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# Interrelationships in Inventory Turnover Performance Between Supplier and Customer Firms

**Joseph J. Henry[1], Peter Christensen[2], James C. Brau[3]**

**Abstract:** *Using inventory turnover to measure the efficiency of corporate inventory management, we perform econometric analyses to verify whether the inventory efficiency of a firm's supply chain partners is a statistically significant driver of the firm's own inventory efficiency. We test two mutually exclusive hypotheses. First, suppliers hold inventory on behalf of customers, effectively displacing inventory up the supply chain and resulting in a negative correlation between supplier and customer inventory turnover. Alternatively, inventory efficiency is integrated along the supply chain, resulting in a positive correlation between supplier and customer inventory turnover. Our bivariate and multivariate analyses of both firm- and industry-level data support the "integration" hypothesis of higher inventory efficiency along the supply chain. Our findings highlight the importance of expanding the research and practice of working capital management beyond the firm-level.*

**Keywords:** Inventory Turnover, Supply Chain Efficiency, Inventory Factor Model

**JEL:** L140, M41, C51

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## 1. Introduction

Inventory turnover (hereinafter IT), or the cost of goods sold divided by the firm's average inventory level, is a common measure of inventory productivity and firm performance (Brau, Fawcett, & Morgan, 2007; Chen, Frank, & Wu, 2007, Cho, Ke, & Han, 2019). For the first time in more than 50 years, inventory practices in automotive supply chains are transforming, resulting in dramatic shifts in IT across all echelons of the supply chain (McLain, 2021). Similar changes to IT are occurring throughout other industries such as manufacturing (Kwak, 2019) and retail (Kesavan, Kushwaha, & Gaur, 2016). The last time such transformations were observed in managing IT can be linked to the invention of lean inventory practices, which were heralded as the "most important productivity enhancing management innovation since the turn of the century" (Schonberger, 1987).

Gaur, Fisher, and Raman (2005, hereafter GFR) develop a firm-level model that estimates how much inventory a firm should hold using "gross margin (*GM*), capital intensity (*CI*), and sales surprise (*SS;* the ratio of actual sales to expected sales per year)" (p. 181). The GFR model allows for better managerial decision making and performance analysis at the firm-level (Gaur et al., 2005; Rajagopalan, 2013), however it omits the ripple effect supply chain partners have on each other (Sterman, 1989; Ivanov, Sokolov, & Dolgui, 2014;

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[1] Asst. Prof., Rowan University, Rohrer College of Business, Accounting & Finance Department, Glassboro, NJ USA, henryj@rowan.edu
[2] Pre-PhD Student, Brigham Young University, Marriott School of Business, School of Accountancy, Provo, UT, USA, peterlc@byu.edu
[3] Prof., Brigham Young University, Marriott School of Business, Department of Finance, Provo, UT, USA, jbrau@byu.edu (Corresponding Author)

Birkie & Trucco, 2020; Li, Chen, Collignon, & Ivanov, 2021). These ripple effects are evident in the supply chain of automaker Toyota. Responding to recent difficulties in acquiring parts, "Toyota asked its suppliers to stockpile parts, the antithesis of just in time. The on-hand inventory held by Toyota's largest supplier, Denso Corp., rose to around 50 days' worth of supply in the year ended March 2020, up from 38 days in 2011, according to its financial filings" (McLean, 2021). Post-disruption changes to inventory management practices such as these demonstrate how the partners in a supply chain are not independent actors and changes to IT in one firm can impact the supply chain as a whole.

Despite the vast amount of research on inventory practices within various industries (Eroglu & Hofer, 2011; Rajagopalan, 2013; Hançerlioğulları, Şen, & Aktunç, 2016; Chuang, Oliva, & Heim, 2019), there has been little focus on the spillover effects of inventory management across supply chain partners (Barker, Hofer, Hoberg, & Eroglu, 2022). Therefore, the goal of this research is to provide further insight into the positive or negative externalities associated with supply chain partners' IT along the supply chain. Specifically, we test two competing hypotheses to identify whether there is a displacement of inventory across supply chain partners (i.e., partners of a firm with high IT hold greater inventory; "Displacement Hypothesis") or an integration of high inventory efficiency across supply chain partners (i.e., partners can simultaneously have high IT; "Integration Hypothesis").

We build upon the GFR model of inventory turnover (IT) to test our competing hypotheses. Specifically, we add to the GFR model an explanatory variable representing the average IT of a firm's significant customers. A positive and statistically significant relationship between a firm's IT and the average IT of its significant customers would support the Integration Hypothesis, while a negative relationship would support the Displacement Hypothesis. Because our firm-level analysis is limited to publicly traded firms that must disclose significant customers, we estimate a similar model on industry-level data. These industry-level data contain activity from all firms, both publicly traded and privately held, and allow us to observe the IT of up-chain supplier industries in addition to the down-chain IT of customer industries.

The analysis of a large sample of publicly traded manufacturing firms spanning from 1977 to 2019 reveal that IT significantly impacts supply chain partners' inventories. The results provide further insights into the specific effects of IT of firms on neighboring supply chain partners' inventories. Our findings contribute to inventory theory through broadening the boundaries beyond one organization. We also contribute to theory by extending the GFR model to include supply chain partner firm effects, thus providing another tool for researchers to evaluate inventory practices.

The implications of our study are applicable to both managers and policy makers. Our study provides a method to help practitioners model their inventory and implies that synergies can be gained up and down the supply chain as firms become more efficient. Policy makers can use the findings while considering regulations of inventory practices at the firm and industry levels (Rajagopalan & Malhotra, 2001).

The remainder of this paper begins with a literature review and hypothesis development section. We then discuss the empirical methods and strategy, followed by the empirical results. The final section discusses applications of our findings and concludes.

