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Does Inventory Productivity Predict Future Stock Returns? A Retailing Industry Perspective

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We find that inventory productivity strongly predicts future stock returns among a sample of publicly listed U.S. retailers during the period from 1985 to 2010. A zero-cost portfolio investment strategy, which consists of buying from the two highest and selling from the two lowest quintiles formed on inventory turnover, earns more than 1% average monthly abnormal return benchmarked to the Fama–French–Carhart four-factor model. Our results are robust to different measures of inventory productivity, distinct from the well-known firm characteristics known to generate abnormal returns, and not driven by a particular subsample period. A longitudinal analysis of portfolio returns over longer holding periods shows that although inventory productivity is predictive of stock returns, its information dissipates about one to two years after release.

Keywords: operations–finance interface; retail operations; inventory productivity; empirical asset pricing
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1. Introduction

Inventory is a key management item in the retailing industry. Retailers emphasize inventory productivity as a means to improve competitiveness and try to reduce the optimal levels of inventory required by their businesses by redesigning their supply chains and improving processes. They adopt paradigms such as responsive supply chains, inventory pooling, information sharing, and revenue management to move to a higher inventory productivity frontier. Given the practical importance of effective inventory management, the academic literature has focused on improving methods for benchmarking inventory productivity (Gaur et al. 2005, Rumyantsev and Netessine 2007b), assessing improvements in inventory productivity over time (Chen et al. 2007, Rajagopalan and Malhotra 2001), and evaluating the impact of firms' decisions on inventory productivity (Huson and Nanda 1995, Balakrishnan et al. 1996). Despite the theoretical and practical advancements in inventory productivity, managerial incentives are usually tied to the stock market valuation of the firm because it can be measured more easily and more accurately. Thus, it is of interest to both managers and shareholders of firms to know whether improvement in inventory productivity is systematically related to stock performance.

In this paper, we conduct portfolio-based asset pricing tests and investigate whether inventory productivity predicts future stock returns of retail firms. From an efficient market perspective, if investors are capable of computing the inventory productivity of a retailer from its financial statements and determining its impact on future performance, then we expect the effect of inventory productivity to be absorbed into stock prices soon after this information becomes publicly available. As a result, inventory productivity should not be a useful signal in implementing a portfolio trading strategy even if it positively influences the profitability of a firm. On the other hand, prior studies in operations management show that inventory information is not fully understood by market participants. For example, Raman et al. (2005) present a case study of a hedge fund manager who invests in retail stocks on the basis that inventory assessment is subjective and is not fully absorbed into stock prices; Kesavan et al. (2011) and Kesavan and Mani (2013) show that equity analysts are unable to incorporate abnormal inventory growth in their sales forecasts and earnings forecasts, respectively, up to several months after the release of financial statements. Motivated by this literature, we investigate whether the level of and change in inventory productivity are predictive of future stock returns.

Using the sample of U.S. retailers traded on the New York Stock Exchange, the American Stock Exchange, and NASDAQ over the period from 1985 to 2010, we document strong return predictability of inventory performance metrics. For example, when we use *Inventory Turnover* (*IT*) as a measure of inventory productivity, we observe an increasing return pattern across quintile portfolios sorted on inventory turnover. In particular, an equal-weighted zero-cost portfolio investment strategy with annual rebalancing, which consists of buying the top 40% and selling the bottom 40% of the firms based on *IT* in each retail segment, yields 0.97% average monthly excess return (in excess of the risk-free rate) and 1.08% average monthly abnormal return (alpha) benchmarked to the Fama–French–Carhart four-factor model (Fama and French 1993, Carhart 1997). Our time-series analyses indicate that these return numbers are statistically significant ($p < 0.0001$).

We consider different measures of inventory productivity, including gross margin return on inventory and adjusted inventory turnover (Gaur et al. 2005). In addition, we test both level-based and annual change-based measures for all of these inventory productivity variables. The return predictability in our study remains both economically and statistically significant on portfolios formed on all level- or change-based metrics of inventory productivity. Moreover, cross-portfolios, e.g., 5×5 portfolios formed on inventory turnover and annual change in inventory turnover, yield a larger spread of returns. An examination of the year-to-year performance of portfolios shows that the returns are not attributed to any specific subperiod in our data set. Stocks with high *IT* outperform stocks with low *IT* in 22 years over a 25-year sample period, and stocks with high ΔIT outperform stocks with low ΔIT in 23 of 25 years. Sections 3.1 and 3.2 of this paper present these results.

Is the predictive power of inventory productivity distinctive from well-documented firm characteristics in the accounting and finance literature? These firm characteristics include operating and nonoperating accrual (Sloan 1996, Dechow et al. 2011), changes in inventories (Thomas and Zhang 2002), changes in noncurrent assets and capital expenditures (Hribar 2002), abnormal capital expenditure (Titman et al. 2004), operating leverage (Novy-Marx 2011), etc. Such variables could be distinct from but related to inventory productivity. In addition, inventory productivity metrics may be correlated with sales growth, gross margin, and other financial ratios. Therefore, in §4, we test whether the explanatory power of inventory productivity is distinct from accruals, operating leverage, capital expenditure, as well as several measures of profitability and control variables. Applying the Fama and MacBeth (1973) cross-sectional regression approach, we find that all these control variables cannot explain the positive relation between inventory productivity and subsequent returns.

Having established return predictability, in §5, we examine whether our results support an information-based explanation, i.e., that investors do not fully incorporate inventory-related information from the financial reports of a firm when valuing its stock. We find several types of evidence supporting this explanation. First, a longitudinal analysis of portfolio returns over five-year holding periods reveals that the zero-cost portfolio return spreads dissipate after the first or the second year for each inventory productivity metric. Second, there are return differences across firms that transit into a portfolio from below (due to a relative improvement in inventory productivity) or from above (due to a relative deterioration in inventory productivity), or stay in the same portfolio. Third, changing the fiscal year-end (FYE) cutoff date for portfolio formation from January 31 to December 31 weakens the results. This is the case because most retailers have fiscal year-end dates on January 31. Setting the cutoff date to December 31 causes the model to use one-year-older financial information for such retailers. Thus, we find that although inventory productivity is predictive of stock returns, its information gets incorporated in stock returns approximately one to two years after release.

On the basis of the above tests and robustness analyses, we conclude that inventory productivity is a strong predictor of future stock returns. Chen et al. (2005, 2007) were the first to investigate this important question in the operations management literature. They found that, for manufacturing firms, middle decile portfolios formed on inventory yield abnormal stock returns, and, for retailer and wholesaler firms, low quintile portfolios (high inventory) yield negative abnormal stock returns, whereas high quintile portfolios (low inventory) do not yield any abnormal returns. Our findings contrast with those of Chen et al. (2005, 2007) because of differences in methodology. They employed a parametric method to normalize and merge data across Standard Industry Classification (SIC) categories, whereas we use a nonparametric method, which better accounts for differences in skewness of inventory productivity metrics across SIC categories of retailers. We use a January 31 fiscal year-end cutoff date, which is applicable to the retailing industry. We also extend their analysis by using alternative inventory productivity metrics, conducting robustness tests to verify whether inventory turnover is merely serving as a proxy for well-known variables that explain stock returns, and investigating potential explanations for the observed relationship between inventory productivity and future stock returns.

Other recent papers have related operational performance with financial performance. Hendricks and Singhal (2005, 2009) pioneered the use of event studies to investigate the negative impact of announcements related to operational problems, such as supply chain glitches and excess inventory, on stock returns in short time windows of one to five days after the announcement. These papers underscore the relevance of operational events to the market value of a firm. Rumyantsev and Netessine (2007a) and Gaur et al. (1999) showed that firms with higher inventory productivity have higher contemporaneous return on assets and stock returns, respectively. Kesavan et al. (2011) and Kesavan and Mani (2013) showed the impact of abnormal inventory on analysts' forecasts of future sales and earnings; Kesavan and Mani (2013) additionally showed that retailers with high abnormal inventory growth have negative abnormal stock returns. Ramdas et al. (2013) found in the airline industry that flight cancellations and long delays are the greatest source of reduction in contemporaneous stock prices. Our research adds to this literature by focusing on the cross-sectional difference between efficient and inefficient firms in the context of the retailing industry, and showing that even simple metrics of inventory productivity predict future stock returns.

Table 1 **Compustat Data Fields for Variables for Retailer *i* in Fiscal Year *t***

Variable name	Description	Field name in Compustat
AP_{it}	Accounts payable	AP
CE_{it}	Capital expenditures	CAPX
$COGS_{it}$	Cost of goods sold	COGS
$EIDO_{it}$	Extraordinary items and discontinued operations	XIDOC
GFA_{it}	Property, plant and equipment (gross)	PPEGT
$IBEI_{it}$	Income before extraordinary items	IBC
INV_{it}	Inventory	INVT
$LIFO_{it}$	LIFO reserve	LIFR
NFA_{it}	Property, plant and equipment (net)	PPENT
OCF_{it}	Net cash flow from operating activities	OANCF
$RENT_{it\tau}$	Rental commitments in year $\tau \in \{1, \ldots, 5\}$	MRC1, …, MRC5
$Sales_{it}$	Annual sales	SALE
SGA_{it}	Sales, general, and administrative expenses	XSGA
TA_{it}	Total assets	AT

2. Research Setup

We use three types of data: firm specific annual accounting data from the Compustat database, monthly stock returns from the Center for Research in Security Prices (CRSP) database, and data on common risk factors. All these data are accessed through Wharton Research Data Services (WRDS). We describe the variables in §2.1, the data set in §2.2, and the portfolio formation method in §2.3.

2.1. Inventory Productivity Metrics

Many measures of inventory productivity have been proposed in the literature, including inventory turnover, sales-to-inventory ratio, and gross margin return on inventory. Furthermore, the level of a metric and the annual change in the metric convey different kinds of information. The level of a metric can be interpreted as a firm's baseline inventory productivity, whereas the annual change in the metric can be interpreted as the recent improvement (or setback) in a firm's inventory productivity. Given these choices, it becomes important to determine (i) if the type of metric influences the nature of results and (ii) if its level and its annual change lead to similar inferences. Therefore, we include several alternative metrics and their annual changes in our analysis. For uniformity, we construct each metric such that a higher value indicates greater efficiency or greater inventory productivity. We collectively refer to them as measures of inventory productivity to ease the presentation of this paper.

From the Compustat annual data for firm i in fiscal year t, let $Sales_{it}$ denote the total sales revenue; let $COGS_{it}$ denote the corresponding cost of goods sold; let GFA_{it} denote the gross fixed assets, which include land, plant, property and equipment; let $RENT_{it1}, \ldots, RENT_{it5}$ denote rental commitments for the next five years; let TA_{it} denote total assets; let $LIFO_{it}$ denote the last-in, first-out (LIFO) reserve; and, last, let INV_{it} denote the ending inventory. Table 1 presents the relevant fields in the Compustat annual database.

