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

In part A of this appendix, we test the robustness of our results on the distinctiveness of inventory productivity metrics (presented in §4 of the paper) using alternative definitions of accrual and operating leverage. In part B, we provide a detailed description of the matched portfolio analysis presented in §5 part (ii) of the paper. In part C, we present supplementary tables of results referenced in the main text.

A. Additional Robustness Checks

In this section, we first introduce alternative formulas for accruals and operating leverage. Then we discuss the results of Fama-MacBeth regressions we run using these alternative formulas.

Accrual. Dechow et al. (2011) provide an excellent summary of research on various definitions of accruals. Sloan's (1996) definition focuses on current operating assets and liabilities (operating accrual), and is computed using items from the balance sheet of a firm. According to this definition, accrual for firm i in year t is defined as

$$Acc_{it}^{[1]} = \frac{NCOA_{it} - NCOA_{i,t-1}}{TA_{i,t-1}}, \tag{1}$$

where $NCOA_{it}$ denotes net current operating assets and is computed as $NCOA_{it} = (CA_{it} - Cash_{it}) - (CL_{it} - STD_{it} - ITP_{it})$, CA denotes current assets, CL denotes current liabilities, STD denotes short term debt, ITP denotes income taxes payable, and TA denotes total assets. A second definition is given by Hribar and Collins (2002), who also focus on operating accrual, but compute it using income-statement items. This definition is used in the main text of our paper. Hribar and Collins (2002) define accruals as the difference between earnings and operating cash flows, scaled by total assets. That is,

$$Acc_{it}^{[2]} = \frac{IBEI_{it} - (OCF_{it} - EIDO_{it})}{TA_{i,t-1}}, \tag{2}$$

where $IBEI$, OCF, $EIDO$, and TA denote the income before extraordinary items, operating cash flows, extraordinary items and discontinued operations, and total assets, respectively. The values of accrual computed from the first two definitions are approximately equal to each other except in special situations such as mergers and divestments; see Hribar and Collins (2002) for discussion and analysis. A third definition, given by Richardson et al. (2005), focuses on total accruals, and measures them as the sum of changes in current net operating assets, non-current net operating assets, and net financial assets. After some algebraic manipulation shown in Dechow et al. (2011), this definition results in the formula,

$$Acc_{it}^{[3]} = \frac{(OE_{it} - OE_{i,t-1}) - (Cash_{it} - Cash_{i,t-1})}{TA_{i,t-1}}, \tag{3}$$

where OE denotes total owners' equity. Total accrual can also be computed from either the balance sheet or the income statement. The above formula gives the balance sheet-based computation.

Since operating assets are the closest to inventory, the first two formulas are closer to our study.

Operating Leverage. In the main text of the paper, we define operating leverage as

$$OL_{it}^{[1]} = \frac{NFA_{it}}{TA_{i,t-1}}, \tag{4}$$

where NFA denotes net fixed assets. One alternative measure of operating leverage is to replace net fixed assets by gross fixed assets plus capitalized leases in the formula presented in §4. Thus, operating leverage can be defined as

$$OL_{it}^{[2]} = \frac{GFA_{it} + CapL_{it}}{TA_{i,t-1}}, \tag{5}$$

where GFA and $CapL$ denote gross fixed assets and capitalized leases, respectively. As a second alternative, we measure operating leverage from the income statement as the ratio of Selling, General, and Administrative (SGA) expenses to the sum of SGA expenses and Cost of Goods Sold (COGS). That is,

$$OL_{it}^{[3]} = \frac{SGA_{it}}{SGA_{it} + COGS_{it}}. \tag{6}$$

Previous research has shown that COGS is correlated with change in sales. Thus, COGS is sometimes used as a proxy for total variable costs and SGA expenses as a proxy for fixed costs. A potential concern with this metric is that both COGS and SGA can contain fixed as well as variable expenses. For example, SGA expenses are also generally correlated with both Sales and COGS.

Table A5 reports the average inventory productivity coefficients of Fama-MacBeth regressions using alternative accrual and operating leverage formulas. Our analyses show that alternative accrual and operating leverage formulas yield consistent results. In particular, the coefficients of inventory productivity metrics are statistically indistinguishable irrespective of which definition of accrual and operating leverage we employ.

B. Detailed Description of the Matched Portfolio Analysis

Our analysis is based on the procedure described on pages 584-585 of Clarke et al. (2004) [Section IV.A of their paper]. Hereafter, we refer to Clarke et al. (2004) as CDK.