## 2. Literature Review and Hypotheses

### 2.1. Relevant Literature

Past literature offers mixed views regarding the impact of IT on supply chain partners' IT. The literature streams may be split into two overarching categories: 1) high IT can increase efficiency throughout the supply chain, and 2) high IT can cause inefficiency throughout the supply chain.

The first stream of literature suggests that high IT may have positive effects throughout the supply chain through adoption of inventory efficiency standards (Chen & Sarker, 2010; Eroglu & Hofer, 2011; Barker et al., 2022) and integration between firms (Rungtusanatham, Salvador, Forza, & Choi TY, 2003; Lee, Kwon & Severance, 2007). Firms with a higher inventory turnover do not have to lower their prices as dramatically as other firms to deal with negative shocks to demand; they are able to change their purchasing behavior to take some of the burden off their gross margin, making the entire supply chain more responsive to demand (Kesavan, Kushwaha, & Gaur, 2016). When a firm decides to increase its IT rate, it can carefully select and/or put pressure on its suppliers to change product and shipping offerings (Luo, Wu, Rosenberg, & Barnes, 2009; Wu & Barnes, 2011), and suppliers often accommodate the buyers' demands (Robinson & Timmerman, 1987). The mathematical model developed by Omar, Sarker, and Othman (2013) provides a method by which both buyer and supplier can maximize the total efficiency of the supply chain as long as the firms share all cost information (see also Kros, Kirchoff, & Falasca, 2019). However, literature suggests open communication does not always lead to a net change in supply chain efficiency (Robinson & Timmerman, 1987).

The second strand of literature addresses the possible negative externalities associated with high IT, where inventory is pushed off from one firm to a supply chain partner. According to Davis (1993), a common sequence of events starts with a firm reducing inventory to cut costs, which has a side effect of harming customer service. To compensate, "heightened pressure is put on suppliers (which might be the [production] line running just across the aisle) to improve their performance. If this can be achieved only by increasing the supplier's own inventory, the downstream operation's inventory reductions might be completely canceled out" (p. 36). Similarly, Fazel (1997) and Newman (1988) indicate that suppliers to firms with high IT often must produce and store large batches despite delivering small quantities. Thus, supply chain researchers have long postulated that firms with high IT might cause inefficiency in their supply chain neighbors, but few papers have attempted to quantify this relationship (Barker et al., 2022). To the best of our knowledge, we are the first to study the possible negative effects of high IT on supply chain partners. In the following section, we develop competing hypotheses rooted in the literature and practice.

### 2.2. Hypotheses

The literature leads to two competing hypotheses. First, the Displacement Hypothesis formulates the notion that when one member of the supply chain operates with a higher IT, their up-stream suppliers may need to increase their inventory stores (i.e., decrease IT) to satisfy the demands of their down-stream buyer. Mathematically, the prediction is $\rho(IT_C , IT_S) < 0$, where ρ is the correlation coefficient between the IT of the customer ($IT_C$) and the supplier ($IT_S$). Under this hypothesis, the effect of a firm increasing its IT on its suppliers is negative. Our proposed explanation, should this hypothesis prove to fit the data, is that the suppliers of a firm are pressured by the firm into keeping larger stores of inventory to account for either a shorter lead time on orders or the unpredictability of the sizes of such orders. We know that such an arrangement does occur in some cases (see Graban, 2021), but these may or may not be the norm.

The Displacement Hypothesis challenges the view that IT improves net supply chain efficiency by postulating that an increase in IT of one firm is often counterbalanced by a decrease in IT of other firms in the supply chain. As anecdotal evidence for the Displacement Hypotheses in practice, Dell Technologies Inc.'s JIT was deemed "fake" because it "could pressure suppliers into keeping WEEKS of inventory in a nearby 'supplier logistics center'" for the fulfillment of JIT orders (Graban, 2021). Similarly, "Toyota asked its suppliers to stockpile parts, the antithesis of just in time," such that the "on-hand inventory held by Toyota's largest supplier, Denso Corp., rose" by 32% (McClain, 2021).

Second, the Integration Hypothesis argues that the efficiencies of higher IT can be shared along the supply chain. An example is as Romano (2003) argues, "Thus, SCM [supply chain management] can help firms to improve the competitiveness of the supply network, which should translate into … reduction in supply network inventories…." (p. 119). In some cases, supply chain neighbors can assist with supply chain finance solutions through inventory management (Ronchini, Moretto, & Caniato, 2021). Mathematically, the prediction is that $\rho(IT_C , IT_S) > 0$ where ρ is the correlation coefficient between the IT of the customer ($IT_C$) and the supplier ($IT_S$). Under this hypothesis, the effect of a firm having higher IT on its suppliers is positive. Our proposed explanation, should this hypothesis prove to fit the data, is that a higher IT may lead to an increase in communication with the firm's suppliers, allowing the suppliers to become more efficient in step with the firm (Shockley & Fetter, 2015). The suppliers may even increase their IT, creating a ripple effect that makes its way up and down the supply chain leading to increased efficiency at every level. Additionally, firms that have higher IT may work harder on their forecasting to predict inventory needs and convey that information to their suppliers (Fawcett, Osterhaus, Magnan, Brau, & McCarter, 2007; Aviv, 2022). The increased efficiency from more accurate forecasting could induce efficiency along the supply chain (Brau, Aloysius, & Siemsen, 2023). Anecdotal evidence of the Integration Hypotheses in practice include: “Ford set up the Ford Production System to match the one named after Toyota. Top suppliers did too, for their own suppliers lower down the pyramid” (McClain, 2021) and “...and JIT, which originated at Toyota, had spread to many of the auto maker's 220 suppliers, and beyond” (Walters, 1984).