We make standard adjustments to the data to compute inventory-related productivity metrics; similar adjustments are made in Kesavan et al. (2011). First, we add the LIFO reserve ($LIFO_{it}$) to the ending inventory (INV_{it}) and to total assets (TA_{it}), and subtract the change in the LIFO reserve ($LIFO_{it} - LIFO_{i,t-1}$) from the cost of goods sold ($COGS_{it}$) to eliminate differences in inventory valuation methods, which arise because of the use of first-in, first-out versus last-in, first-out methods. Second, we compute the discounted present value of rental commitments, i.e., $\sum_{\tau=1}^{4} RENT_{it\tau}/(1+d)^{\tau} + RENT_{it5}/d(1+d)^{4}$, assuming that the commitment in the fifth year will continue as a perpetuity into the future, and add it to GFA_{it} and TA_{it} to account for the impact of operating leases on a retailer's gross fixed assets and total assets. We use an annual discount rate of $d = 8\%$. Setting $d = 6\%$ or $d = 10\%$ does not change our qualitative insights.

We define the following inventory productivity metrics for firm i in year t:

(i) *Inventory Turnover* (IT):

$$IT_{it} = \frac{COGS_{it} - LIFO_{it} + LIFO_{i,t-1}}{INV_{it} + LIFO_{it}}.$$

(ii) *Gross Margin Return on Inventory* ($GMROI$):

$$GMROI_{it} = \frac{Sales_{it} - COGS_{it} + LIFO_{it} - LIFO_{i,t-1}}{INV_{it} + LIFO_{it}}.$$

(iii) *Adjusted Inventory Turnover* (AIT): Despite serving as proxies for a retailer's inventory productivity, IT and $GMROI$ omit the interdependencies between inventory investment and other firm characteristics. Prior literature identifies several factors that affect a firm's inventory productivity. Rumyantsev and Netessine

(2007b) analyze the determinants of a firm's aggregate inventory investment using item-level inventory theoretic models (e.g., economic order quantity, newsvendor). They find empirical evidence for a positive correlation between inventory levels and the primitives of the classical inventory models such as demand uncertainty, lead times, and margins. Similar to our paper, Gaur et al. (2005) focus on inventory productivity (rather than the monetary value of inventory or changes in inventory) and show that inventory turnover is correlated with gross margin, capital intensity, and sales surprise. They propose a metric, adjusted inventory turns, to control for these correlations in performance assessment.

Following Gaur et al. (2005), we compute *AIT* as an alternative metric to control the correlation of inventory turnover with other firm characteristics. To compute *AIT*, we first define three additional variables for firm i in year t:

Gross Margin:

$$GM_{it} = \frac{Sales_{it}}{COGS_{it} - LIFO_{it} + LIFO_{i,t-1}}.$$

Capital Intensity ($d = 8\%$):

$$CI_{it} = \frac{GFA_{it} + \sum_{\tau=1}^{4} \frac{RENT_{it\tau}}{(1+d)^{\tau}} + \frac{RENT_{it5}}{d(1+d)^4}}{TA_{it} + LIFO_{it} + \sum_{\tau=1}^{4} \frac{RENT_{it\tau}}{(1+d)^{\tau}} + \frac{RENT_{it5}}{d(1+d)^4}}.$$

Sales Surprise:

$$SS_{it} = \frac{Sales_{it}}{Sales_{i,t-1}}.$$

Gross margin serves as a proxy for firm profitability, which is an important metric both in operations and finance. A higher gross margin is correlated with higher fill rate, greater product variety, and higher quality products, each of which leads to slower inventory turns. Hence, inventory turnover and gross margin are negatively correlated. This negative correlation is commonly referred to as the *earns versus turns* trade-off in retailing. Capital intensity serves as a proxy for a firm's supply chain infrastructure. A high *CI* firm should have lower inventory because a high *CI* reduces safety stock requirements through better inventory allocation, information sharing, and demand forecasting capabilities. Sales surprise has a positive correlation with inventory turnover because a high sales realization compared to previous year's sales leads to lower ending inventory, which implies higher inventory turnover. Our sales surprise metric also serves as a proxy for economic shocks, which are known to influence a firm's investment decisions and stock performance (Novy-Marx 2011).

AIT adjusts *IT* for changes in gross margin, capital intensity, and sales surprise. We fit the following regression model to compute *AIT* for each firm in each year:

$$\log IT_{it} = F_{j[i]} + b_1 \log GM_{it} + b_2 \log CI_{it} + b_3 \log SS_{it} + \epsilon_{it}, \tag{1}$$

where $F_{j[i]}$ is the intercept for retail segment j to which firm i belongs. (We define retail segments in §2.2.) Then *AIT* is computed as the residual from this regression.

Our definition of *AIT* differs from the one proposed by Gaur et al. (2005) as follows. First, Gaur et al. (2005) fit a longitudinal regression model using panel data, whereas we fit a separate regression model for each year t. Fitting cross-sectional regression models allows us to avoid look-ahead bias and ensure that accounting variables are known before they are used to form portfolios. Second, we have a segment-specific fixed-effect for each retail segment, whereas having a larger sample size allows Gaur et al. (2005) to introduce segment-specific coefficients for explanatory variables (i.e., gross margin, sales surprise, and capital intensity). Finally, the explanatory variables are defined slightly differently for simplicity and to allow observations in which sales are less than the cost of goods sold. Despite these differences, panel and cross-sectional regressions generate similar insights regarding the impact of gross margin, capital intensity, and sales surprise on inventory turnover.

(iv) *Change in IT*: $\Delta IT_{it} = (IT_{it} - IT_{i,t-1})/IT_{i,t-1}$ denotes the annual percentage change in inventory turnover.

(v) *Change in GMROI*: $\Delta GMROI_{it} = (GMROI_{it} - GMROI_{i,t-1})/GMROI_{i,t-1}$.

(vi) *Change in AIT*: $\Delta AIT_{it} = (AIT_{it} - AIT_{i,t-1})/AIT_{i,t-1}$.

We apply the above six variables as inventory productivity metrics. Inventory productivity could be correlated with other financial metrics of a firm, such as selling, general and administrative expenses, accrual, operating leverage, and capital expenditure. Those variables could potentially explain the ability of inventory productivity to predict stock returns. We define such variables in §4 and test whether the predictive power of inventory productivity variables is distinctive from them.

2.2. Data Description

We collect financial data for fiscal years 1983–2010 for all U.S. public retailers identified by the four-digit SIC code assigned to each firm based on its primary industry segment. Our final data set contains 36,164 firm-month observations across 399 firms corresponding to 26 firms per quintile portfolio on average.

We form our first portfolio in July 1985. The choice of start date is based on prior research, which finds that modern inventory management tools and methods, such as just-in-time and electronic data interchange, were put into use mostly in the early 1980s after

Table 2 Data Classification Into Retailing Segments Using the Four-Digit SIC Codes

Description	Segment	SIC codes	Examples of firms	No. of firms	No. of firm year observations
General merchandise stores	53	5311, 5331, 5399	Wal-Mart, Target, Costco	98	826
Grocery stores	54	5411	Safeway, Whole Foods	73	695
Apparel and accessory stores	56	5600–5699	Foot Locker, Finish Line	106	1,050
Radio, TV, electronics, computer and software stores	57	5731, 5734	Best Buy, CompUSA	39	246
Catalog, mail order, and e-retail stores	59	5961	Amazon.com, Buy.com	83	527
			Total	399	3,344

advances in information technology (Rajagopalan and Malhotra 2001). We group some of the SIC categories together when there is a significant commonality among products sold by the firms in these categories. Thus, our data set comprises five segments in the retailing industry. Although four-digit SIC codes imply more accurate comparison across retailers, they also lead to fewer retailers in each segment. Grouping related SIC codes into one segment instead of having a separate segment for each four-digit SIC code enables us to have a larger number of firms within each segment. This is useful for forming portfolios because we rank firms in each retail segment by a chosen metric and divide the segment into quintile portfolios.

We exclude retailers that are classified as eating and drinking places (SIC 5812–5813) and automotive dealers and service stations (SIC 5511–5599) because service is a significant component of their businesses. We also exclude some four-digit categories because their inventories have fewer commonalities with the remaining retailers within the same two-digit classification, e.g., floor covering stores (SIC 5713), or their inventory levels could be driven by macroeconomic conditions and raw material prices, e.g., jewelry stores (SIC 5944). Table 2 shows the description of each segment and the corresponding four-digit SIC codes.

The initial extract of our data set contains 4,576 firm-year observations across 480 firms. A firm cannot be included in any portfolio for the first two years of its data series because LIFO reserve adjustments and the computation of sales surprise require one year of sales data at the beginning of each time series, and the computation of change in productivity metric (e.g., ΔIT) requires an additional year. We omit firm-year observations that had missing data in the fields required to compute IT, $GMROI$, and AIT. This leaves 3,344 observations across 399 firms, an average of 8.4 years of data per firm.

We merge these data with the corresponding monthly stock returns for each firm. Firms that get delisted from the stock exchange in a particular month require special treatment if their monthly stock return is not available. We replace missing monthly stock returns with the delisting return if available. If neither the monthly return nor the delisting return is available, then we set the monthly stock return equal to the value-weighted market return. We remove firms that do not have stock return data for any month in the CRSP database. This then gives our final merged data set.

Table 3 presents summary statistics for the main performance variables used in our study for the 399 firms classified by retail segments. Note that all of the first three moments of inventory turnover vary across segments. For example, consumer electronics (SIC 57) has the lowest standard deviation (1.91) and skewness (1.36), whereas catalog, mail-order, and e-retailers (SIC 59) have the highest standard deviation (12.20) and the highest skewness (6.17).

2.3. Portfolio Formation Methodology

Two aspects of our portfolio formation method are important to describe: the fiscal year-end dates and

Table 3 Summary Statistics for Inventory Turnover, Sales Surprise, Gross Margin, and Capital Intensity

	Inventory turnover				Sales surprise		Gross margin		Capital intensity	
Segment	Median	Average	Std. dev.	Skewness	Median	Average	Median	Average	Median	Average
53	3.49	4.22	2.61	2.90	1.08	1.12	1.46	1.46	0.54	0.52
54	9.01	10.02	4.26	2.00	1.06	1.08	1.35	1.36	0.66	0.63
56	4.14	4.45	2.24	2.50	1.10	1.12	1.57	1.62	0.70	0.67
57	4.13	4.36	1.91	1.36	1.16	1.14	1.43	1.52	0.55	0.53
59	5.73	9.42	12.20	6.17	1.13	1.44	1.62	1.73	0.23	0.25

Notes. We report the standard deviation and the skewness of inventory turnover to show the intersegment differences in inventory productivity. Skewness measures the degree of asymmetry of a distribution. A positive skew indicates that the right tail is longer than the left tail. Thus, the majority of the observations lie to the left of the mean.

