time-series of observations for each retailer. Because our analysis uses annual data, we would need several decades worth of data for each retailer to estimate such a model. To overcome the paucity of data, we assume that all firms in a given segment are homogeneous, i.e., we assume that the coefficients $\boldsymbol{\beta}_2$ are identical for all retailers within a given segment and estimate these coefficients at the segment level. Thus, our estimation equation is

$$\Delta is_{it} = \Delta \mathbf{x}'_{it}\boldsymbol{\beta}_{2,\,s(i)} + \Delta\eta_{it}, \tag{1c}$$

where $s(i)$ denotes the corresponding segment-specific coefficients for firm i.

We can now obtain the expected logged inventory growth from the above equation, $E(\Delta is_{it})$, and then compute abnormal inventory growth in the following way. Let $\{IS_{it}/IS_{it-1} - 1\}$ denote the actual inventory per store growth and $AIG_{it} = (\{IS_{it}/IS_{it-1} - 1\} - \{\exp(E(\Delta is_{it})) - 1\})$ denote the abnormal inventory per store growth or, in short, abnormal inventory growth for a retailer i in fiscal year t. We estimate Equation (1c) and use the coefficients to compute abnormal inventory growth. Thus, $AIG_{it} > 0$ implies that retailer i has abnormally high inventory growth whereas $AIG_{it} < 0$ implies that retailer i has abnormally low inventory growth compared to the norm of the segment to which the retailer belongs, after controlling for firm-level differences.

Kesavan et al. (2010) showed that historical gross margin contains information valuable to forecast sales. Further, they showed that inventory and gross margin are highly correlated for retailers, so we calculate abnormal change in gross margin in a similar manner as AIG and use it as a control variable in our analysis. Similar to Equation (1c), the first differenced equation for gross margin can be written as

$$\Delta gm_{it} = \Delta \mathbf{x}'_{it}\boldsymbol{\beta}_{3,\,s(i)} + \Delta v_{it}, \tag{2}$$

where $\Delta \mathbf{x}'_{it} = (1, \Delta cs_{it}, \Delta is_{it}, \Delta gm_{it-1})'$. We calculate abnormal change in gross margin (ACGM) for retailer i in fiscal year t as $ACGM_{it} = (\{GM_{it}/GM_{it-1} - 1\} - \{\exp(E(\Delta gm_{it})) - 1\})$.

Next, we explain the data used to measure AIG_{it-1} from (1c). We use data till fiscal year $t-2$ to estimate (1c). We avoid data from fiscal year $t-1$ in the estimation because firms announce their financial results at different times of the year, which could lead to a potential look-ahead that could bias our results about the relationship between AIG and one-year-ahead earnings. Once a retailer's financial results are announced for fiscal year $t-1$, we use our coefficient estimates to measure the AIG_{it-1} for *that* retailer. We follow this process for all retailers in our test sample, i.e., $t = 2004$, 2009. We follow a similar approach to obtain $ACGM_{it-1}$.

We considered two different techniques to estimate Equations (1c) and (2). We used the instrument variable generalized least squares (IVGLS) method used in Kesavan et al. (2010) to estimate the equations and also a simpler single-equation technique, a generalized least squares (GLS) method, as a cross-check. We found the results to be similar. Because the IVGLS method requires defining an additional equation containing new variables, we choose to report the results of the GLS technique that is simpler to implement and explain. The GLS method handles heteroskedasticity and panel-specific autocorrelation in the data.

Table 4 reports sample results of our estimation of Equations (1c) and (2) using data from 2002–2007. These coefficient estimates were then used to calculate AIG and ACGM for fiscal year 2008, which are then used to predict earnings for fiscal year 2009. Figure 1(a) presents the histogram of AIG for all retailers in our EPS sample ($n = 560$) during the period $t = 2004, \ldots, 2009$. We find that 63% of retailers have AIG > 0 and 37% have AIG < 0. We find that the average, lowest, highest, and standard deviations of AIG for this time period are 2.28%, −17.33%, 26.21%, and 8.76%, respectively. Descriptive statistics are reported in Table 5. For the average retailer in our sample, with $1.2 million of inventory per store, the mean (2.28%) and mean plus one standard deviation (11.04%) of AIG correspond to $27,380 and $132,480 of abnormal inventory per store. The average AIG across the different retail segments for the same period is 2.67% (apparel), 0.17% (food), 2.32% (general), 2.69% (home), and 1.63% (miscellaneous). The magnitudes of correlations between AIG and sales per store, sales growth, and store growth are less than 0.21. These weak correlations indicate that AIG is not specific to retailer characteristics such as average sales volume per store or growth rate. We also find that the relative rank of retailers based on AIG varies considerably from year to year, indicating that AIG is not persistent.

Table 4 Estimation Results of Inventory and Gross Margin Equation for Each Retail Segment, 2002–2007