We describe the procedure for the 1-year average buy-and-hold abnormal return of the IT portfolio consisting of the top 40% of the retailers (portfolios 4 and 5), hereafter referred to as 'our IT portfolio' or 'IT portfolio'. Then we depict the empirical test distribution and discuss longer horizon buy-and-hold abnormal returns for IT, AIT, ΔIT, and ΔAIT portfolios to explain how we obtain the return values presented in §5(ii) in our paper.

Step 1: Creation of 210 possible matching portfolios. At the end of July each year from 1985 through 2009, we sort all NYSE common stocks based on their market capitalizations to determine decile breakpoints. (Decile one (ten) consists of stocks with the smallest (largest) market capitalization.) We further divide the first decile into quintiles. After determining portfolio breakpoints, we sort all NYSE, AMEX, and NASDAQ common stocks into 14 size portfolios based on their market capitalizations at the end of July.

Within each of the 14 size portfolios, we sort all firms into quintiles based on their market-to-book ratios (M/B) at the end of July. We require firms with positive book value of equity at the time of portfolio formation. (In order to compute the book value of equity at the end of July in year t, we use accounting information for fiscal years ending from February 1 of year $t-1$ to January 31 of year t. This approach makes the construction of matching portfolios consistent with our portfolio formation methodology.) The sequential sort gives us 70 size$\times$M/B portfolios.

Within each size$\times$M/B portfolio, we further sort firms into terciles based their past one-year stock returns. (Following the momentum literature, we skip the most recent month while computing past one-year stock returns.) This procedure finally gives us $14 \times 5 \times 3 = 210$ *reference* portfolios. On average, we have 22 firms in each reference portfolio. (CDK (footnote 14 on page 584) report 20 firms in each reference portfolio.)

Step 2: Matching. For each retailer i in year t, we first look up this retailer's reference portfolio rank q_{it}, which is a 3-dimensional vector where the first, the second, and the third elements denote the retailer's size, market-to-book, and momentum ranks, respectively. Then we match this retailer with all NYSE, AMEX, and NASDAQ firms with the same reference portfolio rank. Let M_{it} denote the set of all NYSE, AMEX, and NASDAQ firms with the reference portfolio rank q_{it} in year t.

Step 3: Computation of buy-and-hold return. For retailer i in year t, we first calculate the 1-year buy-and-hold return as the total stock return for this retailer from the beginning of August in year t to the end of July in year $t+1$. For a retailer delisted before the end of July in year $t+1$ (i.e., within one year after portfolio formation), the buy-and-hold return stops on the retailers delisting date. CDK use the same procedure.

For retailer i, the buy-and-hold returns for each matching firm (i.e., each firm in M_{it}) are calculated in the same manner. If a matching firm $j \in M_{it}$ is delisted before the end of July in year $t+1$ (or retailer i's delisting date, whichever is earlier), we splice the CRSP value-weighted return into the calculation from the day after the delisting date. This procedure is also described in CDK.

Let R_{it} denote retailer i's 1-year buy-and-hold return in year t. Then retailer i's 1-year buy-and-hold abnormal return (BHAR) in year t is defined as

$$\bar{R}_{it} = R_{it} - \frac{1}{|M_{it}|} \sum_{j \in M_{it}} R_{jt},$$

where $|M_{it}|$ denotes the number of matching firms for retailer i in year t.

Let P_t denote the set of retailers in our *IT* portfolio in year t. This portfolio's 1-year BHAR in year t equals

$$\frac{1}{|P_t|} \sum_{i \in P_t} \bar{R}_{it},$$

where $|P_t|$ is the number of retailers in our portfolio in year t. Note that BHAR is equal weighted, exactly as described in CDK. Finally, taking an average across all portfolio formation years (i.e., 1985,...,2009) gives the average 1-year BHAR of our retail portfolio.