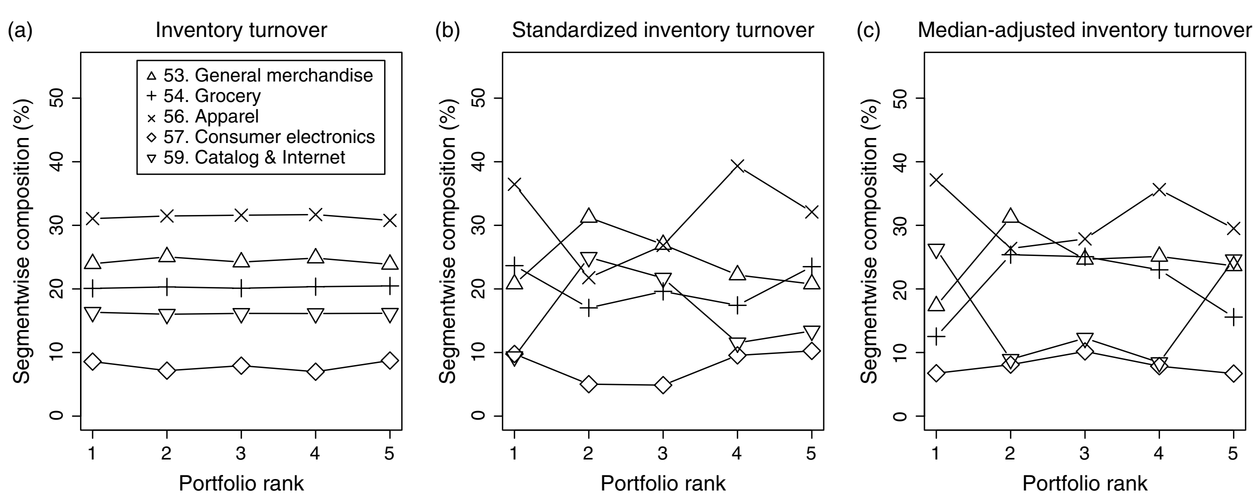
the method of ranking firms. In each year t, we form portfolios on July 31 using accounting information for fiscal years ending from February 1 of year $t-1$ to January 31 of year t. For example, if a firm has a fiscal year-end date of July 31, then the information used for this firm to form portfolios is from 12 months ago. This method allows at least six months for the accounting information to be announced and absorbed by the market, as per the norm in the asset pricing literature. We make one modification to the method that originates from Fama and French (1993). Whereas they use a FYE cutoff date of December 31 to form portfolios on June 30, we use a cutoff date of January 31 to form portfolios on July 31. This is done because a sizable fraction of retailers (45% in our sample) have FYE dates in January to allow for the peak holiday selling season. Portfolios formed on July 31 of year t are liquidated on July 31 of year $t+1$, and new portfolios are formed using another year of accounting information. We form our first portfolio on July 31, 1985, and last portfolio on July 31, 2009.

For ranking firms, we apply a nonparametric method to mitigate interindustry differences. We explain the method for IT. The same method is applied for all other metrics. At the end of July in year t, we rank firms in each of the five retail segments by IT in ascending order and divide each segment into five quintiles. Then we form portfolio p by aggregating the firms with quintile rank p in each segment. This methodology mitigates the impact of differences in the frequency distribution of the productivity metrics among retail segments, which may be caused by different types of segment-specific characteristics. Thus, it ensures that each retail segment is uniformly represented in each portfolio. Figure 1 shows the results of this method and compares them with two alternatives. Observe, in Figure 1(a), that our method gives approximately equal representation, subject to rounding errors, to each segment in each portfolio.

One alternative to our method is to normalize the productivity metric within each segment by subtracting out its segment mean and dividing by the segment standard deviation, both computed for that year. Commonly used in the literature for variables derived from financial statements, this method has also been used for inventory productivity (e.g., Chen et al. 2005, 2007). It forms portfolios using standardized scores that are sometimes referred to as z-scores or abnormal values. It would have given a uniform representation of segments into portfolios if the data were close to normally distributed. However, it creates a problem for inventory productivity because the skewness of data differs across SIC categories as shown in Table 3. For example, consider Costco Wholesale Corporation (ticker COST), which has a very high inventory turnover compared to other firms in its SIC category and increases the average inventory turnover for the entire segment. This normalization procedure pushes most of the remaining firms in Costco's segment below average and makes their inventory performances look worse than they probably are. Figure 1(b) shows the portfolio composition resulting from this method. Note that the proportion of firms from any given SIC category varies across quintile portfolios.

Another alternative to our method is to scale the inventory productivity metric within each segment by dividing by its segment median. Such an alternative is less sensitive to outliers than standardized scores are. However, Figure 1(c) shows that the representation of each segment again varies substantially across portfolios with this method. We find that this occurs because differences in median values across

Figure 1 **Segmentwise Composition of Quintile Portfolios Formed on (a) Inventory Turnover by Ranking Retailers Within Each Segment, (b) Standardized Inventory Turnover, and (c) Median-Adjusted Inventory Turnover**



Note. See §2.3 for the detailed descriptions of these three portfolio formation methodologies.

segments do not fully capture distributional differences. For instance, consider segments 53 and 54. According to Table 2, segment 53 has a median *IT* of 3.49, and segment 54 has 9.01. Thus, a retailer in segment 53 would need 7 inventory turns to achieve a median-adjusted *IT* value of 2, whereas a retailer in segment 54 would need 18 inventory turns to achieve the same median-adjusted *IT*. Thus, it might be more difficult for segment 54 retailers to achieve high median-adjusted *IT* ranks. As a consequence, portfolios 4 and 5 might have lesser representation of firms from segment 54. Consistent with this example, Figure 1(c) shows that portfolios 4 and 5 have fewer retailers from segment 54 than portfolios 2 and 3.

Thus, Figure 1 illustrates the difficulty of mitigating intersegment differences using parametric methods. If segments are not evenly allocated to portfolios, it is not possible to identify whether the results are due to inventory productivity or due to differences in industry composition of portfolios. This may be one of the reasons why our results, in contrast to the literature (e.g., Chen et al. 2005, 2007), show a positive relation between inventory productivity and subsequent stock returns.

Throughout this paper, we report monthly excess returns for equal-weighted portfolios. On July 31 in year t, we invest \$1 in each portfolio divided equally among the firms in the portfolio. We construct equal-weighted portfolios as opposed to value-weighted portfolios to avoid giving more weight to larger firms. This approach is important because our data set, being industry specific, contains a relatively small number of firms in each portfolio. In value-weighted portfolios, large firms, such as Wal-Mart Stores Inc. (ticker WMT) or Target Corporation (ticker TGT), can significantly influence the mean return on the portfolios that they are in. We calculate the excess monthly return of each portfolio by subtracting the one-month risk-free rate, which is available in the Fama–French Portfolios and Factors database in WRDS, from the portfolio's monthly return. Firms remain in a portfolio until July 31 of year $t+1$, when we reformulate portfolios.

In addition to quintile portfolios, we also form zero-cost portfolios by taking a \$1 long position in retailers that have high inventory productivity (i.e., the top 40% of the firms on the basis of a given metric) and a \$1 short position in retailers that have low inventory productivity (i.e., the bottom 40% of retailers on the basis of a given metric). We consider two quintiles each at the top and bottom to have more firms in each zero-cost portfolio.

3. Inventory Productivity and the Cross Section of Stock Returns

In §3.1, we present the returns of portfolios constructed from all inventory productivity metrics. In §3.2, we apply the Fama–French–Carhart four-factor model to test whether the excess returns from inventory productivity disappear after controlling for common risk factors. After §3.1, we focus on two inventory productivity metrics, *IT* and ΔIT, for brevity of tables. All our level-based inventory productivity metrics yield results similar to *IT*, and our change-based metrics yield results similar to ΔIT. Hence, we present results from other metrics only when they generate additional insights.

3.1. Distributional Characteristics of Portfolio Returns

Table 4 shows average monthly excess returns of equal-weighted quintile portfolios based on all inventory productivity metrics. We find that there is a positive trend in portfolio returns for *IT*, ΔIT, *AIT*, ΔAIT, *GMROI*, and $\Delta GMROI$; that is, the average excess return generally increases in the portfolio rank regardless of the metric chosen. Thus, both inventory productivity and change in inventory productivity are correlated with stock returns.

Table 4 also presents the performance of zero-cost portfolios. These results indicate that the stock returns of firms that have the highest inventory performance tend to exceed the stock returns of firms that have the lowest inventory performance. For instance, the average monthly return of the zero-cost portfolio formed on *IT* by having a short position in the first two quintiles and a long position in the last two quintiles is 0.97% ($p < 0.0001$). Note that this method of forming zero-cost hedge portfolios is not based only on firms with extremely high or low performance; instead, by investing in the top two and bottom two quintiles, we are utilizing 80% of our data set. Hence, this is a robust finding. Statistical test results on zero-cost portfolios are presented in the last row of Table 4. The statistical

Table 4 **Average Monthly Excess Returns (in Excess of the Risk-Free Rate) of Portfolios Formed Based on *IT*, *AIT*, *GMROI*, and Annual Changes in These Metrics**

Portfolio rank	*IT*	ΔIT	*AIT*	ΔAIT	*GMROI*	$\Delta GMROI$
1 (low)	0.24%	0.16%	0.18%	0.28%	0.45%	0.16%
2	0.15%	0.55%	0.25%	0.83%	0.37%	0.63%
3	0.86%	0.88%	0.83%	0.69%	0.73%	0.69%
4	1.21%	1.26%	1.07%	0.88%	0.77%	1.13%
5 (high)	1.12%	0.98%	1.24%	1.02%	1.23%	1.17%
Zero-cost	0.97%	0.76%	0.96%	0.42%	0.60%	0.77%
t-stat.	4.92	3.72	4.84	2.03	2.95	3.93

Notes. We use accounting information for the fiscal year ending from February of year $t-1$ to January of year t to form portfolios at the end of July in year t. At the end of July in year t, we rank firms in each retail segment by a chosen metric in ascending order and divide the segment into quintiles. This gives us five subsets—one for each segment—with the same quintile rank. Then we form portfolio p by aggregating the five subsets that have the quintile rank p. Zero-cost portfolios are formed by having a \$1 long (short) position in the top (bottom) two quintiles.

significance of the portfolio return is consistent across all inventory productivity metrics. The magnitude of returns may also be compared to those obtained in the literature for related metrics, but for different data sets and time periods. For example, Titman et al. (2004) obtain 0.17% monthly excess return by forming portfolios on capital expenditure for their data set, and Novy-Marx (2011) obtains 0.51% monthly excess return by forming portfolios on operating leverage.

We examine the year-to-year performance of zero-cost portfolios to analyze the persistence of the positive relation between inventory productivity and subsequent stock returns. Figure 2 presents the time series of monthly average returns of the *IT* and ΔIT zero-cost portfolios. This plot does not indicate any systematic fluctuations over time. Analyzing the time series of average monthly returns on the zero-cost strategy shows that stocks with high *IT* outperform stocks with low *IT* in 22 years over a 25-year sample period. Similarly, high ΔIT stocks outperform low ΔIT stocks in 23 years. Hence, our results are not due to a specific subperiod in our data set.