		Retail industry segment				
Equation	Variables	Apparel and accessory stores	Food stores	General merchandise stores	Home furnishing stores	Miscellaneous retail
Inventory equation	*Intercept*	−0.009**	−0.010**	−0.011***	−0.008***	−0.002**
		(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
	Δis_{it-1}	−0.049***	−0.044	−0.017*	−0.021***	−0.169***
		(0.011)	(0.084)	(0.009)	(0.002)	(0.029)
	Δcs_{it}	0.880***	0.771***	1.067***	0.902***	0.594***
		(0.036)	(0.063)	(0.029)	(0.043)	(0.017)
	Δgm_{it}	0.115*	0.149***	−0.602***	−0.158*	0.312**
		(0.061)	(0.025)	(0.131)	(0.094)	(0.141)
	Δcs_{it-1}	0.094**	0.252***	0.046*	0.042	0.289***
		(0.039)	(0.067)	(0.025)	(0.084)	(0.038)
	Δpi_{it-1}	−0.014	−0.071*	−0.056**	−0.055*	−0.031**
		(0.022)	(0.039)	(0.023)	(0.031)	(0.012)
	Δg_{it}	−0.099**	−0.194**	−0.070**	−0.075*	−0.276***
		(0.037)	(0.064)	(0.028)	(0.040)	(0.036)
	$\Delta caps_{it-1}$	0.056	0.117**	0.065**	0.024	0.057***
		(0.039)	(0.038)	(0.032)	(0.062)	(0.013)
Gross margin equation	*Intercept*	0.006***	0.003**	2e-4***	0.002***	0.012***
		(0.001)	(0.001)	(3e-5)	(4e-4)	(0.001)
	Δgm_{it-1}	0.038**	0.134**	0.210***	0.189**	−0.012
		(0.019)	(0.041)	(0.016)	(0.063)	(0.022)
	Δcs_{it}	0.187***	0.123***	0.039***	0.012*	−0.684***
		(0.022)	(0.011)	(0.009)	(0.007)	(0.016)
	Δis_{it}	−0.158***	−0.148***	−0.035**	−0.012**	−0.541***
		(0.017)	(0.007)	(0.015)	(0.006)	(0.016)
	n	215	110	112	107	211

Notes. We refer to Equations (1c) and (2) as the inventory equation and gross margin equation. These equations are estimated on a rolling horizon basis with a five-year constant window. The estimation results above were generated based on data from 2002–2007. These coefficients are used to generate abnormal inventory growth for year 2008, which is in turn used to predict earnings, analysts' bias, and stock market returns for 2009. All regressions are run after controlling for panel specific autocorrelation.

$^{***}p < 0.001$; $^{**}p < 0.05$; $^{*}p < 0.1$.

5.1. Abnormal Days of Inventory

We use the abnormal days of inventory (AbI) measure proposed by Chen et al. (2007) as an alternate measure of abnormal inventory growth. Chen et al. (2007) defined abnormal days of inventory (AbI_{it}) as the normalized deviation of the days of inventory (DOI_{it}) of retailer i in fiscal year t from the average days of inventory of its industry peers:

$$AbI_{it} = \frac{(DOI_{it} - \overline{DOI}_{st})}{\overline{\overline{DOI}}_{st}}.$$

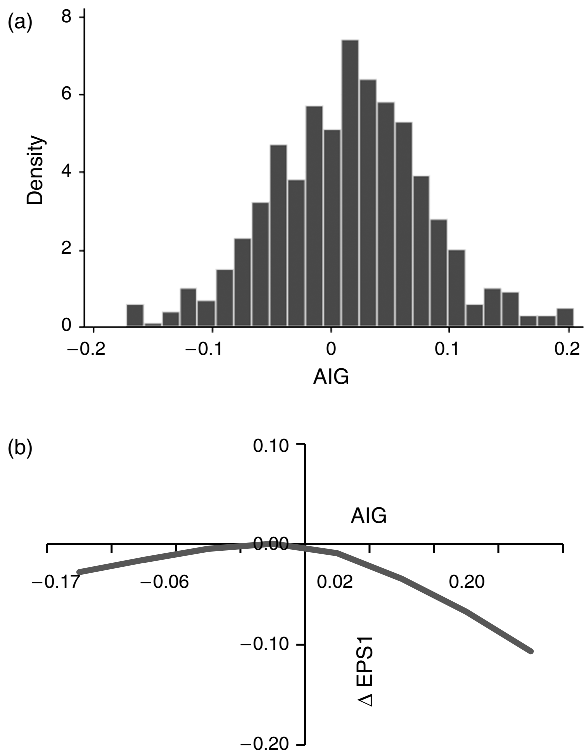
Here $\overline{DOI}_{st}$ and $\overline{\overline{DOI}}_{st}$ are the average and standard deviations of days of inventory of all retailers in the segment s to which retailer i belongs. If $AbI_{it} > 0$ ($AbI_{it} < 0$), then retailer i holds inventory longer (shorter) than the segment norm in year t. The average, lowest, highest, and standard deviations of AbI during 2004–2009 are 0.23, −2.63, 2.09, and 1.23, respectively. The average abnormal days of inventory across the different segments for the same period is 0.15 (apparel), 0.07 (food), 0.15 (general), 0.17 (home), and 0.11 (miscellaneous).

The main difference between the AIG and AbI metrics is that the former controls for factors such as gross margin, capital investment, store growth, and accounts payable that have been identified as important factors driving inventory levels in operations literature, whereas the AbI metric does not. However, the use of lagged variables in the regression used to estimate AIG requires at least three years of data to measure AIG for a retailer. The AbI metric, however, can be computed even for a retailer that has just one year of data. We use both metrics to test the relationship between abnormal inventory growth and one-year-ahead earnings.

6. Results

In this section, we discuss results of our statistical tests of the relationship between AIG and one-year-ahead earnings. Several researchers in accounting have used a first-order autoregressive model for

Figure 1 **Histogram of AIG and Relationship Between AIG and One-Year-Ahead Earnings**



Note. The relationship between AIG and one-year-ahead earnings per share is illustrated using coefficient estimates obtained from Table 6 (model 4(b)).

change in one-year-ahead earnings. We adopt the same model to test the relationship between AIG and one-year-ahead earnings. Accounting literature has also found that accruals predict one-year-ahead earnings (Sloan 1996). Because one component of accruals is change in inventory, we use accruals as a control variable to examine whether AIG provides information beyond that contained in accruals to predict earnings. This gives us the following model to test the relationship between AIG and one-year-ahead earnings:

$$\Delta EPS1_{it} = \alpha_o^{eps} + \alpha_t^{eps} + \alpha_1^{eps}\Delta EPS1_{it-1} + \alpha_2^{eps} Acc_{it-1} + \alpha_3^{eps} AIG_{it-1} + \alpha_4^{eps} AIG_{it-1}^2 + \varepsilon_{it}^{eps}. \quad (3)$$

Table 5 **Definitions and Summary Statistics of AIG, IG, ACGM, and AbI for 2004–2009**

Definitions	Variables	Mean	Standard deviation	Min	Max
Abnormal inventory growth	AIG_{it}	2.281	8.760	−17.332	26.214
Inventory growth	IG_{it}	2.853	11.768	−37.328	136.912
Abnormal change in gross margin	$ACGM_{it}$	−1.558	4.024	−13.061	61.162
Abnormal days of inventory	AbI_{it}	0.23	1.23	−2.63	2.09

Note. Descriptive statistics are based on sample size = 560 observations.