## 3. Data

### 3.1. Firm-Level Data

We utilize both firm- and industry-level data in our analysis. Our firm-level data allow us to identify specific pairs of publicly traded supplier firms and their major customer firms that are also publicly traded. The industry-level data allow us to measure the activity of both privately held and publicly traded firms. In addition, we can observe important up-chain supplier industries and important down-chain customer industries, which is not possible using available firm-level data. Firm- and industry-level data are both available for manufacturing-related industries.

Like Eroglu and Hofer (2011), we focus our analysis on manufacturing industries. First, manufacturing firms exhibit substantial inventory usage and capacity for value-adding inventory efficiency improvements. Second, firm- and industry-level data are both available only for manufacturing-related industries. Consistent with both Eroglu and Hofer (2011) and the practices of the U.S. federal government, we define industries according to the North American Industry Classification System (NAICS). NAICS industries are defined based on production methods, which is an important characteristic when studying inventory management. In contrast, the Standard Industrial Classification (SIC) system is categorized by output. Manufacturing-related NAICS industries begin with the first two digits 31, 32, or 33.

Our firm-level sample (1977-2019) includes annual data for publicly traded firms from the Compustat North America and Compustat Historical Segment databases, available through Wharton Research Data Services (WRDS). To be included in our sample, firms must have available Compustat annual financial data, including share price, total assets, sales, total inventory, and 5-digit NAICS industry code. In addition, we require information on each firm’s major customer firms, which we describe next.

We identify down-chain customer firms based on the annual disclosure by suppliers of major customers that account for at least 10% of sales (via the Compustat Segment database). In other words, the supplier firm publicly identifies the customer firms that are important to its business. This disclosure is made to satisfy certain U.S. accounting standards, specifically Statement of Financial Accounting Standards No. 14 (SFAS 14), SFAS 30, and SFAS 131. (See Footnote 6 of Patatoukas (2012) for additional details.) Although some firms disclose additional minor customers, we enforce the 10% minimum sales threshold. In addition, we limit the sample to supplier-customer links where the major customer belongs to NAICS sectors with high inventory-to-assets ratios (i.e., Retail, Wholesale, Construction, Manufacturing, or Agriculture). Other customer firms belonging to industries with low inventory-to-assets ratios are less likely to receive physical inventory from our sample of manufacturing suppliers. Since there is no equivalent disclosure of major suppliers, our firm-level analysis is limited to the inventory efficiency of up-chain suppliers in relationship to their major down-chain partners. (From the perspective of the customers linked to suppliers through the supplier disclosure, identified suppliers are generally very small and unlikely to be critical to the customer.)

Table 1 reports the classification of data into the manufacturing segments we use via the North American Industry Classification System (NAICS) code system. The column *Firm-year* reports the sum of annual observations across all firms by industry (N=13,388 in total). For example, if we were to observe financial and supply chain data for Tyson Foods in all years from 1979 to 2019 (43 years), then this firm would account for 43 of the 505 observable firm-years in NAICS subsector 311: Food Manufacturing. Computer, Electronic Product Manufacturing is the largest subsample with 4,815 firm-year observations (36% of the total firm-years). The next three closest industries are Chemical (1,802, 14%), Transportation Equipment

(1,429, 11%), and Machinery (1,115, 8%). The three lowest populated industries are Textile Product Mills (45), Petroleum and Coal (41), and Wood Products (0), each of which make up about half of a percent or less of the total. *Prominent firms* are provided as examples for each subsector and are selected by revenue and number of observations.

**Table 1.** Classification of Data into Manufacturing Segments Using NAICS Codes

| NAICS | Segment description | Firm-years | Prominent firms |
|---|---|---|---|
| 311 | Food Mfg. | 505 | Tyson Foods, Kraft Heinz, General Mills |
| 312 | Beverage and Tobacco Product Mfg. | 87 | Pepsico, Altria Group, Dr. Pepper Snapple Group |
| 313 | Textile Mfg. | 121 | Springs Industries, Polymer Group Inc., Fieldcrest Cannon |
| 314 | Textile Product Mills | 45 | Collins and Aikman Corp., Westpoint Stevens Inc., Pillowtex Corp. |
| 315 | Apparel Mfg. | 558 | Ralph Lauren Corp., Hanesbrands Inc., Jones Group |
| 316 | Leather and Allied Product Mfg. | 157 | Nike, Reebok International, Nine West Group |
| 321 | Wood Product Mfg. | 0 | UFP Industries, Masonite International, Louisiana-Pacific |
| 322 | Paper Mfg. | 121 | Kimberly-Clark, Sonoco Products Co., MeadWestvaco |
| 323 | Printing, Related Support Activities | 71 | ACCO Brands, Multi-Color Corp., Devon Group |
| 324 | Petroleum and Coal Products Mfg. | 41 | Valero Energy, Nustar Energy, Tosco Corp. |
| 325 | Chemical Mfg. | 1,802 | Procter and Gamble, Roche Holding Ag, Pfizer |
| 326 | Plastic and Rubber Products Mfg. | 408 | Jarden Corp., Armstrong Holdings, Pactiv Corp. |
| 327 | Nonmetallic Mineral Product Mfg. | 66 | USG Corp., Anchor Glass Container Corp., Harvard Industries |
| 331 | Primary Metal Mfg. | 191 | AK Steel Holding Corp., LTV Corp., Reynolds Metals Co., Armco Inc. |
| 332 | Fabricated Metal Product Mfg. | 444 | Gillette, Masco Corp., Ball Corp. |
| 333 | Machinery Mfg. | 1,115 | Canon Inc., Stanley Black and Decker Inc., Cummins Inc. |
| 334 | Computer, Electronic Product Mfg. | 4,815 | Intel Corp., Sharp, Broadcom |
| 335 | Electric Lighting Equipment Mfg. | 426 | Nidec Corp., Maytag, Eaton Corp. |
| 336 | Transportation Equipment Mfg. | 1,429 | Aptiv Plc, Johnson Controls, Magna International |
| 337 | Furniture Mfg. | 90 | Masco Corp., HNI Corp., Bassett Furniture |
| 339 | Miscellaneous Mfg. | 896 | Newell Brands Inc., Mattel Inc., Hasbro Inc. |