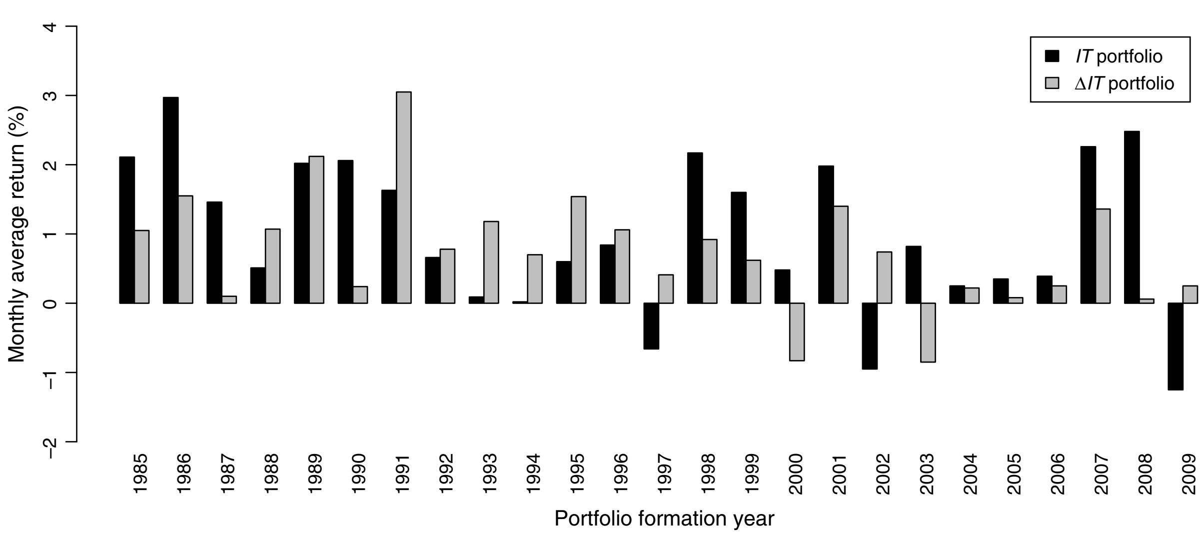
Since we use both level- and change-based metrics of inventory productivity, we find that the portfolio ranks of firms vary across these types of metrics. For example, Costco is always in the top quintile with respect to inventory turnover, but has an average rank of 2.92 based on annual change in inventory turnover. Thus, it is useful to examine whether level and change metrics interact with each other. In Table 5, we show average excess returns of cross-portfolios formed on the basis of inventory turnover and change in inventory turnover. In general, we observe that portfolios with a combination of low *IT* and low ΔIT values (i.e., the upper triangle of the return matrix presented in Table 5) have relatively low stock returns compared to portfolios that have a combination of high *IT* and high ΔIT values (i.e., the lower triangle of the return matrix). For example, the average excess return of the portfolio of firms that have the lowest *IT* and ΔIT values is −0.48% per month, whereas the average excess return of firms that have highest *IT* and ΔIT values is 0.99%. These statistics show that the level of inventory turnover and the amount of recent improvement in inventory turnover provide different types of information and are both important predictors of excess returns. Intuitively, *IT* can be interpreted as a firm's baseline inventory productivity, whereas ΔIT can be interpreted as the recent improvement (or setback) in a firm's inventory productivity.

Table 5 Average Monthly Excess Returns of Cross-Portfolios Formed on *IT* and ΔIT

Rankings based on *IT*	Rankings based on ΔIT				
	1 (low)	2	3	4	5 (high)
1 (low)	−0.48%	0.57%	0.62%	1.07%	0.14%
2	−0.32%	0.86%	0.90%	0.20%	0.46%
3	0.60%	0.26%	0.61%	1.42%	1.59%
4	0.41%	0.77%	1.51%	1.46%	1.56%
5 (high)	1.56%	1.22%	0.86%	1.54%	0.99%

We obtain qualitatively similar returns for portfolios and cross-portfolios that are constructed based on other inventory productivity metrics (i.e., *AIT* and *GMROI*). Furthermore, from the distributional characteristics of the quintile and zero-cost portfolios, we find that the standard deviation of monthly returns does not vary across portfolios. We also observe that the positive relation between inventory productivity and subsequent stock returns is not driven by outliers because the mean return is close to the median and is between the first and the third quartiles in all portfolios. This occurs because of our nonparametric portfolio formation method and use of equal-weighted portfolio returns.

Figure 2 Monthly Average Returns of Zero-Cost Portfolios Formed on *IT* and ΔIT



3.2. Risk Adjusted Portfolio Returns

Although our portfolio formation methodology controls for interindustry differences by having a separate ranking for each segment, it does not control for common risk factors. Thus, we use a standard empirical asset pricing framework that originates from Fama and French (1993) and Carhart (1997). We refer to this model as the Fama–French–Carhart four-factor model. Let RET_{pm} denote the monthly excess return for (equal-weighted) portfolio p in month m. Then, according to the Fama–French–Carhart four-factor model, the following regression explains the return of portfolio p:

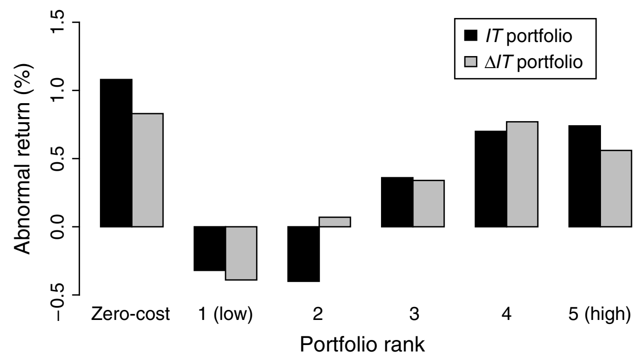
$$RET_{pm} = \alpha_p + \beta_{1p} MKTRF_m + \beta_{2p} SMB_m + \beta_{3p} HML_m + \beta_{4p} UMD_m + \xi_{pm}. \qquad (2)$$

Here, α_p is the intercept of portfolio p and is called the monthly abnormal return of portfolio p; $MKTRF_m$ is the value-weighted market return minus the risk-free rate in month m; and SMB_m, HML_m, and UMD_m are month m returns on zero-cost factor mimicking portfolios to capture size, book-to-market, and momentum effects, respectively. More specifically, *SMB* is the difference between the return on a portfolio of stocks with small market capitalization (the bottom 50%) and the return on a portfolio of stocks with large market capitalization (the top 50%). *HML* is the difference between the return on a portfolio of high book-to-market stocks (the top 30%) and the return on a portfolio of low book-to-market stocks (the bottom 30%). Last, *UMD* is the difference between the return on a portfolio of stocks with high prior year returns (the top 50%) and the return on a portfolio of stocks with low prior year returns (the bottom 50%). See Fama and French (1993), Carhart (1997), and Jegadeesh and Titman (1993) for details. The intercept α_p should not be different from zero if the common risk factors fully explain the excess return of portfolio p. If α_p differs significantly from zero, then portfolio p's return is not fully explained by the standard factors. Thus, α_p can be interpreted as the monthly abnormal return in excess of that achieved by passive investments.

Figure 3 plots the estimated abnormal returns for *IT*- and ΔIT-based quintile portfolios. There is a positive trend in α_p values for both metrics; that is, higher ranked portfolios tend to have higher alpha values. Table 6 shows the corresponding regression results. We observe that the estimated intercepts for the zero-cost portfolios based on *IT* and ΔIT are both significantly positive. More specifically, after taking the four risk factors into account, the zero-cost *IT* portfolio still earns, on average, an excess monthly return of 1.08% ($p < 0.0001$). Similarly, the zero-cost ΔIT portfolio earns an average monthly excess return of 0.83% ($p < 0.0001$).

The abnormal return of zero-cost portfolios can occur in three ways: (i) if lower ranked firms have an abnormal negative return, but higher ranked firms do not have any abnormal return; (ii) if higher ranked firms have an abnormal positive return, but lower ranked firms do not have an abnormal negative return; or (iii) if both types of firms have abnormal returns with opposite signs. In our setting, we observe that portfolios 4 and 5 have positive and statistically significant abnormal returns for both *IT* and ΔIT firms; portfolios 1 and 2 have negative abnormal returns, but with weaker statistical significance. This finding is useful for investors because it implies that they can benefit from using inventory productivity just by investing in the high inventory productivity firms without having to conduct expensive short selling of low inventory productivity firms.

Figure 3 **Abnormal Returns (i.e., the Intercepts of the Fama–French–Carhart Four-Factor Regressions) of Zero-Cost Portfolios Formed on *IT* and ΔIT**



A further look at Table 6 reveals that the coefficients of *MKTRF*, *SMB*, and *UMD* do not differ across quintile portfolios. In other words, all portfolios are similar to each other with respect to their loadings on these risk factors. However, the coefficient of *HML* for the *IT* has a downward trend in portfolio rank. This suggests a subtle point that high *IT* firms *behave* like growth firms, whereas low *IT* firms *behave* like value firms. Past research shows that value firms earn higher expected returns than growth firms—this is the well-known value premium. Interestingly, our result is the opposite because higher ranked portfolios have higher abnormal returns in our study, but have factor loadings similar to those of growth firms. Thus, the return difference between operationally efficient (high *IT*) firms and operationally inefficient (low *IT*) firms is not explained by the return difference between value firms and growth firms.

For further robustness checks, we estimate the abnormal returns of *IT* and ΔIT portfolios using additional factors and alternative models proposed in the recent finance literature. This stream of literature seeks to improve the explanatory power of the Fama–French–Carhart four-factor model by identifying additional factors that explain the cross section of stock returns. Particularly, we augment the Fama–French–Carhart

Table 6 The Fama–French–Carhart Four-Factor Regression Results for Zero-Cost and Quintile Portfolios Formed on *IT* and Δ*IT*

	IT portfolios					Δ*IT* portfolios				
Rank	α	*MKTRF*	*SMB*	*HML*	*UMD*	α	*MKTRF*	*SMB*	*HML*	*UMD*
1 (low)	−0.32%	1.04	0.76	0.59	−0.41	−0.39%	1.11	0.81	0.42	−0.40
	−1.24	17.87	9.52	6.77	−7.81	−1.32	16.52	8.77	4.15	−6.61
2	−0.40%	1.02	0.77	0.41	−0.31	0.07%	0.97	0.68	0.32	−0.32
	−1.55	17.44	9.59	4.62	−5.81	0.29	17.63	8.99	3.86	−6.55
3	0.36%	1.01	0.73	0.33	−0.34	0.34%	0.96	0.68	0.42	−0.27
	1.23	15.15	7.96	3.24	−5.62	1.41	17.42	8.94	5.07	−5.41
4	0.70%	1.08	0.65	0.29	−0.36	0.77%	1.02	0.61	0.38	−0.36
	2.67	18.21	7.96	3.26	−6.75	2.96	17.23	7.49	4.24	−6.84
5 (high)	0.74%	1.02	0.64	0.10	−0.43	0.56%	1.06	0.71	0.27	−0.50
	2.67	16.29	7.45	1.05	−7.54	1.85	15.41	7.52	2.63	−8.07
Zero-cost	1.08%	0.02	−0.13	−0.32	−0.03	0.83%	0.00	−0.08	−0.05	−0.07
	5.53	0.40	−2.05	−4.80	−0.75	3.92	−0.03	−1.24	−0.76	−1.61

Notes. Zero-cost portfolios are formed by having a $1 long (short) position in the top (bottom) two quintiles. The first row for each portfolio reports the Fama–French–Carhart regression coefficients; the second row reports the corresponding t-statistic.

four factors with short-term and long-term reversal factors, the Pastor and Stambaugh (2003) market liquidity factor, and the Frazzini and Pedersen (2014) betting-against-beta (leverage and margin constraint) factor. We also augment the market return factor with the Novy-Marx (2013) industry-adjusted value-momentum-profitability three factors. In short, our baseline results are hardly changed—the monthly alphas of zero-cost portfolios range from 0.92% to 1.11% for *IT* portfolios and from 0.79% to 0.83% for Δ*IT* portfolios, and all are statistically significant ($p < 0.0001$). For brevity, these results are untabulated in the main text, but are provided in Table A3 in the online appendix (available at https://my.vanderbilt.edu/yasinalan/research/).