Here $\Delta EPS1_{it}$ denotes change in EPS deflated by the previous fiscal year's ending stock price to homogenize firms ranging broadly in size (Durtschi and Easton 2005). We use a full set of year dummies (α_t^{eps}) to account for macroeconomic factors that might impact earnings of all retailers. In addition, we use coefficient estimates of α_3^{eps} and α_4^{eps} to determine the relationship between AIG and change in one-year-ahead earnings.

Model 1 in Table 6 reports results for the base model, i.e., a first-order autoregressive model of EPS with accruals. Consistent with the accounting literature, we find that accruals have predictive power over one-year-ahead earnings. Model 2 gives the estimated coefficients of Equation (3). We find that the coefficients of AIG_{it} and AIG_{it}^2 are negative and significant ($p < 0.001$) and provide support for an inverted-U relationship between AIG and change in one-year-ahead EPS. We perform a Wald test to confirm that the addition of AIG_{it} and AIG_{it}^2 improves the fit of our model ($p < 0.001$). We also perform several robustness checks to confirm the inverted-U relationship. First we control for ACGM, as Kesavan et al. (2010) showed that this variable contains information useful to predict sales. The correlation between AIG and ACGM is low ($\rho = -0.21$) and not significant. The results, shown for model 3 in Table 6, continue to show the inverted-U relationship between AIG and one-year-ahead EPS. Second, we add segment dummies to model 3; the estimation results are shown in model 4(a). Finally, we add change in accruals as an additional control, as shown in model 4(b). Our conclusions about the inverted-U relationship remain unchanged with the addition of these variables. We also compute the variance inflation factor (VIF) for model 4(b) and find that to be 1.4. This result rules out any multicollinearity among our explanatory variables, as the VIF is less than 10 (Maddala 2001).

To ensure that outliers are not driving the inverted-U relationship, we follow Aiken and West (1991) to statistically test this relationship. Aiken and West (1991) recommend performing tests to determine the significance of slopes spanning observations on either side of the turning point and to verify the change in sign of these slopes. In the full model, model 4(b), the turning point occurs at a value of -0.053 ($-\alpha_3^{eps}/2\alpha_4^{eps}$), which is less than one standard deviation away from the mean and well within the range of our sample, $[-0.173, 0.262]$. We find that 21% of our observations lie to the left of the turning point. We then perform t-tests of simple slopes using coefficient estimates from the full model and report the results in Table 7. Because the simple slopes at values of AIG that are two standard deviations below and above mean are both statistically significant and opposite in sign, we conclude that the inverted-U

Table 6 Relationship Between AIG and One-Year-Ahead Earnings, 2004–2009

Independent variables	Dependent variable: Change in EPS1				
	Model 1	Model 2	Model 3	Model 4(a)	Model 4(b)
Intercept	0.093***	0.007***	0.008***	0.010***	0.009***
	(0.009)	(0.001)	(0.001)	(0.002)	(0.002)
$\Delta EPS1_{it-1}$	0.074***	0.067***	0.075***	0.055**	0.046**
	(0.015)	(0.014)	(0.015)	(0.018)	(0.018)
AIG_{it-1}		−0.076***	−0.075***	−0.097***	−0.103***
		(0.008)	(0.013)	(0.011)	(0.012)
AIG^2_{it-1}		−1.042***	−1.127***	−0.991***	−0.980***
		(0.098)	(0.097)	(0.105)	(0.109)
$ACGM_{it-1}$			0.111***	0.049**	0.063**
			(0.023)	(0.024)	(0.025)
Acc_{it-1}	−1.501***	−1.722***	−1.581***	−1.534***	−1.774***
	(0.075)	(0.124)	(0.143)	(0.126)	(0.133)
ΔAcc_{it-1}					−0.300***
					(0.088)
Segment dummies	No	No	No	Yes	Yes
Wald χ^2	3,531.80	8,179.53	9,789.20	11,920.09	24,830.96
n	560	560	560	560	560

Notes. All regressions are run after controlling for year fixed effects and panel specific autocorrelation. Model 4(b) is the full model with all the controls. Standard errors are reported in parentheses below the coefficients.
$^{***}p < 0.001$; $^{**}p < 0.05$; $^{*}p < 0.1$.

relationship between AIG and one-year-ahead earnings is supported within the range of our data, and not driven by outliers.

We use the coefficient estimates (α_3^{eps}, α_{34}^{eps}) from the full model to graphically illustrate the inverted-U relationship between AIG and the change in one-year-ahead earnings as shown in Figure 1(b). The mean AIG in our sample is 0.023 and the standard deviation is 0.09. At the mean, the impact of increasing AIG by 0.01 leads to a decrease in the dependent variable, i.e., the change in EPS scaled by price, by 0.0016. To put this number in perspective, we multiply it by the sample average price-to-earnings ratio of 16 to obtain the percentage decrease in EPS in the following year compared to the average retailer. This shows that a retailer whose AIG was 0.01 more than the average AIG in our sample would find its earnings per share to be 2.56% lower than the retailer with the average AIG, holding everything else constant. At a higher level of distribution, corresponding to the mean plus two times the standard deviation, increasing AIG by 0.01 is associated with a decrease in EPS of 8.2% in the following year. At a lower distribution level (corresponding to the mean minus two times the standard deviation), further decreasing AIG by 0.01 unit is associated with a 3.4% decline in EPS in the next year.