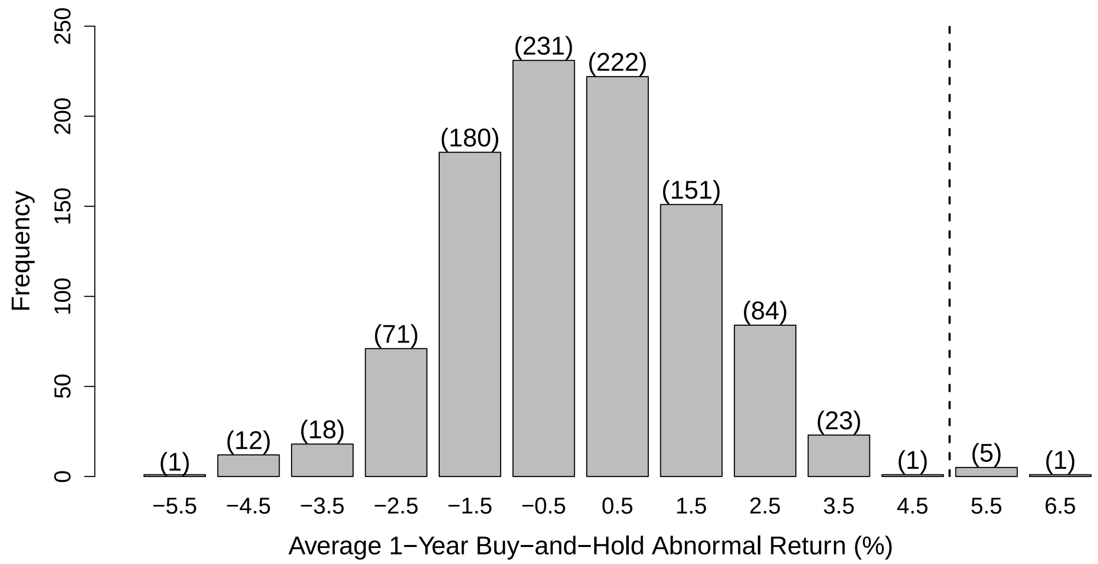
As we report in the paper, the average 1-year BHAR for the *IT* portfolio is 5.0%.

Step 4: Computation of bootstrapped standard errors for statistical inference. For each retailer i in our portfolio in year t, we randomly select (with replacement) a firm from the set M_{it} (i.e., the set of firms with the same size$\times$market-to-book$\times$momentum portfolio rank at the time of the portfolio formation). This gives us a pseudo-portfolio consisting of one matching firm for every firm in our *IT* portfolio. By construction, this pseudo-portfolio has the same number of firms as well as the same size, M/B, and momentum characteristics as our *IT* portfolio. We compute the 1-year BHAR of this pseudo-portfolio using the approach described above in step 3 for each year in 1985-2009. Then we average those numbers to obtain the average 1-year BHAR of this pseudo-portfolio.

We repeat this routine 1,000 times so that we have 1,000 average 1-year buy-and-hold abnormal returns. We test the null hypothesis that the average 1-year BHAR of our retail portfolio is significantly less than the average 1-year BHAR across the 1000 pseudo-portfolios. The p-value from the empirical distribution equals the number of pseudo-portfolios with the mean abnormal return greater than or equal to the mean abnormal return of our retail portfolio divided by 1,000.

Figure A1 presents the empirical distribution of the 1-year buy-and-hold abnormal returns of 1,000 matching portfolios. We find that only 6 of the 1,000 portfolios have higher returns than our IT portfolio's return of 5.0%. Thus, the p-value of the average one-year BHAR for the IT portfolio is $< .01$ (0.006 to be exact). These numbers are obtained after winsorizing the buy-and-hold abnormal returns at the 1% and 99% to remove the influence of outliers. (We perform winsorization to be consistent with CDK, but our results and their statistical significance hold without winsorization as well.)

Figure A1: *Empirical distribution of the 1-year buy-and-hold abnormal returns of 1,000 matching portfolios.*



Notes. The vertical dashed line shows where the average 1-year buy-and-hold abnormal return of our retail portfolio (5.0%) lies on this empirical distribution. The numbers in parentheses show the number of pseudo-portfolios in each bar.

Longer time horizons and alternative inventory productivity metrics: We perform similar analysis for longer time horizons. For a 2-year time horizon, the buy-and-hold return is computed over two years instead of one year. For example, the buy-and-hold return of a retailer in our portfolio on July 31, 2000 will be the total return from August 1, 2000 to July 31, 2002. Note that a new portfolio will be formed on July 31, 2001, whose buy-and-hold return will be computed from August 1, 2001 to July 31, 2003.

As we report in the paper, the 2-, 3-, 4-, and 5- year buy-and-hold abnormal returns for the IT portfolio are 9.2%, 8.5%, 8.1%, and 2.7%, respectively. We run a separate statistical test for each return window using the bootstrapping approach described above. We repeat our analysis by forming portfolios on ΔIT, AIT, and ΔAIT as well.

Table A1 reports the buy-and-hold abnormal returns up-to five years after portfolio formation for portfolios formed on IT, ΔIT, AIT, and ΔAIT. (In the paper, we only report the results for IT and ΔIT for brevity.) The numbers in brackets are the p-values computed via bootstrapping. For example, the ΔIT portfolio generates a 2.7% 3-year BHAR. It has a p-value of 0.243, which means that 243 out of 1,000 pseudo-portfolios outperformed the ΔIT portfolio three years after portfolio formation.