We conclude this section by noting that inventory productivity explains the cross section of future stock returns after controlling for the Fama–French–Carhart common risk factors as well as the new factors proposed in the aforementioned literature.

4. Distinctiveness of Inventory Productivity

In this section, we explore whether the positive relation between inventory productivity and subsequent stock returns can be explained by other known variables that are related to a firm's inventory productivity. We consider two types of variables. First, we borrow from the accounting and finance literature, which documents several factors affecting stock returns. Of these, we identify three factors that can be connected to inventory: accruals, operating leverage, and capital expenditure. Second, we construct profitability-related metrics from the financial statements of firms. Such metrics can be correlated with inventory productivity and can also predict stock returns (Fama and French 2008, Novy-Marx 2013). Given financial data, one could construct many potential explanatory variables. Our intent is to rely on the literature for variables that predict stock returns and can logically be expected to be correlated with inventory productivity. Studying these variables is important to understand whether inventory productivity is fundamental to our findings.

4.1. Alternative Metrics

This section defines the variables of interest.

Accruals (*Acc*). Accruals are defined as the noncash component of earnings. Sloan (1996) shows a robust result that accruals are overpriced and that forming portfolios based on the accrual component of earnings generates abnormal returns. He defines accruals as the year-to-year change in current operating assets minus the change in current operating liabilities, scaled by the total assets of the firm to facilitate comparison across firms of different sizes. Note that change in inventory is a component of this formula. In fact, Thomas and Zhang (2002) show that changes in inventory explain a significant portion of abnormal stock returns from accrual-based trading strategies. Thus, we control for accruals in our study.

Sloan's (1996) work sparked a large body of literature in accounting. In fact, there are many definitions of accrual in the literature (Dechow et al. 2011), which focus on operating accrual, nonoperating accrual, or total accrual, and are derived from either balance sheet or income statement variables. We use an income statement-based definition of operating accrual, given by Hribar and Collins (2002), in the main text of this paper, because operating assets are the closest to inventory. In the online appendix, we supplement this paper with results from two alternative definitions of accruals.

Following Hribar and Collins (2002), we define

$$Acc_{it} = \frac{IBEI_{it} - (OCF_{it} - EIDO_{it})}{TA_{i,\,t-1}},$$

where *IBEI*, *OCF*, *EIDO*, and *TA* denote the income before extraordinary items, operating cash flows, extraordinary items and discontinued operations, and total assets, respectively. See Table 1 for the details of the variables. This definition is also used in a recent paper by Kesavan and Mani (2013).

Operating Leverage (*OL*). A firm's operating characteristics affect the sensitivity of its operating cash flows to economic shocks (Carlson et al. 2004 and references therein), which in turn should affect its stock returns. A commonly used operating characteristic in the accounting and finance literature is operating leverage. It measures the extent of economies of scale of a firm and is defined as the ratio of fixed costs to total costs. Novy-Marx (2011) argues that the risk of a firm should be increasing in operating leverage, and therefore higher operating leverage firms should have higher expected stock returns.

We relate inventory productivity to operating leverage. Higher operating leverage firms can be expected to have made higher investments in their supply chains, which increases inventory productivity. For example, adding centralized distribution centers to a firm will increase its fixed costs and also improve inventory turnover. Mechanically, operating leverage might create a positive relation between inventory productivity and stock returns because inventory affects a firm's asset composition (i.e., the proportion of current assets to total assets). Following one standard approach in the literature (Saunders et al. 1990), we define operating leverage for firm i in year t as

$$OL_{it} = \frac{NFA_{it}}{TA_{i,\,t-1}},$$

where *NFA* denotes the net fixed assets (Compustat item PPENT). We use this definition because fixed and variable components of costs cannot be directly observed from the income statements of firms. In this definition, fixed assets are used as a proxy for fixed costs. However, like accrual, the literature provides alternative measures of operating leverage. We describe two alternatives in the online appendix.

Abnormal Capital Expenditure (*ACE*). Capital expenditure can be predictive of stock returns and can be correlated with inventory productivity. Combining these two arguments, we see that it could potentially explain our results. The rationale for the first argument is that a firm's new investment decisions affect its future earnings by incurring additional operating costs and generating new income. Furthermore, the stock market reacts to investment decisions because these decisions can signal future demand prospects and managerial competence. Indeed, Titman et al. (2004) show that firms with a cash surplus tend to overinvest, which leads to poor stock returns in the subsequent periods.The rationale for the second argument is that capital expenditure includes investment in supply chain infrastructure, which should improve the inventory productivity of a firm. Gaur et al. (2005) show that capital intensity, a measure related to capital expenditure, is correlated with inventory turnover.

Following Titman et al. (2004), we define abnormal capital expenditure for firm i in year t, ACE_{it}, as

$$ACE_{it} = \frac{CE_{it}}{(CE_{i,\,t-1} + CE_{i,\,t-2} + CE_{i,\,t-3})/3} - 1,$$

where CE_{it} is firm i's capital expenditures (Compustat item CAPX) divided by its sales in year t.

Gross Margin (*GM*). Gross margin serves as a proxy for a firm's profitability. Although *AIT* and *GMROI* take gross margin into account, *IT* cannot directly capture profitability. Thus, it is of interest to see if there is a relationship between gross margin and subsequent stock returns. Gross margin for firm i in year t is defined as

$$GM_{it} = \frac{Sales_{it}}{COGS_{it} - LIFO_{it} + LIFO_{i,\,t-1}}.$$

Sales-to-Selling, General, and Administrative Expenses Ratio (*StSGA*). This ratio could proxy for operational efficiency because a high *StSGA* retailer can generate the same sales volume with less selling, general, and administrative (SGA) expenses, ceteris paribus. We define it as

$$StSGA_{it} = \frac{Sales_{it}}{SGA_{it}},$$

where SGA_{it} denotes firm i's SGA expenses in year t (Compustat item XSGA).

Accounts Payable-to-Inventory Ratio (*APtINV*). A firm with a high *APtINV* would rely on trade credit to finance a larger fraction of its inventory. Such a firm would have a lower working capital requirement. Moreover, according to the case study by Raman et al. (2005), such a firm may also have a higher proportion of fresh inventory, which could increase sales and profit in the future. Thus, such a firm could have potentially higher stock returns in the future due to both lower working capital and fresher inventory. We define this ratio as

$$APtINV_{it} = \frac{AP_{it}}{INVT_{it} + LIFO_{it}},$$

where AP_{it} denotes firm i's accounts payable in year t (Compustat item AP).

Sales Surprise (*SS*). Because we used *Sales Surprise* to construct *AIT*, we explicitly test the effect of *SS* in this section. We compute *SS* simply as annual sales growth rate, i.e., as $SS_{it} = Sales_{it}/Sales_{i,\,t-1}$. Using this variable helps us control for the correlation of inventory productivity with change in sales. To be more precise, one may consider sales growth and sales surprise as two different variables, with sales surprise computed

Table 7 Operational and Financial Characteristics of Quintile Portfolios

											Market cap. ($M)		Market-to-book	
IT rank	*Acc*	*OL*	*ACE*	*GM*	*StSGA*	*APtINV*	*SS*	*AIG*	*RET*1 (%)	*RET*2_12 (%)	Mean	Median	Mean	Median
1 (low)	−0.01	0.29	0.16	1.70	3.39	0.39	1.22	0.04	−1.03	8.46	787	148	1.84	1.47
2	−0.03	0.33	0.05	1.58	3.86	0.48	1.20	0.03	−0.76	8.43	1,617	343	2.14	1.59
3	−0.04	0.33	0.10	1.55	4.03	0.56	1.13	0.00	0.12	16.29	1,756	398	2.41	1.75
4	−0.04	0.34	0.04	1.49	4.60	0.72	1.14	0.00	−0.38	17.98	3,146	404	2.78	1.98
5 (high)	−0.07	0.35	0.03	1.39	5.95	1.11	1.18	−0.04	−0.14	21.34	5,777	254	3.50	2.02

Notes. We report the average values of accrual (*Acc*), operating leverage (*OL*), abnormal capital expenditure (*ACE*), gross margin (*GM*), sales-to-SGA ratio (*StSGA*), accounts payable-to-inventory ratio (*APtINV*), sales surprise (*SS*), abnormal inventory growth (*AIG*), the most recent one-month return prior to portfolio formation (*RET*1), and the past one-year cumulative return skipping the most recent one month (*RET*2_12). See §4.1 for variable definitions. We also report the mean and the median market capitalization and market-to-book ratio for each quintile portfolio to show the impact of outliers.

with respect to a forecast of sales. However, doing so would make us lose the first few years of observations for each firm and would reduce the degrees of freedom of the Fama–MacBeth regression. Moreover, the effects of sales growth and sales surprise are directionally the same—high values of these variables lead to high inventory productivity. Therefore, to keep things simple, we consider a single variable.

Abnormal Inventory Growth (*AIG*). Kesavan and Mani (2013) define abnormal inventory growth of a retailer as its annual inventory growth rate adjusted for several covariates. We use this metric as a control to distinguish our findings from those in their paper. We implement the method described in their paper over rolling five-year windows to compute the *AIG* of each firm in each year. The only difference is that we do not normalize variables to a per-store basis because of the unavailability of data on number of stores for many of the firms over the time period of our data set. We note that *AIG* is a change-based metric similar to our ΔIT and ΔAIT metrics.