Table 7 *t*-Tests for Simple Slopes at Different Values of AIG

AIG value[a]	Simple slope	Standard error	Significance
−0.173	0.236	0.071	3.324**
−0.152	0.196	0.072	2.730**
−0.065	0.024	0.019	1.247
−0.053[b]	0.000	0.017	0.000
0.023	−0.148	0.018	−8.215***
0.111	−0.320	0.031	−10.313***
0.198	−0.492	0.041	−11.989***
0.262	−0.617	0.051	−12.085***

[a]The AIG values are chosen to span the observations on each side of the turning point The simple slope and turning point are calculated based on model 4(b).
[b]Turning point.
$^{***}p < 0.001$; $^{**}p < 0.05$; $^{*}p < 0.1$.

On two attributes of the inverted-U relationship we further elaborate. First, the turning point occurring at a value less than zero is interesting. Recall that our results are picking up the dominant effect as we cannot control for unobservable factors such as management's private information about future demand, service level, or lost sales. Thus, we conjecture that the region $[-0.053, 0]$ is dominated by retailers who became leaner. That is, these retailers were able to reduce their inventory levels without substantial reduction in service level. To ensure that this result is not an artifact of the AIG metric, we re-test model 4(b) by substituting the AbI metric for the AIG metric, based on Chen et al. (2007), and find qualitatively similar results. The coefficients of AbI_{it} and AbI^2_{it} are −0.005 and −0.004 ($p < 0.001$), respectively, indicating the existence of an inverted-U shaped relationship between AbI and change in one-year-ahead earnings. Similar to results obtained with the AIG metric, we find the turning point to be negative and within one standard deviation of the mean.

The values of the turning point, minimum, and maximum values of AbI are −0.63, −2.63, and 2.09, respectively. The results with AbI metric are reported in this paper's online supplement (available at http://dx.doi.org/10.1287/msom.1120.0389). Thus, our results appear to be robust to the method used to compute abnormal inventory carried by retailers.

Second, consistent with Chen et al. (2007), who examined long-term stock market returns of retailers, we find that our strongest results are for retailers with abnormally high inventory growth, whose subsequent performance was poor. Some retailers in this region (AIG > 0) likely were able to increase their service level to more closely approximate the optimal level, and subsequently increased their profitability. However, those retailers appear to be dominated by retailers who simply had excess inventory.

Because AIG predicts sales (Kesavan et al. 2010), and earnings are a function of sales, we want to determine if the relationship between AIG and earnings are driven only by AIG's ability to predict sales, or if AIG might predict earnings for additional reasons. As we argue in §3, AIG might also provide reasons to predict higher expenses such as for advertising to clear merchandise, or for holding costs and inventory write-downs. Because these expenses are not readily available as separate line items in retailers' income statements, we test this argument indirectly by adding one-year-ahead sales growth (SG_{it}) to model 4(b) to control for changes in EPS due to any change in sales for a given retailer, as follows:

$$\begin{aligned}\Delta EPS1_{it} = {} & \alpha_o^{eps} + \alpha_t^{eps} + \alpha_1^{eps}\Delta EPS1_{it-1} + \alpha_2^{eps} Acc_{it-1} \\ & + \alpha_3^{eps} AIG_{it-1} + \alpha_4^{eps} AIG_{it-1}^2 + \alpha_5^{eps} ACGM_{i,t-1} \\ & + \alpha_6^{eps}\Delta Acc_{it-1} + \alpha_7^{eps} SG_{it} + \varepsilon_{it}^{eps}. \qquad (4)\end{aligned}$$

Our use of one-year-ahead sales growth makes this analysis conservative because it tests whether AIG can predict expenses that are not correlated with revenues. Model 5 in Table 8 reports the results of this regression. We find that both the linear and quadratic terms of AIG are significant ($p < 0.001$). We replace sales growth in period t with comparable store sales during that period and obtain similar results, shown in model 6 of Table 8. Thus, we conclude that AIG predicts earnings for retailers because it has information useful to predict sales as well as expenses of retailers.

Additional robustness checks to show that the explanatory power of abnormal inventory measure exists even when standard accounting "abnormal accruals" measures (Jones and Modified Jones models) are used as control variables is provided in the online supplement.

Table 8 Relationship Between AIG and Future Expenses, 2004–2009

	Change in EPS1	
Independent variables	Model 5	Model 6
Intercept	0.079***	0.011***
	(0.008)	(0.002)
$\Delta EPS1_{it-1}$	0.048**	0.034*
	(0.015)	(0.019)
AIG_{it-1}	−0.101***	−0.92***
	(0.008)	(0.018)
AIG_{it-1}^2	−0.822***	1.249***
	(0.071)	(0.155)
$ACGM_{it-1}$	0.067**	0.091**
	(0.024)	(0.038)
ΔAcc_{it-1}	−0.353***	−0.901***
	(0.059)	(0.132)
Acc_{it-1}	−1.178***	−2.474***
	(0.153)	(0.197)
SG_{it}	0.091***	
	(0.007)	
$COMPS_{it}$		0.019***
		(0.001)
Segment dummies	Yes	Yes
Wald χ^2	24,853.60	20,621.27
n	560	494

Notes. Models 5 and 6 add sales growth (SG_{it}) and comparable store sales growth ($COMPS_{it}$) to model 4(b) shown in Table 6, respectively. Because SG_{it} and $COMPS_{it}$ are contemporaneous to the dependent variable, $\Delta EPS1_{it}$, models 5 and 6 test if abnormal inventory growth can predict the portion of expense changes not correlated with revenue growth.
$^{***}p < 0.001$; $^{**}p < 0.05$; $^{*}p < 0.1$.