Table A1: *Buy-and-hold average abnormal returns for retail portfolios for different buy-and-hold periods benchmarked to sequential sort size $\times$ market-to-book ratio $\times$ momentum matched portfolios.*

Years after portfolio formation	IT portfolio	ΔIT portfolio	AIT portfolio	ΔAIT portfolio
1	5.00%	4.10%	4.40%	4.70%
	[0.006]	[0.008]	[0.004]	[0.008]
2	9.20%	5.10%	7.70%	2.50%
	[0.009]	[0.043]	[0.001]	[0.173]
3	8.50%	2.70%	10.20%	2.80%
	[0.007]	[0.243]	[0.005]	[0.224]
4	8.10%	2.50%	9.90%	1.60%
	[0.071]	[0.313]	[0.033]	[0.350]
5	2.70%	1.00%	8.30%	1.50%
	[0.319]	[0.418]	[0.095]	[0.384]

C. Tables

In this section, we provide the following tables:

A2. Table A2 shows segment-wise monthly excess returns of all portfolios. It also shows the monthly excess returns obtained if the entire retail industry is treated as a single pool.

A3. Table A3 tabulates monthly abnormal returns benchmarked to different factor models, as referenced in §3.2.

A4. In §3.3, we discuss the implications of choosing a December 31 fiscal year-end cutoff date and a June 30 portfolio formation date (as opposed to a January 31 cutoff date and a July 31 portfolio formation date). Table A4 presents the corresponding estimation results.

A5. Table A5 reports the average inventory productivity coefficients of the Fama-MacBeth regressions using alternative accrual and operating leverage formulas.

Table A2: *Segmentwise decomposition of average monthly excess returns (in excess of the risk-free rate) of portfolios formed on IT.*

Column #	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IT Rank	All Retailers	Our Data Set	53	54	56	57	59
1 (Low)	0.29%	0.24%	0.30%	0.11%	0.44%	0.13%	0.19%
2	0.44%	0.15%	0.35%	0.23%	0.46%	-1.29%	0.04%
3	1.01%	0.86%	0.58%	1.03%	0.90%	0.20%	1.30%
4	0.82%	1.21%	0.43%	1.00%	1.60%	0.98%	1.99%
5 (High)	1.01%	1.12%	0.60%	0.82%	1.31%	2.36%	1.31%
Zero-cost	0.51%	0.97%	0.26%	0.76%	1.04%	2.10%	1.60%
t-stat	2.04	4.92	0.57	2.66	2.95	2.55	2.75

Notes. Column 1 shows returns of IT portfolios formed by investing in the entire retail industry after grouping retailers based on two-digit SIC codes. Column 2 replicates our analysis from the main text of the paper. Columns 3, 4, 5, 6, and 7 report returns of IT portfolios formed by investing in segments 53, 54, 56, 57, and 59, respectively.

Table A3: *Monthly average abnormal returns benchmarked on various factor models, including Fama-French long-term and short-term reversal factor, Novy-Marx industry-adjusted profitability factor (Novy-Marx 2013), Pastor-Stambaugh market liquidity factor (Pastor and Stambaugh 2003), and Frazinni-Pedersen Betting Against Beta (BAB) factor (Frazzini and Pedersen 2013).*

	IT Portfolios			
Portfolio Rank	Fama-French Reversal-Factor α	Novy-Marx Profitability-Factor α	Pastor-Stambaugh Liquidity-Factor α	Frazzini-Pedersen BAB-Factor α
1 (Low)	-0.33%	0.03%	-0.33%	-0.41%
	-1.29	-0.09	-1.26	-1.59
2	-0.43%	-0.17%	-0.52%	-0.52%
	-1.70	-0.53	-2.05	-2.03
3	0.26%	0.51%	0.29%	0.25%
	0.92	1.46	1.00	0.86
4	0.64%	0.81%	0.67%	0.60%
	2.50	2.59	2.57	2.31
5 (High)	0.67%	0.89%	0.70%	0.69%
	2.47	2.73	2.52	2.49
Zero-cost	1.04%	0.92%	1.11%	1.11%
	5.26	4.20	5.62	5.59

	ΔIT Portfolios			
Portfolio Rank	Fama-French Reversal-Factor α	Novy-Marx Profitability-Factor α	Pastor-Stambaugh Liquidity-Factor α	Frazzini-Pedersen BAB-Factor α
1 (Low)	-0.45%	-0.09%	-0.45%	-0.49%
	-1.53	-0.23	-1.52	-1.65
2	0.06%	0.19%	0.05%	0.01%
	0.23	0.63	0.21	0.03
3	0.28%	0.44%	0.27%	0.25%
	1.17	1.48	1.10	1.03
4	0.71%	0.89%	0.69%	0.69%
	2.83	2.91	2.69	2.67
5 (High)	0.50%	0.79%	0.55%	0.49%
	1.66	2.19	1.78	1.60
Zero-cost	0.81%	0.79%	0.82%	0.83%
	3.82	3.41	3.88	3.90

Notes. The first row for each portfolio reports monthly average abnormal returns; the second row reports the corresponding t-statistics.