4.2. Analysis and Results

Table 7 provides a summary of operational and financial characteristics of each *IT*-rank portfolio with respect to alternative metrics and control variables. Accruals, gross margin, and abnormal inventory growth are monotone decreasing in portfolio rank, whereas operating leverage, sales-to-SGA ratio, and accounts payable-to-inventory ratio are monotone increasing. Abnormal capital expenditure has a decreasing trend in portfolio rank, but is not monotone. Sales surprise has no evident trend. In Table 7, we also show summary statistics regarding commonly used control variables in the asset pricing literature. The average past one-month return has an increasing trend in portfolio rank. The average past one-year cumulative return skipping the most recent month, the market capitalization, and the market-to-book ratio are also increasing in portfolio rank. Past returns represent momentum, market capitalization represents firm size, and market-to-book ratio represents expectations regarding future growth.

We further explore the relationship between inventory productivity and these variables by computing their correlations with inventory turnover. Table 8 presents Pearson and Spearman correlation coefficients. Consistent with Table 7, inventory turnover is positively correlated with operating leverage, sales-to-SGA ratio, and accounts payable-to-inventory ratio. It is

Table 8 Pearson (Lower Triangle) and Spearman (Upper Triangle) Correlation Coefficients for Inventory Turnover (*IT*), Accrual (*Acc*), Operating Leverage (*OL*), Abnormal Capital Expenditure (*ACE*), Gross Margin (*GM*), Sales-to-SGA Ratio (*StSGA*), Accounts Payable-to-Inventory (*APtINV*), Sales Surprise (*SS*), Abnormal Inventory Growth (*AIG*), the Most Recent One-Month Return Prior to Portfolio Formation (*RET*1), the Past One-Year Cumulative Return Skipping the Most Recent One Month (*RET*2_12), Market Capitalization (*MCAP*), and Market-to-Book Ratio (*MB*)

	IT	*Acc*	*OL*	*ACE*	*GM*	*StSGA*	*APtINV*	*SS*	*AIG*	*RET*1	*RET*2_12	*MCAP*	*MB*
IT	1	−0.22	0.30	0.00	−0.50	0.48	0.70	−0.04	−0.12	0.03	0.09	0.14	0.15
Acc	−0.09	1	−0.11	0.10	0.11	−0.01	−0.22	0.34	0.35	−0.02	−0.07	−0.01	0.13
OL	0.05	−0.12	1	0.08	−0.22	0.29	0.08	−0.12	0.04	0.03	0.07	0.27	0.00
ACE	0.00	0.06	0.00	1	0.03	0.07	0.03	0.14	0.18	−0.01	−0.05	0.15	0.15
GM	−0.19	0.05	−0.21	0.04	1	−0.83	−0.34	0.06	0.02	0.00	−0.01	−0.04	0.09
StSGA	0.19	0.06	0.08	−0.02	−0.53	1	0.25	0.09	0.04	0.03	0.06	0.32	0.14
APtINV	0.85	−0.10	−0.03	0.07	−0.05	−0.01	1	0.05	−0.05	0.01	0.05	0.07	0.15
SS	−0.01	0.10	−0.08	0.01	0.03	−0.01	0.03	1	0.05	0.00	−0.01	0.12	0.44
AIG	−0.10	0.30	0.03	0.13	0.02	0.00	−0.01	0.01	1	−0.01	−0.08	0.06	0.08
*RET*1	0.02	−0.03	0.00	−0.02	−0.01	0.01	0.00	0.00	−0.03	1	0.04	0.04	0.00
*RET*2_12	0.03	−0.06	−0.01	−0.06	−0.01	0.01	−0.01	0.08	−0.10	0.00	1	0.07	−0.01
MCAP	0.01	−0.03	0.14	0.00	−0.07	0.07	0.00	−0.01	0.00	−0.01	−0.02	1	0.51
MB	0.02	−0.07	−0.04	0.02	0.11	−0.01	0.01	0.10	−0.05	−0.01	0.00	0.03	1

Table 9 **Average Monthly Excess Returns (in Excess of the Risk-Free Rate) of Portfolios Formed on Accrual (*Acc*), Operating Leverage (*OL*), Abnormal Capital Expenditure (*ACE*), Gross Margin (*GM*), Sales-to-SGA Ratio (*StSGA*), Accounts Payable-to-Inventory Ratio (*APtINV*), Sales Surprise (*SS*), and Abnormal Inventory Growth (*AIG*)**

	Acc	*OL*	*ACE*	*GM*	*StSGA*	*APtINV*	*SS*	*AIG*
1 (low)	0.51%	0.45%	0.59%	0.96%	0.64%	0.15%	0.49%	0.21%
2	0.96%	0.48%	1.12%	0.51%	0.44%	0.58%	0.83%	0.60%
3	1.09%	0.73%	0.71%	0.81%	0.53%	0.82%	0.77%	0.74%
4	0.64%	0.82%	0.86%	0.58%	0.70%	0.93%	0.94%	0.86%
5 (high)	0.41%	0.88%	0.57%	0.72%	1.02%	0.91%	0.62%	1.09%
Zero-cost	−0.23%	0.40%	−0.16%	−0.10%	0.33%	0.56%	0.13%	0.56%
t-stat.	−1.02	2.16	−0.76	−0.46	1.51	2.90	0.53	2.89

Notes. We use accounting information for the fiscal year ending from February of year $t-1$ to January of year t to form portfolios at the end of July in year t. At the end of July in year t, we rank firms in each retail segment by a chosen metric and divide the segment into quintiles. This gives us five subsets—one for each segment—with the same quintile rank. Then we form portfolio p by aggregating the five subsets that have the quintile rank p. Zero-cost portfolios are formed by having a $1 long (short) position in the top (bottom) two quintiles.

negatively correlated with accruals and gross margin. These observations imply that one or more of these variables could potentially explain at least a portion of the positive relationship between inventory productivity and stock returns. *IT* has negligible correlation with other variables.

We form quintile and zero-cost portfolios using *Acc*, *OL*, *ACE*, *GM*, *StSGA*, *APtINV*, *SS*, and *AIG*, applying our nonparametric ranking method to be consistent with our treatment of inventory productivity metrics. Table 9 reports the returns of these portfolios. Quintile portfolios formed on *Acc*, *ACE*, *GM*, and *SS* do not generate any clear return patterns. Furthermore, the zero-cost portfolios formed on these variables lead to insignificant returns. In contrast, there is a positive trend in quintile portfolio returns for *OL*, *StSGA*, *APtINV*, and *AIG*. The zero-cost portfolios formed on *OL*, *StSGA*, *APtINV*, and *AIG* generate 0.40% ($p = 0.007$), 0.33% (0.02), 0.56% (0.002), and 0.56% (0.002) average monthly returns, respectively. These returns and their statistical significance are weaker compared to the ones we obtain using inventory productivity metrics. Recall, for example, that the zero-cost portfolio formed on *IT* generates an average monthly return of 0.97% ($p < 10^{-6}$).

Although obtaining weaker returns using these variables shows the superiority of our metrics in generating positive returns, it does not rule out the possibility that a combination of alternative metrics might influence the relationship between inventory productivity and stock returns. Therefore, to account for common risk factors, alternative metrics and control variables, we conduct Fama and MacBeth (1973) cross-sectional regressions in a multivariate setting. This framework allows us to test whether inventory productivity has predictive power *after* controlling for the known drivers of stock returns. At the end of each month in our sample period (August 1985 to July 2010), we first perform cross-sectional regressions of stock returns. In these regressions, we regress individual retail stocks' excess returns in month m on their inventory productivity and other explanatory variables as of month $m-1$. To be conservative and consistent with our portfolio approach, we construct all accounting variables using the most recent fiscal year-end cutoff date of January 31. After obtaining regression coefficients for each explanatory variable in each month, we estimate time-series averages of these regression coefficients and use their time-series standard errors to compute t-statistics.

Table 10 summarizes our findings. Each column relates to a different measure of inventory productivity. In addition to using raw measures of inventory productivity, we also use each stock's quintile rankings of inventory productivity to allow nonlinearity and to mitigate the effect of extreme observations in estimating coefficients. The rank coefficients can be directly compared with our portfolio results in the presence of firm characteristic controls. We observe that, among level measures, the coefficients of *IT* rank, *AIT*, and *AIT* rank are positive and statistically significant, whereas the coefficient of raw *IT* is not. Among change measures, all four coefficients are positive, but only the coefficient of ΔIT rank is statistically significant. Those rank coefficients that are significant are also well aligned with return spreads in our portfolio analysis. For example, the *IT* rank coefficient in column 1 equals 0.22% (t-stat. $= 2.85$). All else being equal, this coefficient implies that the zero-cost portfolio formed based on *IT* rank by having a short position in the first two quintiles and a long position in the last two quintiles generates $0.22 \times (((5+4)-(2+1))/2) = 0.66\%$ average monthly return. Thus, we conclude that the predictive power of level-based inventory productivity metrics prevails despite adding all the control variables.

AIG has negative and statistically significant estimates in the first four columns. These estimates are consistent with those of Kesavan and Mani (2013) and replicate their result on our data set—firms with high abnormal inventory generate lower stock returns. Moreover, the significance of our metrics in these columns shows that our metrics have predictive power

Table 10 Fama and MacBeth (1973) Cross-Sectional Regression Results

Column no.	1	2	3	4	5	6	7	8
Variable	*IT* rank	*IT*	*AIT* rank	*AIT*	Δ*IT* rank	Δ*IT*	Δ*AIT* rank	Δ*AIT*
Inventory productivity	0.0022	−0.0001	0.0019	0.0053	0.0015	0.0253	0.0010	0.0197
	2.85	−0.32	2.56	2.06	2.31	1.93	1.51	0.87
Acc	0.0047	0.0027	0.0040	0.0037	0.0030	0.0046	0.0021	0.0039
	0.36	0.20	0.30	0.29	0.23	0.33	0.16	0.29
OL	0.0053	0.0041	0.0035	−0.0020	0.0043	0.0055	0.0059	0.0016
	0.53	0.40	0.34	−0.20	0.42	0.52	0.58	0.15
ACE	0.0061	0.0095	0.0069	0.0116	0.0094	0.0105	0.0082	0.0103
	0.68	1.03	0.75	1.28	1.02	1.10	0.89	1.05
StSGA	0.0006	0.0012	0.0007	0.0008	0.0010	0.0008	0.0009	0.0006
	1.11	2.11	1.20	1.38	1.89	1.44	1.62	1.13
GM	0.0076	0.0072	0.0043	0.0053	0.0067	0.0072	0.0065	0.0077
	1.91	1.78	1.03	1.24	1.71	1.61	1.63	1.55
APtINV	0.0004	0.0025	0.0005	−0.0020	0.0025	0.0042	0.0020	0.0040
	0.14	0.76	0.20	−0.64	0.99	1.50	0.78	1.34
SS	−0.0054	−0.0060	−0.0061	−0.0048	−0.0048	−0.0093	−0.0050	−0.0032
	−1.22	−1.33	−1.36	−1.07	−1.08	−1.59	−1.07	−0.47
AIG	−0.0199	−0.0203	−0.0194	−0.0182	−0.0117	0.0034	−0.0155	−0.0158
	−2.65	−2.69	−2.59	−2.42	−1.32	0.23	−1.84	−1.28
MB	−0.0001	0.0000	−0.0001	−0.0001	0.0000	−0.0002	0.0000	−0.0004
	−0.24	0.06	−0.18	−0.23	−0.08	−0.59	−0.05	−0.89
MCAP	0.0009	0.0008	0.0008	0.0011	0.0008	0.0010	0.0008	0.0009
	1.25	1.18	1.20	1.52	1.19	1.39	1.19	1.34
*RET*1	−0.0352	−0.0343	−0.0357	−0.0354	−0.0343	−0.0340	−0.0341	−0.0344
	−3.32	−3.23	−3.38	−3.34	−3.23	−3.12	−3.22	−3.17
*RET*2_12	0.0025	0.0027	0.0023	0.0024	0.0023	0.0020	0.0026	0.0018
	0.74	0.78	0.69	0.71	0.69	0.55	0.76	0.51