7. Economic Significance of Information Contained in AIG

In this section, we investigate the economic significance of our finding. First, we examine whether equity analysts take information contained in AIG into account when generating earnings forecasts. Second, we test whether stock prices incorporate this information. The former test would show whether even sophisticated investors could benefit from knowing information contained in AIG, and the latter would indicate whether AIG can form the basis for an investment strategy.

7.1. Do Equity Analysts Ignore Information in Abnormal Inventory Growth in EPS Forecasts?

We examine whether or not equity analysts ignore information contained in AIG as follows. Analysts issue earnings forecasts at different times during a year and revise those forecasts as more information becomes available. These forecasts are time stamped with the dates they are issued. Because financial information for the previous fiscal year are released on the earnings announcement date (EAD), the information required to compute AIG for a retailer is available after its EAD. If analysts incorporate into their forecasts information from lagged AIG, then their forecasts issued subsequent to EAD should not generate errors that can be predicted by lagged AIG. If, however, they do not incorporate this information, then lagged AIG will have predictive power over their forecast errors.

Our tests are conducted using the I/B/E/S detailed (individual) forecasts of annual EPS. We perform this analysis using data obtained for fiscal years 2004–2009. We consider analysts' earnings forecasts for the forthcoming fiscal year issued after a retailer's EAD in the prior fiscal year. In some cases, analysts might have to wait till retailers file their 10-K statement with the SEC to have access to their financial statements. To be conservative, we drop any analyst forecasts made before the SEC filing date, as well. We obtain the SEC filing date for each retailer from Morningstar Document Research, accessible from http://www.10kwizard.com/. If multiple forecasts are made by an analyst for a retailer, we use the most recent forecast, as that should contain the latest information available to the analyst.

We find that analysts' forecasts were available for 435 observations of our 560 total. For each firm-year, we determine the median of analysts' forecasts made for each of the $m = 1$ to 12 months after EAD for fiscal year $t-1$, and use that as a single consensus forecast from which to generate analysts' consensus forecast error. We compute forecast errors by subtracting the consensus EPS forecast from realized EPS. We also deflate the forecast error by the previous fiscal year's ending stock price (Gu and Wu 2003). For forecasts made three months after the EAD for fiscal year $t-1$, the average, standard deviation, minimum, and maximum deflated analysts' forecast error between 2004 and 2009 are −0.038, 0.163, −0.911, and 0.052, respectively. The average forecast error of −0.038 shows that analysts are optimistic, on average, consistent with prior accounting literature.

Next, we statistically test whether analysts' forecast errors are biased, as predicted by lagging AIG, by running the following regression:

$$FE_{itm} = \chi_0 + \chi_t + \chi_1 AIG_{i,\,t-1} + \chi_2 AIG^2_{i,\,t-1} + \chi_3 ACGM_{i,\,t-1} + \chi_4 Acc_{i,\,t-1} + \boldsymbol{\gamma}\mathbf{Y}'_{itm} + \psi_{it}. \quad (5)$$

Here FE_{itm} is the deflated forecast error of analysts' consensus forecast generated m months before the end of fiscal year t for retailer i. The χ_0 term captures the bias common to all retailers, χ_t is the bias specific to a given fiscal year, χ_1 and χ_2 capture that bias correlated with the previous year's AIG, χ_3 is the bias correlated with the previous year's ACGM, and $\mathbf{Y}'_{itm}$ is the vector of control variables found to be related to forecast bias in the accounting literature (Gu and Wu 2003). These variables include dispersion among analysts' forecasts, analyst coverage, market value, unexpected earnings from a seasonal random-walk model, and a dummy variable to capture ex ante any expectation of loss in earnings. Detailed descriptions of the variables are provided in the note below Table 9.

Table 9 Bias in Deflated Analysts' EPS Forecasts Due to Lagged AIG, 2004–2009

Independent variables	Dependent variable: deflated analyst forecast error m months after EAD_{t-1}			
	$m = 1$ month	$m = 3$ months	$m = 6$ months	
Intercept	−0.057***	−0.031***	−0.027***	−0.035***
	(0.011)	(0.006)	(0.004)	(0.006)
AIG_{it-1}	−0.098***	−0.074***	−0.043**	−0.031*
	(0.009)	(0.008)	(0.018)	(0.017)
AIG^2_{it-1}	−0.067	−0.071	−0.070	−0.081
	(0.091)	(0.087)	(0.071)	(0.101)
$ACGM_{it-1}$	0.191***	0.183***	0.271**	0.161*
	(0.051)	(0.041)	(0.121)	(0.090)
Acc_{it-1}	0.075***	−0.066***	−0.026**	−0.018*
	(0.011)	(0.013)	(0.012)	(0.001)
$DISP_{itm}$	1.102***	−0.854***	−0.378**	−0.218**
	(0.148)	(0.159)	(0.167)	(0.103)
$LGMV_{it-1}$	0.112***	0.012***	0.005***	0.003**
	(0.014)	(0.002)	(0.001)	(0.001)
$LGFFW_{it-1}$	−0.049	−0.010	−0.005	−0.004
	(0.044)	(0.018)	(0.010)	(0.011)
$Loss_{it-1}$	−0.075**	−0.035**	−0.023**	−0.017*
	(0.032)	(0.016)	(0.011)	(0.009)
SUE_1_{it-1}	0.481**	0.141*	0.031*	0.028*
	(0.211)	(0.071)	(0.018)	(0.015)
SUE_2_{it-1}	0.314	−0.027	0.003	0.005
	(0.299)	(0.024)	(0.010)	(0.015)
FE_SALE_{itm}				91e-4*
				(5.2e-4)
n	391	435	435	375
Wald (χ^2)	8,479.63	5,345.24	2,141.14	2,402.65