Table A4: *The impact of the portfolio formation date on portfolio returns*

	July 31		June 30	
Portfolio Rank	IT	ΔIT	IT	ΔIT
1 (Low)	0.24%	0.16%	0.29%	0.50%
2	0.15%	0.55%	0.54%	0.40%
3	0.86%	0.88%	0.81%	1.08%
4	1.21%	1.26%	0.99%	0.92%
5 (High)	1.12%	0.98%	1.07%	0.81%
Zero-cost	0.97%	0.76%	0.63%	0.41%
t-stat	4.92	3.72	3.06	1.88

Notes. The first two columns represent our original portfolio formation methodology in which we use accounting information for the fiscal year ending from February 1 of year $t-1$ to January 31 of year t to form portfolios on July 31 in year t. The third and the fourth columns represent an alternative portfolio formation methodology in which we use accounting information for the fiscal year ending from January 1 of year $t-1$ to December 31 of year $t-1$ to form portfolios on June 30 in year t.

Table A5: Fama-MacBeth cross-sectional regression results for alternative accrual and operating leverage formulas.

	Alternative Accrual and Operating Leverage Formulas				
Productivity Metric	(Acc1, OL1)	(Acc2, OL1)	(Acc3, OL1)	(Acc2, OL2)	(Acc2, OL3)
IT Rank	0.0021	0.0022	0.0022	0.0022	0.0023
	2.71	2.85	2.89	2.82	3.03
IT	-0.0002	-0.0001	-0.0001	0.0000	0.0000
	-0.50	-0.32	-0.35	0.07	-0.13
AIT Rank	0.0019	0.0019	0.0019	0.0021	0.0021
	2.49	2.56	2.60	2.68	2.82
AIT	0.0053	0.0053	0.0053	0.0066	0.0056
	2.01	2.06	1.99	2.41	2.15
ΔIT Rank	0.0015	0.0015	0.0016	0.0017	0.0015
	2.28	2.31	2.35	2.54	2.24
ΔIT	0.0253	0.0253	0.0244	0.0257	0.0221
	1.95	1.93	1.90	1.97	1.70
ΔAIT Rank	0.0012	0.0010	0.0012	0.0011	0.0011
	1.73	1.51	1.79	1.65	1.52
ΔAIT	0.0181	0.0197	0.0243	0.0285	0.0166
	0.77	0.87	1.04	1.27	0.73

Notes. The first (second) row for each inventory productivity variable reports its time-series average (t-stat) under various accrual and operating leverage definitions. Acc1, Acc2, and Acc3 correspond to equations 1, 2, and 3 presented in part A, respectively. Similarly, OL1, OL2, and OL3 correspond to equations 4, 5, and 6 presented in part A, respectively. (Acc2, OL1) column is identical to the results we present in Table 10 in the main text of the paper.

References

Clarke, J., C. Dunbar, K. Kahle. 2004. The long-run performance of secondary equity issues: A test of the windows of opportunity hypothesis. *The Journal of Business* **77**(3) 575–603.

Dechow, P.M., N.V. Khimich, R.G. Sloan. 2011. The accrual anomaly. *The Handbook of Equity Market Anomalies: Translating Market Inefficiencies Into Effective Investment Strategies* **2** 23.

Frazzini, A., L.H. Pedersen. 2013. Betting against beta. *forthcoming in Journal of Financial Economics* .

Hribar, P., D.W. Collins. 2002. Errors in estimating accruals: Implications for empirical research. *Journal of Accounting Research* **40**(1) 105–134.

Novy-Marx, R. 2013. The other side of value: The gross profitability premium. *Journal of Financial Economics* **108**(1) 1–28.

Pastor, L., R.F. Stambaugh. 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* **111**(3) 642–685.

Richardson, S.A., R.G. Sloan, M.T. Soliman, I. Tuna. 2005. Accrual reliability, earnings persistence and stock prices. *Journal of Accounting and Economics* **39**(3) 437–485.

Sloan, R.G. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting Review* 289–315.