Given our multi-decade sample, we evaluate the potential impact of changes in accounting rules – specifically U.S. Generally Accepted Accounting Principles (GAAP) – using the timeline of major GAAP changes compiled by Zeff (2005). The last major changes in inventory accounting were the introduction of Last In, First Out (LIFO) and average cost inventory accounting in the early 1950s, years before we draw our sample. During the 1990s and early 2000s, accounting standard setters were primarily focused on executive non-cash compensation, securities/derivatives, impairments, and consolidations/goodwill, none of which we expect to materially affect our data.

### 3.2. Manufacturing Industry Data

We use industry-level financial data that are jointly produced by the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center for Economic Studies (CES), i.e., the NBER-CES Manufacturing Industry Database. These data include the activities of private and publicly traded firms in manufacturing industries from 1977 to 2016. Using North American Industry Classification System (NAICS) codes, we aggregate the data into industry sectors by 3-digit NAICS code to match our sector-level supply chain data (described below). We use the total net selling value of products shipped (VSHIP) as a proxy for sales, the total cost of materials (MATCOST) as a proxy for the cost of goods sold (COGS), end-of-year inventories (INVENT) as our measure of inventory, and the total real capital stock (CAP) as a proxy for gross fixed assets.

We identify supply chain links at the industry using the annual Use Tables from the U.S. Bureau of Economic Analysis (BEA), which report the industry outputs ("commodities") used as intermediate inputs by each industry to produce its own output. Specifically, we use the annual BEA Use Tables/Before Redefinitions/Producer Value for 1963-1996 (65 industries) and 1997-2016 (71 industries), mapped to 3-digit NAICS industries. We assume that all commodities are produced by the primary industry associated with that commodity (e.g., the Primary Metals industry produces Primary Metals commodities).

To ensure adequate supply chain visibility for our tests, we require that at least 10% of each industry subsector's input flows from other subsectors, and that at least 10% of output flows to other subsectors. We apply these filters using the BEA's Total Intermediate Use variable for each commodity (i.e., variable T001), as well as Total Intermediate Output for each industry (i.e., variable T005). These filters approximate the threshold for the disclosure of firm-level customers and helps ensure meaningful supply chain visibility in our sample.

With the NBER-CES and BEA data combined, we observe the aggregate inventory practices of related manufacturing industries, both down-chain *and* up-chain. Thus, in addition to including private firms, the industry sample provides some visibility of up-chain inventory practices.

## 4. Empirical Methods

As in GFR, our outcome of interest is inventory turnover (IT), a popular measure of inventory efficiency equal to the ratio of a firm's cost of goods sold (COGS) and average inventory level. We reproduce the GFR model of IT in Equation 1, with subscripts removed for simplicity, and the variable mnemonics for the Compustat database in **bold**:

$$Ln(IT) = F + c + \beta_1 Ln(GM) + \beta_2 Ln(CI) + \beta_3 Ln(SS) + e \quad (1)$$

Where,

*IT* is inventory turnover, or COGS divided by average year-end inventory for years *t* and *t-1* (**cogs** / $\overline{\mathbf{invt}}$),

*F* is a set of indicators, one for each firm *i* (i.e., a time-invariant, firm-fixed effect),

*c* is a set of indicators, one for each fiscal year *t* in the sample (i.e., a year-fixed effect),

$\beta_1$ through $\beta_3$ are the respective coefficients,

*GM* is gross margin, or sales net of the cost of goods sold (COGS), divided by sales ((**sale**-**cogs**)/**sale**),

*CI* is capital intensity, or the average of year-end gross property, plant, & equipment ($\overline{\mathbf{ppegt}}$) divided by the sum of average inventory and average property, plant, & equipment ($\overline{\mathbf{ppegt}}$/($\overline{\mathbf{invt}}$+$\overline{\mathbf{ppegt}}$)),

*SS* is the annual sales surprise, or the ratio of actual annual sales to forecasted sales (**sale**/Forecasted Sales), where *Forecasted Sales* is estimated using Holt's method of linear exponential smoothing of prior annual sales data for the three most recent years at minimum and up to 10 years maximum, and

*e* is the error term for firm *i* in fiscal year *t*.

In Equation 1, the firm-fixed effects adjust for time-invariant differences between firms that are not otherwise accounted for in the regression model. Similarly, the year-fixed effects adjust for differences across fiscal years that are common to all firms (e.g., changing macroeconomic conditions). Gross margin (GM) is included as a predictor of IT based in part on surveyed managers reporting a tradeoff between inventory turns and gross margin. Capital intensity (CI) proxies for the use of logistics management technology and similar investments that improve inventory efficiency. Sales surprise (SS) is included to capture the impact of unexpectedly high or low sales on resulting inventory levels.