Notes. FE_SALE_{itm} = deflated analyst sales forecast error. This regression also includes the following control variables from Gu and Wu (2003): $DISP_{itm}$ = analyst dispersion, i.e., the standard deviation of deflated forecasts for each month m in year t; $LGMV_{it-1}$ = log(market value); $LGFFW_{it-1}$ = log(analyst coverage); $Loss_{it-1}$ = an ex ante loss dummy variable that takes a value of 1 if the forecasted current earnings are negative and 0 otherwise; SUE_1_{it-1} and SUE_2_{it-1} are price deflated lag-one and lag-two unexpected earnings from a seasonal random walk model. All regressions are run after controlling for year fixed effects and panel-specific autocorrelation. Standard errors are reported in parentheses below the coefficients.

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$.

We estimate (5) by using the GLS technique. Table 9 provides the formal statistical test of the relation between analysts' forecast errors and lagged AIG. We find that the bias in analysts' forecasts due to AIG continues to remain significant ($p < 0.05$) up to six months from the prior fiscal year's EAD, as shown in Table 9. The magnitude of reported coefficients may be interpreted in the following way. Consider the forecasts made $m = 6$ months after EAD for the prior fiscal year ($m = 6$, column 3 in Table 9). We find the coefficient of AIG to be -0.043 ($p < 0.05$). This implies that, for an average retailer in our sample with a price-to-earnings ratio of 16, a one-standard-deviation increase in AIG is associated with an increase in forecast errors equivalent to 6.19% of earnings. We do not find the quadratic term of AIG to be significant, indicating a linear relationship between AIG and analysts' forecast errors. Finally, we find that coefficients of four of the six control variables are significant and in the same directions as reported in prior accounting literature (Gu and Wu 2003). The remaining two control variables are directionally similar but not significant. Our result that analysts miss information in inventory useful to predict earnings is consistent with the results documented in accounting literature (Bradshaw et al. 2001, Abarbanell and Bushee 1997).

Next, we want to determine whether our result that AIG predicts bias in analysts' EPS forecasts is driven by analysts' failure to incorporate only information contained in AIG to predict sales, as shown by Kesavan et al. (2010), or to predict expenses as well. To do so, we pick analysts' sales forecasts made $m = 6$ months after the EAD for the prior fiscal year (column 4, Table 9). Sales forecasts were available for only 375 of the 435 total observations in our sample. We add contemporaneous error in analysts' sales forecasts to Equation (5) for this sample ($m = 6$) and find that AIG remains a significant predictor of bias in analysts' forecasts of EPS ($p < 0.1$) indicating that analysts also fail to fully incorporate information in inventory that is useful to predict expenses for retailers. We obtain consistent results for $m = 1$ and 3 months, as well, with stronger results ($p < 0.05$).

To summarize, our results show that analysts fail to fully incorporate information in AIG to predict earnings. These results not only support the results from Kesavan et al. (2010), but add to them by showing that analysts fail to fully utilize information contained in AIG to predict expenses, as well.

7.2. Does an Investment Strategy Based on AIG Yield Abnormal Returns?

In this section, we examine whether investments based on AIG can yield abnormal returns. In other words, we examine whether AIG is an "anomaly" variable. The accounting and finance literature define anomaly variables as those that help to identify patterns in stock returns that are not explained by the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965). Fama and French (2008) surveyed various methodologies used to identify anomalies in prior literature, and identified two common approaches based on the extensive literature. The first approach is based on sorting, and the second is based on regressions. We follow both approaches to examine whether an investment strategy based on AIG would yield abnormal stock returns.

First, consider the approach based on sorting, a simple method that examines how the average abnormal monthly returns of stocks vary across the range of an anomaly variable (AIG in our case). This approach involves constructing quintile portfolios of firms based on ranks of their AIG in the previous fiscal year. An important consideration is that all information required to construct a portfolio for a given fiscal year is available at the time the portfolio is created. Because firms file their 10-K statements with the SEC at different times in the year, the information required to construct a portfolio comprising all the retailers in our sample becomes available at different times. For our test sample, we find that the month of April had the most SEC filings (243), followed by March (82) and May (50). The remaining months had fewer than 20 filings each.

We follow Fama and French (2008) to calculate the abnormal monthly return of each stock in the following way. First, we match each stock to its benchmark portfolio using that stock's size and book-to-market value (BM). The matching benchmark portfolio is one of 25 portfolios value weighted (VW) by size and BM, obtained from Ken French's website.[1] These 25 benchmark portfolios are themselves formed at the end of June each year, based on the market equity and book-to-market values of all NYSE, AMEX, and NASDAQ stocks. The abnormal monthly return of each stock is obtained by subtracting the VW monthly return of the benchmark portfolio from that of the stock return.

Next, we sort firms in our test sample into portfolios and calculate the average abnormal monthly return of each portfolio, as illustrated here for 2004: We calculate the AIG value for each retailer that filed a 10-K statement with the SEC during the period March–May 2004. Then we sort the retailers into five portfolios, P0, P1, …, P4, such that portfolio P0 contains firms with AIG in the bottom quintile and portfolio P4 contains firms with AIG in the top quintile. We then compute the equal weighted (EW) average abnormal monthly return of each portfolio for each month from July 2004 to June 2005. At the end of June 2005, we re-sort the firms into the five portfolios based on AIG computed, using 10-K information released during March–May 2005. We repeat the process of calculating average abnormal monthly return and re-sorting for each of the years 2005–2009. Thus, we sort firms into portfolios six times during 2004–2009, giving us 72 observations of the average

[1] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 10 Average Abnormal Returns and t-Statistics for Portfolios Formed Using Sorts on AIG, ACC, and INVG, 2004–2009