Notes. At the end of each month in our sample, we first regress individual stocks' returns on the variables shown above. After obtaining cross-sectional regression coefficients for each month, we estimate time-series averages of these coefficients and use their time-series standard errors to compute t-statistics. The first (second) row for each variable reports its time-series average (t-statistic). Each column represents a different inventory productivity metric. For instance, column 3 tests the relationship between *AIT* rank and stock returns after controlling for accrual (*Acc*), operating leverage (*OL*), abnormal capital expenditure (*ACE*), sales-to-SGA (*StSGA*), gross margin (*GM*), accounts payable to inventory (*APtINV*), sales surprise (*SS*), abnormal inventory growth (*AIG*), market to book (*MB*), size measured by market capitalization (*MCAP*), the most recent one-month return prior to portfolio formation (*RET*1), and the past one-year cumulative return skipping the most recent one month (*RET*2_12).

distinct from *AIG*. To understand this, note that *AIG* is a change-based metric, whereas our metrics in the first four columns are level-based metrics, and we saw from the cross-portfolios in Table 5 that level- and change-based metrics are both predictors of excess return. Furthermore, the last four columns of Table 10 show that when we use our change-based inventory productivity metrics, *AIG* is insignificant. None of our change-based metrics, except Δ*IT* rank, are significant either. This occurs due to multicollinearity between *AIG* and our change-based metrics, which causes the standard errors of coefficients to increase without affecting their magnitudes. Indeed, when we remove *AIG* from the Fama–MacBeth regression, all of our inventory productivity metrics, with the exception of raw *IT*, become statistically significant.

Comparing the coefficients of the inventory productivity metrics provides a further justification for our portfolio formation methodology. Recall that the raw *IT* coefficient (presented in column 2) is insignificant, whereas the *IT* rank, *AIT*, and *AIT* rank coefficients are significant. Insignificance of the raw *IT* coefficient is to be expected based on our initial claim that a direct comparison of inventory turnover values across different segments is misleading because of interindustry distributional differences in *IT*. Running Fama–MacBeth cross-sectional regressions with raw *IT* suffers from the same problem because it implicitly pools all retailers into a single sample and tests whether retailers with high inventory turnover generate higher stock returns. Running Fama–MacBeth regressions with *AIT* (column 4), on the contrary, does not face this problem because *AIT* explicitly controls for intersegment differences. See (1) for our *AIT* formula. As a consequence, *AIT* values are comparable across segments, which leads to a statistically significant coefficient for *AIT*.

In summary, this analysis shows that the cross-sectional return predictability of inventory productivity is not subsumed by market capitalization, market-to-book equity, past returns, accruals, operating leverage, abnormal capital expenditure or other productivity metrics such as gross margin, sales-to-SGA ratio, accounts payable-to-inventory ratio, sales surprise, and abnormal inventory growth. In Table A5 in the online appendix, we report additional Fama–MacBeth regression results for alternative accrual and operating leverage formulas. The results of those additional regressions are consistent with the ones we present in Table 10.

5. Potential Explanations

The relationship between inventory productivity and future stock returns suggests a potential market inefficiency that investors do not fully use public information about inventory productivity. There can be at least two potential explanations for this phenomenon. The first is an information-based explanation. Changes in inventory may be predictive of near-term sales and profits because inventory contains information about future demand, supply, write-downs, etc. If investors fail to fully incorporate this information in pricing stocks, then inventory information will be predictive of near-term stock returns and will dissipate gradually into the market. Prior literature suggests the plausibility of this explanation by showing that inventory is predictive of future sales and earnings (e.g., Kesavan et al. 2011, Kesavan and Mani 2013). The results of our Fama–MacBeth regression—that AIG and metrics of change in inventory productivity have predictive power—are also consistent with this explanation. The second is an efficiency-based explanation. Firms with higher inventory productivity may be more operationally efficient, and thus may achieve higher abnormal stock returns due to the benefits of operational efficiency.[1]

In this section, we investigate these potential explanations in a few ways—by varying the length of the time period over which portfolio returns are computed to see how fast the predictive power of inventory information dissipates, by varying the fiscal year-end cutoff date to assess the value of recency of inventory information, and by using historical inventory information for more than one year to assess the value of consistency of inventory productivity. Sections 5.1 and 5.2 report the results of longitudinal analyses compared to two different benchmarks. Here, we estimate portfolio returns for durations longer than one year with the expectation that a portfolio formed in year t should cease to have excess returns in years $t+1$ and further out as inventory information is absorbed by the market. In §5.3, we investigate the effect of fiscal year-end cutoff date in forming portfolios. In §5.4, we use past inventory information for two years when forming portfolios and analyze differences in returns among firms that transitioned up into a higher ranked portfolio from one year to the next, those that stayed in the same portfolio, and those that transitioned down into a lower ranked portfolio from one year to the next. Finally, in §5.5, we analyze the excess returns of those firms that consistently had high or low inventory productivity (i.e., belonged to portfolios 4 or 5 or portfolios 1 or 2) over three years preceding the portfolio formation date. Our findings in this section support an information-based explanation, and also show that consistently productive firms generate high excess stock returns. Thus, the predictive power of inventory metrics seems to be a combination of these two explanations.

5.1. Longitudinal Performance Benchmarked to Fama–French–Carhart Factors

To explore when inventory productivity information is incorporated into stock prices, we track IT and ΔIT portfolio returns up to five years after the portfolio formation date. More specifically, we construct quintile portfolios at the end of July in year t, but rather than liquidating them in July of year $t+1$, we hold them for four more years and liquidate them in July of year $t+5$. We calculate monthly average returns of the quintile portfolios over each year during the five-year holding horizon. For instance, the average portfolio return in the second year after portfolio formation is computed using monthly returns from August of year $t+1$ through July of year $t+2$.

Table 11 shows detailed results of our analysis, including quintile excess returns, abnormal returns (the Fama–French–Carhart four-factor alphas), and the average number of firms in each year after portfolio formation. First note that the number of firms declines as a portfolio is held for a longer time period. This is to be expected because some stocks get delisted. However, we point out that on average there are still 16–20 stocks in each quintile five years after portfolio formation, which alleviates potential concerns of imprecise inferences from undiversified portfolios. The average monthly abnormal return of the zero-cost IT portfolio decreases substantially from 1.08% (t-stat. $= 5.5$) in year 1 to 0.44% (t-stat. $= 2.2$) in year 2. The decreasing alpha mainly comes from the increased excess returns of the bottom two IT quintiles over time. Beyond year 2, we observe no significant returns or return reversals. The zero-cost ΔIT portfolio returns are similar, except that the portfolio return becomes insignificant after year 1. Overall, the rapidly disappearing returns of IT and ΔIT portfolios imply that investors do not immediately incorporate the most recent inventory productivity information into their decisions, but over time, they either learn about a firm's inventory productivity or inventory productivity starts to have an impact on other metrics.

[1] We thank the anonymous referees, who suggested distinguishing between these explanations. One referee termed the first explanation as an inventory confusion effect, and the second as market learning about inventory productivity.

Table 11 Average Monthly Excess in Excess of the Risk-Free Rate (r_e) and Abnormal (α) Returns of Quintile and Zero-Cost Portfolios Formed on IT and ΔIT up to Five Years After Portfolio Formation

	Holding periods														
	Year 1			Year 2			Year 3			Year 4			Year 5		
	r_e	α	n	r_e	α	n	r_e	α	n	r_e	α	n	r_e	α	n
IT rank															
1 (low)	0.24%	−0.32%	27	0.51%	−0.02%	24	0.76%	0.21%	22	0.76%	0.17%	20	0.70%	0.14%	19
	0.54	−1.25		1.17	−0.08		1.76	0.84		1.75	0.64		1.60	0.49	
2	0.15%	−0.40%	25	0.60%	0.04%	23	0.63%	0.15%	21	0.52%	−0.00%	20	0.82%	0.24%	19
	0.36	−1.55		1.36	0.15		1.41	0.53		1.22	−0.01		1.73	0.72	
3	0.86%	0.36%	26	0.82%	0.29%	23	0.58%	0.10%	22	0.77%	0.18%	20	0.60%	0.18%	19
	1.95	1.23		1.88	1.10		1.36	0.39		1.87	0.67		1.35	0.63	
4	1.21%	0.70%	25	0.81%	0.28%	24	0.62%	0.16%	22	0.73%	0.36%	20	0.60%	0.20%	18
	2.77	2.67		1.81	1.03		1.38	0.57		1.61	1.25		1.36	0.66	
5 (high)	1.12%	0.74%	28	1.04%	0.61%	25	0.89%	0.52%	23	0.87%	0.41%	22	0.67%	0.23%	20
	2.51	2.67		2.42	2.18		2.07	1.83		2.23	1.52		1.71	0.83	
Zero-cost	0.97%	1.08%		0.37%	0.44%		0.06%	0.16%		0.17%	0.31%		−0.12%	0.03%	
	4.92	5.53		1.82	2.16		0.28	0.75		0.73	1.37		−0.52	0.12	
ΔIT rank															
1 (low)	0.16%	−0.39%	25	0.69%	0.21%	23	0.70%	0.23%	20	0.63%	0.07%	19	0.64%	0.19%	18
	0.34	−1.33		1.42	0.69		1.53	0.79		1.45	0.23		1.45	0.67	
2	0.55%	0.07%	24	0.64%	0.11%	21	0.87%	0.47%	20	0.40%	−0.09%	18	1.00%	0.47%	17
	1.38	0.29		1.62	0.45		1.94	1.70		0.99	−0.35		2.20	1.44	
3	0.88%	0.34%	25	0.86%	0.27%	23	0.94%	0.43%	22	0.72%	0.27%	21	0.84%	0.36%	20
	2.25	1.41		2.08	1.06		2.48	1.84		1.86	1.00		2.04	1.26	
4	1.26%	0.77%	23	0.59%	0.09%	21	0.31%	−0.16%	19	0.96%	0.55%	18	0.31%	−0.11%	16
	3.02	2.96		1.38	0.35		0.66	−0.55		2.15	1.82		0.71	−0.36	
5 (high)	0.98%	0.56%	25	0.97%	0.41%	22	0.65%	0.11%	20	0.66%	0.10%	19	0.76%	0.29%	17
	2.05	1.85		2.11	1.48		1.48	0.38		1.49	0.35		1.68	0.98	
Zero-cost	0.76%	0.83%		0.12%	0.09%		−0.30%	−0.37%		0.30%	0.34%		−0.28%	−0.24%	
	3.72	3.92		0.60	0.44		−1.49	−1.80		1.40	1.55		−1.21	−0.99	

Notes. The columns r_e, α, and n report excess returns, abnormal returns, and the average number of retailers in each portfolio, respectively. The second row for each portfolio reports the t-statistic corresponding to r_e or α. See §5 for details.