We test the importance of IT down the supply chain by adding a fourth factor to the GFR model of IT. Our augmented GFR model with customer IT is as follows:

$$Ln(IT) = IY + \llbracket \beta\_1\ Ln(Cust.IT) + \beta \rrbracket\ \_2\ Ln(GM) + \beta\_3\ Ln(CI) + \beta\_4\ Ln(SS) + \qquad (2)$$

Where,

$Cust.IT$ is the average inventory turnover, weighted by the fraction of disclosed sales to major customers that account for 10% or more of supplier sales, and

$IY$ is a set of indicators for each combination of industry and fiscal year (i.e., an industry-by-year fixed effect). We define industries using 5-digit North American Industry Classification System (NAICS) codes.

Our primary variable of interest is the natural logarithm of average customer IT ($Ln(Cust.IT)$), which allows us to test our competing hypotheses of inventory displacement or the integration of inventory efficiency between customers and an up-chain supplier, on average. Note that $Cust.IT$ is based on a supplier firm's own public disclosure of who its major customers are. Given our need for variation in average customer IT in order to estimate coefficient $\beta_1$, we use a set of industry-by-year indicators (*IY*) in Equation 2 instead of separate sets of firm and year indicators (*F*, *c*). Supply chain partners are much more likely to vary across firms than over time within one firm. The industry-by-year indicators ensure that we are comparing IT across firms within the same industry *and* the same fiscal year, ruling out many potentially confounding variables that are not otherwise accounted for in our empirical model. In a further extension of this model, we also include measures of the average sales ratio between the major customer and the supplier firm (*RelSize*), as well as an average measure of sales surprise (SS) among the firm's major customers.

In our industry-level analysis, greater data availability allows us to include the average IT of both customer *and* supplier industries in an extended version of Equation 2. At the industry level, *Cust. IT* now represents the weighted average IT of the industry's important customers in aggregate in our industry-level tests. *Supp. IT* is interpreted similarly as the weighted average inventory efficiency of the industry's suppliers in aggregate. *GM*, *CI*, and *SS* are calculated similarly using the industry-level proxies for sales, COGS, inventory, and gross fixed assets described in Section 3.2.

Given the aggregated nature of the industry-level data, there are likely to be time-invariant, unobservable differences across industry groups. In addition, variation in customer and supplier IT is more likely over time at the industry level. For these reasons, we use separate industry (by 3-digit NAICS code) and calendar year fixed effects instead of the industry-by-year fixed effect in Equation 2.

Table 2 summarizes our annual observations of publicly traded firms in the manufacturing sector (NAICS sector 31-33) from 1977 to 2019, where observations must have available annual financial data for the firm's customer(s) (N=13,388). If the supplier firm has multiple major customer firms in a given year, then we take the weighted average IT or sales surprise (SS) according to the fraction of disclosed purchases from the supplier among all major customers. The average firm has sales of $1.9 billion in 2020-adjusted dollars.

Average IT is 5.4, suggesting that the average manufacturing firm in our sample sells and replaces ("turns over") its inventory approximately 5.4 times during the fiscal year. The average customer IT is even faster at 7.1. In contrast, the average sales surprise of supplier (1.071) and customer firms (0.945) is similar.

**Table 2.** Summary Statistics Firm-Year Level

| Variable | Mean | Std Dev | 25th Pctl | 50th Pctl | 75th Pctl |
|---|---|---|---|---|---|
| Sales (2020 USD, Millions) | 1,895 | 6,396 | 58 | 224 | 937 |
| Inventory turnover (IT) | 5.427 | 5.311 | 2.673 | 4.015 | 6.235 |
| Gross margin (GM) | 0.374 | 0.189 | 0.231 | 0.340 | 0.494 |
| Capital intensity (CI) | 0.676 | 0.189 | 0.556 | 0.707 | 0.826 |
| Sales surprise (SS) | 1.071 | 0.470 | 0.862 | 0.995 | 1.147 |
| Customer IT | 7.123 | 6.003 | 3.580 | 5.754 | 8.856 |
| Customer SS | 0.945 | 0.258 | 0.888 | 0.989 | 1.044 |
| Supplier-to-customer size (RelSize) | 0.050 | 0.121 | 0.002 | 0.009 | 0.039 |

Table 3 reports the summary statistics for the 18 manufacturing industries in our sample, with annual observations from 1977 to 2016. At the industry level we can identify important up-chain supplier industries and down-chain customer industries. In the event of multiple major customer industries, we take the weighted average IT and sales surprise (SS) according to the fraction of the supplier industry's primary output that is consumed by the customer industry. We take a similar weighted average of multiple supplier industries based on each customer subsector's relative consumption of the primary output of each supplying subsector. In Table 3, the mean industry size is $215 billion in 2016-adjusted dollars, with somewhat lower average IT than at the firm-level (4.4 versus 5.4 turns). In addition, an industry's average IT is lower than both its' customer industries (5.5) and supplier industries (4.9). In general, the variability across observations is much lower for the industry-level sample compared to the firm-level sample in Table 2, as expected. For example, the ratio of the standard deviation to the mean (i.e., the coefficient of variation) is greater than 3 in our firm-level sample (Table 2), but less than one at the industry level (Table 3).