	Average monthly abnormal returns (AR)						t-statistic for AR					
Sorting on	P0	P1	P2	P3	P4	High–Low (P4–P0)	P0	P1	P2	P3	P4	High–Low (P4–P0)
AIG	0.22	0.14	0.05	−0.45*	−0.70***	−0.92***	0.64	0.41	0.10	−1.75	−3.14	−3.18
ACC	0.18	0.08	0.06	−0.20	−0.61**	−0.79**	0.32	0.20	0.09	−1.56	−2.02	−2.22
INVG	0.16	0.24	−0.10	−0.42	−0.55*	−0.71*	0.62	0.61	−0.19	−0.83	−1.73	−1.75

Notes. We sort stocks into portfolios at the end of June of each year t, and compute value weighted abnormal returns for July of t to June of $t+1$. Each year, we sort the firms based on each of the anomaly variables into five quintiles (P0 (lowest) to P5 (highest)). We assign firms to matching BM and size portfolios using the quintile breakpoints form from Ken French's website. The abnormal monthly return on a stock is measured net of the value-weight return on a matching portfolio formed on size and BM. The average monthly equal-weight return for each portfolio is shown above. All returns presented in the table are expressed as percentages.

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$.

abnormal monthly return for each portfolio. The average abnormal returns of a portfolio represent the portion of anomalous average returns not explained by the size or BM value of the retailers concerned.

Again we follow Fama and French (2008) to report the average of the 72 monthly observations and the t-statistics for each portfolio. The results can be found in Table 10. We find that the average abnormal return for portfolios P0 to P4, based on AIG, vary between 0.22% and −0.70%. We note that the average abnormal returns of portfolios P3 and P4 are significant at $p < 0.1$ and $p < 0.01$, respectively, whereas the average abnormal returns for the rest of the portfolios are not statistically significant. This pattern of significance is common for many anomaly variables, including accruals where positive accruals are associated with significant negative abnormal returns, but negative accruals are not (Fama and French 2008). It is also common in the anomalies literature to compute the return of a hedge portfolio formed based on long/short positions on stocks in the extreme portfolios. In our case, such a hedge portfolio formed by shorting stocks in P4 and going long on stocks in P0 would yield an average abnormal monthly return of 0.92% ($p < 0.01$). This translates to an annual return of about 11%.

We next repeat the analysis by forming portfolios based on other anomaly variables from prior literature, such as accruals (ACC) and the inventory component of accruals (INVG), to compare the returns from these portfolios against those from AIG. Table 10 shows that the average abnormal monthly return of portfolios we formed based on accruals vary between 0.18% and −0.61%, yielding a hedge portfolio return of 0.79% ($p < 0.05$). Thus, we find that the hedge portfolio return based on AIG is higher than that based on accruals. We also find the hedge portfolio returns based on the inventory component of accruals to be 0.71% ($p < 0.1$). Our results are consistent with Thomas and Zhang (2002), who found the relationship between accruals and future abnormal stock returns to be driven mainly by the inventory component of accruals.

The sorting approach has two shortcomings for studying abnormal returns generated by AIG. First, it does not indicate which anomaly variable contains unique information. So, it is unclear whether the information content in AIG is unique or if the information content in AIG is subsumed in another known anomaly variable in the literature, such as accruals, or more specifically, the inventory component in accruals. Second, the sorting approach does not help us determine the functional form of the relationship between an anomaly variable and the abnormal returns it generates. Thus, it is unclear whether the inverted-U relationship observed between AIG and one-year-ahead earnings persists between AIG and abnormal returns. Fama and French (2008) stated that the regression-based approach, in the spirit of Fama and Macbeth (1973), addresses both shortcomings.

In the regression-based approach, we run cross-sectional monthly regressions from July through June of each year, of individual monthly stock returns against AIG and other anomaly variables from the prior fiscal year. For example, we would run a regression of monthly stock returns of each firm in July 2004 against that firm's AIG, computed from information released during the period March–May 2004. We also include a quadratic term of AIG to test for nonlinearity in this relationship. In addition, we use several control variables in this regression, based on Fama and French (2008). The control variables are market cap (in log), book-to-market ratio (in log), momentum, and asset growth (in log). Asset growth is measured as the change in natural log of assets from $t-2$ to $t-1$. Momentum is computed as the cumulative 11-month return in the past year, not including the month before the return to be explained. The prior month's return is not included because of prior evidence showing a negative correlation of month-to-month returns for the prior month (Jagdeesh 1990). The regression explanatory variables are winsorized at 1 and 99 percentiles.

Table 11 Average Slopes and t-Statistics from Monthly Cross Section Regressions, 2004–2009

	Variable	Int	ACC	AIG	AIG^2	AIG (OI)	AIG (UI)	INVG	Asset G	MOM	MC	BM	R^2
Model 1	*Return*	1.97***	−0.306**	−0.337***	−0.004			−0.157	−0.021	0.400**	−0.277***	0.262**	0.15
	t-statistic	3.45	−2.82	−4.94	−1.06			−1.54	−1.31	2.81	−3.47	3.07	
Model 2	*Return*	1.50***	−0.351**	−0.367***	N/A			−0.183	−0.025	0.356**	−0.284***	0.273**	0.12
	t-statistic	3.59	−3.15	−5.44	N/A			−1.61	−1.01	2.42	−3.52	3.25	
Model 3	*Return*	2.91***	−0.325**			−0.571***	0.012	−0.168	−0.023	0.389**	−0.328***	0.265**	0.19
	t-statistic	4.58	−2.96			−6.97	0.58	−1.59	−1.45	2.71	−4.07	3.10	