5.2. Longitudinal Performance Benchmarked to Matched Portfolios

A different method to evaluate the long-term performance of our portfolios is to conduct a matched portfolio analysis, such as in Clarke et al. (2004). In this method, we take the top 40% of the firms in each year on a given inventory productivity metric and find a matched portfolio for each firm—matched via sequential sorts on market capitalization, market-to-book ratio, and stock return over the previous year to yield $14 \times 5 \times 3$ portfolios in each month. Then, the buy-and-hold abnormal return (BHAR) of each firm over one- to five-year time periods is given by the return on that firm's stock over a given time period less the equal-weighted average return on its matched portfolio over the same period. This strategy is repeated each year, and the numbers are averaged across all portfolio formation years to obtain the BHAR for our high inventory productivity portfolio. Furthermore, we compute the test statistic for the BHAR via a bootstrapping pseudoportfolio method to account for overlapping time periods. This method is identical to that in Clarke et al. (2004), and we provide a detailed description in the online appendix.

We apply this method to IT and AIT level- and change-based inventory productivity metrics. For the top 40% of the firms on IT, we find that the BHAR is 5.0% ($p < 0.01$) for one year, 9.2% ($p < 0.01$) for two years, 8.5% ($p < 0.01$) for three years, 8.1% ($p < 0.1$) for four years, and 2.7% ($p = 0.32$) for five years. For the top 40% of the firms on ΔIT, the BHAR is 4.1% ($p < 0.01$) for one year, 5.1% ($p < 0.05$) for two years, 2.7% ($p = 0.24$) for three years, 2.5% ($p = 0.31$) for four years, and 1.0% ($p = 0.42$) for five years. This analysis first confirms that IT and ΔIT are predictive of abnormal returns of retailers. Second, it supports the result from §5.1 that the information content of IT and ΔIT dissipates over time. For IT, the first-year BHAR is 5.0%, and the second-year BHAR is 4.2%, obtained by subtracting the first-year return from the cumulative return of 9.2%. Both these values are significant. The remaining three years do not yield significant buy-and-hold abnormal returns. For ΔIT, the first-year BHAR is statistically significant, and we do not observe significant buy-and-hold abnormal returns beyond the first year. Thus, these results show that the predictive power of inventory productivity disappears over time. We note that the estimation results for AIT are similar to those for IT, and ΔAIT is similar to ΔIT. See the online appendix for details.

5.3. Effect of Fiscal Year-End Cutoff Date

In §2.3, we remarked that we choose a January 31 cutoff date to capture the most recent inventory information about retailers that have a January fiscal year-end date. Given that 45% of the retailers in our data set have a January fiscal year-end, this creates a significant information advantage. What happens to our results if we use a December 31 cutoff date instead? We repeat our analysis using accounting information for fiscal years ending between January 1 and December 31 of year $t-1$ and, correspondingly, forming portfolios on June 30 in year t instead of July 31.

This change affects retailers with a January fiscal year-end date. Shifting the information cutoff and portfolio formation dates by a month forces us to use information from fiscal year $t-1$ to form portfolios in June of year $t+1$ for such firms, whereas in our original analysis, we would have formed portfolios in July of year t using the same information. Thus, rather than waiting for 6 months, we now wait for 17 months to use inventory information for these retailers. We find that this change materially affects our results. The average monthly returns of the zero-cost portfolios formed on IT and ΔIT decline to 0.63% and 0.41%, respectively. Table A4 in the online appendix depicts these estimates.

5.4. Transition of Firms into Portfolios

Table 12 illustrates how the composition of portfolios changes over time by presenting the transition matrix of firms for IT rank portfolios. It shows that the majority of the firms retain their portfolio classification each year. Firms that transition out tend to move to adjacent portfolios. For example, 53% of firms in portfolio 2 stay in the same portfolio in the following year, 18% move to portfolio 1, 21% move to portfolio 3, and 22% move to portfolio 4 or 5.

Table 12 **Transition of IT Ranks From Year t to Year $t+1$**

IT rank in year t	IT rank in year $t+1$				
	1	2	3	4	5
1 (low)	0.75	0.18	0.04	0.01	0.03
2	0.18	0.53	0.22	0.05	0.02
3	0.03	0.21	0.53	0.19	0.03
4	0.02	0.05	0.21	0.56	0.17
5 (high)	0.01	0.01	0.02	0.15	0.80

Notes. Row i and column j of this table shows the proportion of firms that have IT rank j in year $t+1$ among all firms that have IT rank i in year t. For example, 75% of firms with the lowest IT rank in year t also have the lowest IT rank in year $t+1$.

Table 13 **Average Monthly Excess Returns of Cross-Portfolios Formed on IT and the Previous Year's IT Rank**

Rankings based on IT	Previous year's IT rank		
	Lower	Same	Higher
1 (low)	—	0.36%	0.07%
2	−0.02%	0.35%	−0.14%
3	1.14%	0.94%	0.32%
4	1.30%	1.31%	0.88%
5 (high)	1.26%	1.10%	—

Using these data, we evaluate whether portfolio returns in a given year are driven by firms that remained in that portfolio from the previous year or those that entered into the portfolio that year. Table 13 divides the excess return of each portfolio into three parts—the return on firms that transitioned into that portfolio from the lower ranked portfolio(s), the return on firms that had the same portfolio rank in the previous year, and the return on firms that had higher portfolio ranks in the previous year. We find that firms that moved up from the lower portfolio(s) yield higher returns than firms that stayed in the same portfolio, which again yield higher returns than firms that moved down from the higher ranked portfolio(s). For example, for portfolio 3, the excess return on firms with a portfolio rank of 1 or 2 in the previous year is 1.14%, that on firms that had portfolio rank of 3 in the previous year is 0.94%, and that on firms that had portfolio rank of 4 or 5 in the previous year is 0.32%. These results support an information-based explanation because information about inventory productivity of firms that stayed in the same portfolio from the previous year would have disseminated into the market, whereas firms that transitioned between portfolios would carry new information that is predictive of stock returns. Thus, these results are consistent with those from longer holding periods of portfolios.

5.5. Consistency of Inventory Productivity

We test whether consistently productive retailers outperform consistently unproductive retailers by examining the returns of those retailers that stay in high or low portfolios for relatively long intervals. More specifically, we form a zero-cost portfolio by having a long position in the retailers with an IT rank of 4 or 5 in three consecutive years (i.e., years $t-2$, $t-1$, t) and a short position in the retailers with an IT rank of 1 or 2 in years $t-2$, $t-1$, and t. This portfolio generates a 0.55% (t-stat. $=2.27$) monthly average return. Thus, consistently high inventory productivity leads to high stock returns.

In summary, these analyses support an information-based explanation for the relationship between inventory productivity and subsequent stock returns by showing that using inventory productivity metrics in a timely manner generates positive returns, whereas failing to incorporate the most recent inventory information decreases portfolio returns. However, an information-based story does not fully explain the results. In particular, it does not explain why retailers with consistently high inventory productivity outperform retailers with consistently low inventory productivity, because such retailers' inventory performance would have already disseminated into the market. Whereas the information-based evidence is easy to explain on the grounds that investors do not fully incorporate this information in stock valuation, the consistent productivity-based evidence is harder to capture and explain. Possibly, higher inventory productivity firms are more risky and their superior returns are compensation for risk. This risk-based explanation is not mutually exclusive with an information-based explanation. Both types of phenomena can occur simultaneously. A risk-based explanation is plausible because actions taken by a firm to improve its inventory productivity may impact its operational risk. For instance, higher inventory productivity may enable firms to be more responsive to their marketplace, to better manage economic shocks, and to better match supply with demand. Thus, the returns of such firms could comove more with an unidentified state variable that captures future investment opportunity sets than the returns of lower inventory productivity firms. Future research may further investigate this potential explanation as well as examine how investors digest inventory information over time.

6. Conclusion

We find strong evidence of a market anomaly related to the inventory productivity of U.S. retailers. Both the level of and change in inventory productivity explain the cross section of stock returns. This relation is observed during the entire time period in our data set. Different measures of inventory productivity lead to the same qualitative results. Hence, the choice of the inventory productivity metric is immaterial as long as portfolios are formed appropriately by ranking firms within each segment. We show that this result cannot be explained within the Fama–French–Carhart framework. Furthermore, our cross-sectional regression analysis shows that the positive relationship between inventory productivity and subsequent stock returns continues to hold after controlling for several measures of firm profitability and alternative metrics known to generate abnormal returns.

One explanation for the existence of this result is a potential market inefficiency that makes investors fail to utilize inventory productivity information even after it becomes public. Our analysis in §5 supports this explanation because we show that portfolio returns depend on incorporating inventory information into stock investment decisions in a timely manner. This result suggests that managers should communicate the value of superior inventory productivity to investors more effectively.

In addition, we find that consistently high inventory productivity predicts higher stock returns. This finding illustrates the importance of lean operations for a firm's long-run success in a predictive model. It has several managerial implications. First, we show the strong information content of operational efficiency on stock market. Firms spend considerable resources on improving operational efficiency each year. Wal-Mart Stores Inc., Toyota Motor Corporation, and Dell Inc. are commonly cited and emulated for their best practices related to operational efficiency, as well as used as classroom case studies. Previous research has examined the impact of specific operational initiatives, such as quality awards and certifications and implementation of just-in-time manufacturing, on financial performance. Our work complements these studies by showing a strong link between operational efficiency and expected return. Second, we show that incentives and performance measurements that are tied to a firm's stock performance seem to be well aligned with the ones that are tied to a firm's operational performance. Last, our analysis shows the financial importance of effective inventory management, particularly in the retailing industry.

Industry-focused studies such as ours have advantages and drawbacks compared to cross-industry studies. On one hand, an industry-focused study suffers from the small sample size, which yields large standard errors in stock returns. As a result, it becomes more difficult to find a statistically significant effect. On the other hand, industry-specific data are relatively homogeneous. Since operational metrics are industry specific, e.g., long delays and cancellations for airlines (Ramdas et al. 2013), measuring operational efficiency by a single productivity metric may be questionable in a cross-industry study. Hence, there is value to industry-focused studies. It would be fruitful to generalize the notion of operational efficiency beyond the retailing industry. Thus, future work may focus on similar analyses for other industries, such as wholesaling and manufacturing.

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