**Table 3.** Summary Statistics Industry-Year Level

| Variable | Mean | Std Dev | 25th Pctl | 50th Pctl | 75th Pctl |
|---|---|---|---|---|---|
| Sales (2016 USD, Millions) | 215,049 | 164,951 | 99,582 | 160,325 | 277,547 |
| Inventory turnover (IT) | 4.421 | 2.068 | 3.291 | 4.171 | 5.001 |
| Gross margin (GM) | 0.485 | 0.075 | 0.422 | 0.503 | 0.538 |
| Capital intensity (CI) | 0.795 | 0.074 | 0.734 | 0.800 | 0.855 |
| Sales surprise (SS) | 1.000 | 0.075 | 0.970 | 1.003 | 1.034 |
| Customer IT | 5.546 | 1.581 | 4.439 | 5.368 | 6.341 |
| Customer SS | 1.002 | 0.052 | 0.980 | 1.008 | 1.034 |
| Supplier IT | 4.945 | 0.852 | 4.354 | 4.851 | 5.302 |
| Supplier SS | 0.996 | 0.050 | 0.979 | 1.006 | 1.023 |

## 5. Empirical Results

### 5.1. Pairwise Correlations

We report pairwise correlations in Table 4, with Pearson correlation coefficients reported above the diagonal and Spearman rank correlations below. These correlations are for pairs of the natural logarithm of sales, inventory turnover (*IT*), gross margin (*GM*), capital intensity (*CI*), sales surprise (*SS*), customer inventory turnover (*Cust. IT*), and customer sales surprise (*Cust. SS*), respectively, as defined in Section 4. The second column in Panel A at the firm level, *Ln(IT)*, is of primary interest as a first check. IT is positively and significantly correlated with sales, capital intensity, sales surprise, and customer IT. In contrast, IT is negatively correlated with gross margin. These variables include those used in the GFR model to predict IT, and all of them are found to be correlated with Ln(IT) beyond the p=1% significance level. The positive correlation between IT and customer IT is consistent with the effect posited by the Integration Hypothesis, that when a customer operates with a higher IT, its suppliers are also able to adopt a higher IT, leading to an increase in efficiency along supply chain.

**Table 4.** Pairwise Correlations, Firm Level

| | Ln(Sales) | Ln(IT) | Ln(GM) | Ln(CI) | Ln(SS) | Ln(Cust. IT) | Ln(Cust. SS) |
|---|---|---|---|---|---|---|---|
| Ln(Sales) | 1 | 0.30*** | -0.03*** | 0.26*** | 0.05*** | 0.33*** | -0.01 |
| Ln(IT) | 0.27*** | 1 | -0.41*** | 0.47*** | 0.11*** | 0.22*** | 0.01 |
| Ln(GM) | -0.02** | -0.4*** | 1 | 0.04*** | 0.07*** | -0.07*** | 0.02** |
| Ln(CI) | 0.24*** | 0.37*** | 0.03*** | 1 | -0.02** | 0.16*** | -0.03*** |
| Ln(SS) | 0.04*** | 0.12*** | 0.08*** | -0.04 | 1 | -0.01*** | 0.17 |
| Ln(Cust. IT) | 0.34*** | 0.21*** | -0.07*** | 0.12*** | -0.01 | 1 | 0.04*** |
| Ln(Cust. SS) | 0.00 | 0.01 | 0.03*** | -0.02* | 0.14*** | 0.05*** | 1 |

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

Table 5 reports similar correlations for our sample of manufacturing subsectors, which accounts for the activities of both privately held and publicly traded firms and allows us to observe important supply chain links in both directions (i.e., customer *and* supplier industries). Again, the second column *Ln(IT)* is of primary interest. At the pairwise level, sales, capital intensity (*CI*), sales surprise (*SS*), *Supplier IT*, and *Supplier SS* all have positive and significant correlations. *GM* exhibits a significant negative correlation. The pairwise correlation coefficients for the three GFR factors are all consistent with their model. These industry pairwise correlations lend initial evidence to the Integration Hypothesis using up-chain *Supplier IT*, but not down-chain *Customer IT*, where the correlation is small in magnitude and not statistically significant. While these correlation analyses provide some initial support for the Integration Hypothesis, they do not hold constant other determinants of IT like the GFR factors. In the next section, we conduct multivariate regressions to account for these important IT determinants.

**Table 5.** Pairwise Correlations, Industry Level

| | Ln(S) | Ln(IT) | Ln(GM) | Ln(CI) | Ln(SS) | Ln(Cust. IT) | Ln(Cust. SS) | Ln(Supp. IT) | Ln(Supp. SS) |
|---|---|---|---|---|---|---|---|---|---|
| Ln(Sales) | 1 | 0.09** | 0.03 | 0.00 | -0.05 | 0.30*** | 0.00 | 0.12*** | 0.06* |
| Ln(IT) | 0.22*** | 1 | -0.64*** | 0.56*** | 0.05 | 0.06 | 0.01 | 0.35*** | 0.06 |
| Ln(GM) | -0.04 | -0.67*** | 1 | -0.34*** | 0.07* | 0.16*** | 0.02 | -0.13*** | 0.02 |
| Ln(CI) | 0.03 | 0.54*** | -0.34*** | 1 | -0.06 | -0.10** | -0.03 | 0.23*** | -0.01 |
| Ln(SS) | -0.08* | 0.05 | 0.09** | -0.04 | 1 | 0.09** | 0.64*** | 0.07 | 0.63*** |
| Ln(Cust. IT) | 0.21*** | -0.04 | 0.23*** | -0.13*** | 0.16*** | 1 | 0.11*** | 0.54*** | 0.09** |
| Ln(Cust. SS) | -0.01 | 0.05 | 0.03 | -0.02 | 0.69*** | 0.14*** | 1 | 0.07 | 0.84*** |
| Ln(Supp. IT) | 0.19*** | 0.26*** | -0.07* | 0.21*** | 0.10** | 0.48*** | 0.08* | 1 | 0.13*** |
| Ln(Supp. SS) | 0.09* | 0.09** | 0.03 | -0.02 | 0.68*** | 0.18*** | 0.87*** | 0.15*** | 1 |

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

### 5.2. Firm-Level Multivariate Regressions

Table 6 reports estimates of Equation 2 using our firm-year sample (1977-2019), where the dependent variable is the natural logarithm of the supplier firm's inventory turnover (IT). Gross margin (*GM*) is sales net of COGS, divided by sales. Capital intensity (*CI*) is average gross property, plant, and equipment (PP&E) divided by the sum of average inventory and average PP&E. Sales surprise (*SS*) is the ratio of actual sales to expected sales, where the level of expected sales is estimated from the linear exponential smoothing of up to 10 years of past sales data. *Cust. IT* and *Cust. SS* represent average IT and sales surprise, respectively, weighted by the fraction of disclosed sales to major customers that account for 10% or more of supplier sales. Each regression model includes separate intercepts (i.e., fixed effects) for each industry-by-year combination using 5-digit North American Industry Classification System (NAICS) codes. We also cluster the coefficient standard errors at the same industry-by-year level, which addresses the potential exposure of firms to the same customers.