Notes. This table shows average slopes and their t-statistics from monthly cross-section regressions to predict stock returns. The variables used to predict returns for July t to June of $t+1$ are MC, the natural log of market cap in June of year t (in millions); BM, the natural log of the ratio of book equity for fiscal year $t-1$ divided by market equity in December of $t-1$; AIG, the abnormal inventory growth from fiscal year $t-1$; AIG (OI) and AIG (UI) take the values of positive and negative abnormal inventory growth, respectively, or 0 otherwise; ACC, the accruals from fiscal year $t-1$; INVG, the change in ending inventory from fiscal year $t-2$ to fiscal year $t-1$ deflated by total assets in fiscal year $t-2$; MOM (momentum) for month m, the cumulated continuously compounded stock return from month $m-12$ to month $m-2$, where m is the month of the forecasted return. We measure momentum monthly. Asset G (growth in assets), change in natural log of assets from fiscal year $t-2$ to fiscal year $t-1$. Int is the average regression intercept and the average regression R^2 is adjusted for degrees of freedom. The t-statistics for the average regression slopes use the time-series standard deviations of the monthly slopes.

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$.

Results of the regressions are reported in Table 11 (model 1). The reported coefficients are based on the average of the monthly slopes obtained from the 72 cross-sectional regressions. The reported t-statistics are based on time-series standard deviations of the monthly slopes. We find that AIG is significant ($p < 0.001$), confirming our finding from the tests based on sorts in Table 10. Because AIG is significant even after controlling for other anomaly variables, we conclude that the information content in AIG is not subsumed in previously known anomaly variables.

We find that the quadratic term of AIG is not significant. To confirm our results from sorting, which show abnormal returns for portfolios with negative AIG to be insignificant, we run additional regressions along the lines of Fama and French (2008), by allowing separate slopes for negative and positive AIG. We find the relationship between AIG and abnormal stock returns is driven by positive AIG ($p < 0.001$) only because the slope of negative AIG is not significant as shown in Table 11 (model 3).

We also find that, although sorting stocks based on the inventory component of accruals produces significant abnormal returns (Table 10), it has little marginal ability to predict future returns in the presence of AIG and accruals (Table 11). Because INVG captures the raw change in inventory, our result adds further insight to that of Thomas and Zhang (2002) by showing that the abnormal component of inventory growth, not the normal component, generates abnormal returns.

We perform several robustness tests of these findings. An alternate measure of abnormal returns for long-horizon stock-price performance is the buy-and-hold abnormal return (BHAR) metric (Kothari and Warner 2007). This measure is suitable when investors are expected to hold the portfolio for a fixed period of time. Portfolios are formed as described above, but abnormal returns are calculated using the BHAR metric in the following way:

$$\mathrm{BHAR}_{it} = \prod_{m=1}^{12}(1+R_{imt}) - \prod_{m=1}^{12}(1+R_{\mathrm{benchmark},\,mt}).$$

One difference between the measures reported here based on Fama and French (2008) and those based on the BHAR metric is that the former approach produces average monthly returns whereas the latter produces an annual return for a 12-month period. In our test sample, we find the BHAR of the hedge portfolio that was formed based on AIG to be 8.40% ($p < 0.01$), comparable to returns from the sorting approach, as reported in Table 10. A second method to test robustness is a regression-based method called Jensen-alpha approach or the calendar-time portfolio approach, which controls for retailer size, book-to-market value, and momentum. We obtain consistent results with this approach, as well, as shown in the online supplement. Finally, we found a variation of the regression-based approach in some accounting papers, such as Thomas and Zhang (2002) and Desai et al. (2004), who run the regression of abnormal stock returns against scaled ranks of the anomaly variables instead of continuous variables. This line of literature claims that the use of scaled ranks of anomalous variables is advantageous, as scaled ranks do not force a functional form between returns and the anomalous variables. We obtain consistent results even with this method, as shown in the online supplement.

To summarize, although these various tests differ in their nuances, we find that they yield the same conclusion: an investment strategy based on AIG would yield abnormal returns, a conclusion that is robust to both the method and the measure used to estimate the returns.

8. Conclusion, Limitations, and Future Work

This paper documents an inverted-U relationship between abnormal inventory growth and one-year-ahead earnings for retailers, using publicly available financial data. Thus, it demonstrates that the inverted-U relationship that forms the building block of inventory models at the SKU level can be detected at the firm level as well. In addition, our paper shows that Wall Street analysts and investors do not fully incorporate the information in AIG in their earnings' forecasts and investment decisions, respectively. By quantifying the anomalous stock market returns associated with AIG, our paper shows that a benchmarking metric derived from the operations management literature can serve as a basis for investment strategy.

Our paper does have limitations. First, our paper is limited to the retail sector. It would be interesting to examine other sectors to determine the value of an inventory-based benchmarking metric from an investment stand point. Second, all the analysis reported in this paper are conducted at an annual level. Because annual inventory turns of retailers are typically less than one, it is likely that the effects that we report are larger when observed in quarterly data. In fact, our longitudinal analysis with analysts' forecasts suggests that the bias predicted by AIG disappears six months after the release of 10-K statements. So, future research may perform quarterly analysis to examine if there is an improvement in the hedge portfolio returns. Finally, future research may also consider ways to improve the benchmarking model for retail used in this paper. An extension to the model may consider including data on product variety (Rajagopalan 2010) and competition (Olivares and Cachon 2009) because they have been found to affect inventory levels of retailers. However, data for these two variables are not available in the 10-K statements, so it may be necessary to look for other sources or viable proxies.

Future research may also examine the cause of abnormal returns documented in our study. The accrual literature in accounting points to two possible avenues of research. First, firms with abnormal inventory growth could have a different risk profile. Second, investors might be missing information contained in AIG, leading to a mispricing of these stocks. Knowledge of the underlying cause would enable us to determine whether the abnormal returns associated with AIG would persist in equilibrium or if investors would arbitrage the anomalous returns away with time.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/msom.1120.0389.

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