**Table 6.** Determinants of Supplier Inventory Turnover

| | Dependent Variable = Ln(IT) | | | | |
|---|---|---|---|---|---|
| | (1) GFR (2005) model | (2) Cust. IT | (3) Cust. IT & SS | (4) Cust. IT, conditional on size | (5) Cust. IT & SS, conditional on size |
| Ln(GM) | -0.466*** | -0.463*** | -0.463*** | -0.463*** | -0.463*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(CI) | 0.728*** | 0.723*** | 0.723*** | 0.721*** | 0.720*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(SS) | 0.343*** | 0.344*** | 0.343*** | 0.342*** | 0.340*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(Cust. IT) | | 0.084*** | 0.083*** | 0.088*** | 0.087*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(Cust. IT) × RelSize | | | | -0.094* | -0.081 |
| | | | | (0.074) | (0.115) |
| RelSize | | | | 0.230** | 0.220** |
| | | | | (0.021) | (0.023) |
| Ln(Cust. SS) | | | 0.022 | | 0.092* |
| | | | (0.600) | | (0.064) |
| Ln(Cust. SS) × RelSize | | | | | -0.547*** |
| | | | | | (0.000) |
| Observations | 13,388 | 13,388 | 13,388 | 13,388 | 13,388 |
| Adj. $R^2$ | 0.445 | 0.450 | 0.450 | 0.451 | 0.451 |

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

First, column 1 of Table 6 estimates the original GFR model with industry-by-year fixed effects. The three GFR factors for our sample of manufacturing firms: *GM* (Est. Coeff = -0.466, p<0.001), *CI* (Est. Coeff = 0.728, p<0.001), and *SS* (Est. Coeff = 0.343, p<0.001) are all consistent in sign and significance with GFR. Column 2 of Table 6 estimates Equation 2, which includes our primary variable of interest, customer IT (*Cust. IT)*. Customer IT is positively related to supplier IT in column 2, providing support for the Integration Hypothesis. The estimated coefficient of 0.084 (p<0.001) indicates that a 10% increase in customer IT corresponds to an increase in supplier IT of 0.8%.

In columns 3-5 of Table 6, we add additional explanatory variables to Equation 2 as robustness tests. First, in Column 3, we add the weighted average customer sales surprise to mitigate concerns that customer IT is indirectly capturing a customer sales effect rather than inventory management practices. We find that customer sales surprise is not significantly related to supplier IT after accounting for customer IT and the three supplier GFR factors, leaving our main findings fundamentally unchanged.

In Column 4 of Table 6, we consider differences in size between the supplier and its major customer firms. Specifically, we interact *Ln(Cust. IT)* with the average ratio of supplier-to-major customer total annual sales (*RelSize*). This robustness test addresses two concerns. First, *RelSize* accounts for possible variation in bargaining power along the supply chain (e.g., Bresnahan, 1989; Shastitko & Pavlova, 2017; De Loecker & Eeckhout, 2018). Second, *RelSize* helps address concerns that the relationship between customer and supplier inventory management depends on firm size more generally, given that firm size can be a determinant of inventory levels (Rumyantsev & Netessine, 2007). The baseline coefficient for *Ln(Cust. IT)* is virtually unchanged (0.088). For the interaction of *Ln(Cust. IT)* and *RelSize*, we estimate a coefficient of -0.094 ($p<0.08$), indicating that the customer-supplier IT relationship is attenuated when the supplier is larger. (Note that suppliers are overwhelmingly smaller than their disclosed major customers.) This coefficient implies a marginal decrease of only 0.04% in supplier IT for a 10% increase in customer IT at the average *RelSize* of 5%. Thus, our findings remain qualitatively similar after conditioning on relative supplier-to-customer size. Furthermore, results are qualitatively similar in column 5, where we reintroduce customer sales surprise (SS). Overall, the results in Table 6 provide strong and robust empirical support for the Integration Hypothesis, whereby inventory efficiencies are shared along the supply chain between customers and suppliers.

### 5.3. Industry-Level Multivariate Regressions

In Table 7, we report a complementary analysis of inventory turnover (IT) at the industry level. Industry-level data offer the advantage of including activity by privately held firms in addition to the publicly traded firms studied in most large-sample financial analyses. In addition, at the industry level we can identify important up-chain supplier firms in addition to down-chain customer firms, albeit in aggregate only. We observe 18 manufacturing-related industry sectors annually during the period 1977 to 2016. Each regression model includes separate intercepts (i.e., fixed effects) for each year and industry by 3-digit North American Industry Classification System (NAICS) code. We also cluster the coefficient standard errors at the 2-digit NAICS sector-by-year level, which addresses the potential exposure of industries to the same up-chain supplier industries and/or down-chain customer industries.

Column 1 of Table 7 again reports the original GFR model, here with separate industry- and year-fixed effects. The coefficient estimates for *GM* (Est. Coeff = -1.410, $p<0.001$), *CI* (Est. Coeff = 0.443, $p<0.001$), and *SS* (Est. Coeff = 0.437, $p<0.001$) remain consistent in sign and significance with GFR. Column 2 reports industry-level estimates of Equation 2, adding customer IT to test our competing hypotheses. Consistent with our firm-level results, the relationship of industry IT with down-chain industry customer IT is positive and significant (Est. Coeff = 0.277, $p<0.001$). In aggregate, the behavior of private and publicly traded supply chain neighbors is consistent with the Integration Hypothesis. Results are virtually unchanged in column 3, where we include an additional explanatory variable for the average customer industry's sales surprise as a robustness test.

In Columns 4 and 5 of Table 7, we introduce into our model (average) up-chain industry supplier IT, which is a unique benefit of our industry-level sample. In column 4, the dependent variable, industry IT, is positively related to up-chain industry supplier IT (Est. Coeff = 0.113, $p<0.03$), whereas the relationship with down-chain customer IT remains robust (Est. Coeff = 0.250, $p<0.001$). A 10% increase in *Ln(Supp. IT)* (*Ln(Cust. IT)*) corresponds to an increase in industry IT of approximately 1.1% (2.5%). Results are similar in column 5 after introducing the weighted average sales surprise (SS) of both customer and supplier industries. Columns 4 and 5 of Table 7 suggest that IT is more strongly related to down-chain inventory practices in both magnitude and statistical significance, although both up- and down-chain relationships at the industry level provide strong and robust support for the Integration Hypothesis.

**Table 7.** Determinants of Industry-Level Inventory Turnover

| | Dependent Variable = Ln(IT) | | | | |
|---|---|---|---|---|---|
| | (1)<br>GFR (2005)<br>model | (2)<br>Cust. IT | (3)<br>Cust.<br>IT & SS | (4)<br>Cust. IT &<br>Supp. IT | (5)<br>Cust. & Supp.<br>IT, SS |
| Ln(GM) | -1.410*** | -1.237*** | -1.235*** | -1.198*** | -1.193*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(CI) | 0.443*** | 0.317*** | 0.317*** | 0.322*** | 0.325*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Ln(SS) | 0.437*** | 0.454*** | 0.456*** | 0.453*** | 0.455*** |
| | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Ln(Cust. IT) | | 0.277*** | 0.281*** | 0.250*** | 0.249*** |
| | | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(Cust. SS) | | | -0.063 | | -0.027 |
| | | | (0.754) | | (0.903) |
| Ln(Supp. IT) | | | | 0.113** | 0.127** |
| | | | | (0.027) | (0.014) |
| Ln(Supp. SS) | | | | | -0.170 |
| | | | | | (0.429) |
| Observations | 553 | 553 | 553 | 553 | 553 |
| Adj. $R^2$ | 0.962 | 0.964 | 0.964 | 0.965 | 0.965 |

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

## 6. Conclusion

Using complementary firm- and industry-level samples from the late 1970s through the mid-2010s, we extend the Gaur, Fisher, and Raman (2005) three-factor model of inventory turnover (IT) to include the inventory turnover of the firm's supply-chain partners. We formally test two competing hypotheses, the Displacement Hypothesis and the Integration Hypothesis. The Displacement Hypothesis predicts a negative correlation between the IT of firms that are supply chain partners. That is, if a customer firm maintains higher IT, then the supplier firm must keep additional inventory on hand to satisfy the customer's sudden need for inventory (Hendricks & Singhal, 2009). In contrast, the Integration Hypothesis predicts that firms harmonize efficiency inventory practices across the supply chain, resulting in a positive correlation in IT across supply chain partners (Hopp & Spearman, 2004).

Our firm-level results indicate strong support for the Integration Hypothesis, with a positive and highly statistically significant correlation between supplier firm IT and customer firm IT. At the industry level, the IT metrics of both suppliers and customers along the supply chain are positively correlated. The positive and statistically significant correlation between the IT of supply chain partners at both the firm- and industry-level provide support for the Integration Hypothesis.

This paper advances the literature on inventory management – and working capital management more generally – and has implications for practitioners. For example, Gaur et al. (2005) call for investigation of "why some firms realize higher inventory productivity than others even after controlling for differences in capital investment, gross margin, and sales surprise" (p. 193). More recently, Barker et al. (2022) call for more widespread adoption of a broader view of inventory research beyond the boundaries of a single a single organization. We respond to both calls for additional research, finding a positive correlation between inventory efficiency across firms in the supply chain. For practitioners, our results suggest that inventory-efficient practices by supply chain partners are complementary to the efficiency of other firms in that supply chain, with implications for the initial selection of suppliers and customers and the management of supply chain relationships to unlock additional complementarities. However, more research is needed, as we outline below.

Several questions about interrelationships in inventory management across firms remain unanswered or require further study. For example, it remains unclear *how* the IT of supply chain partners becomes integrated, as our correlation-based evidence shows. Do high-IT supplier firms tend to form and maintain relationships ("match") with high-IT customer firms, and likewise for low-IT firms? If so, then how highly does IT rank as a determinant of supplier selection compared to other characteristics such as product price and quality? As an alternative (or in addition to the matching of firms with similar inventory efficiency), does an increase in IT at one firm *cause* a change in the IT of a supply chain partner? Uncovering the causal relationship between the IT of supply chain partners is very challenging with observational data, and one limitation of our study is that our findings are limited to correlations between the suppliers and customers that choose to transact with each other. Future research might also measure how long it takes for the IT of a customer firm and supplier firm to become integrated. And finally, future research might explore heterogeneity in the interrelationships in inventory management between firms, for example variation in IT interrelationships across different industries or market conditions (e.g., during recessions or the COVID-19 pandemic).

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