Effectiveness of frequent inventory audits in retail stores

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Abstract
We evaluate the impact of inventory audits on operational performance of retail stores. Analysis of sales, inventory and replenishment data is presented that highlights statistical relationships between product attributes and inventory errors. An error-based SKU classification scheme is incorporated in a simulation model of store operations to identify performance tradeoffs for different inventory audit and store replenishment settings. Results show that classifying store inventory and targeting inventory audits accordingly would yield better store performance than store-wide inventory audits.

Keywords: Inventory record inaccuracy, cycle counting, store performance.

Introduction
An efficient execution of store operations requires an effective management of store inventory. To achieve this goal retail firms invest in technology and business process development (Ishfaq et al., 2016a). A key element of such investments is ensuring information quality through technology solutions that help correct errors in system inventory records. Improving the quality of inventory records not only ensures proper utilization of available inventory for in-store sales but also for e-commerce orders that retailers are increasingly filling through their stores (Ishfaq et al., 2016b).

Inventory errors are known to cause major operational issues due to poor inventory management and ineffective store replenishments that lead to lost sales (Hardgrave et al., 2013). According to estimates by IBM Business Consulting Services, inventory errors cost retailers more than $1 billion in lost inventory each year (Alexander et al., 2002). National Retail Federation in its 2015 annual retail security survey (NRSS) reported that inventory errors lead to $44 billion in lost revenue for U.S. retailers. In another study, Kang and Gershwin (2005) noted that the actual number of items in stock (physical inventory) in a store can be off by up to 30% of the retailer's system inventory records in the corporate IT system. While the importance of ensuring accurate inventory records is fully understood by retailers, controlling inventory errors remains a challenge (Barratt et al., 2010). Our study focuses on this issue by specifically addressing how retailers can effectively utilize routine audits to manage the operational effects of inventory errors.

The practice of routine inventory audits has expanded in recent years due to the adoption of RFID technology. Retailers, such as American Apparel, Macy's and Mark & Spencer have reported using RFID technology to count store inventory up to twenty four times a year (Trebilcock, 2013). As more retailers adopt such technologies to conduct routine inventory audits, managers are looking to use detailed inventory error data to devise strategies to counter the operational effects of inventory errors. In this context, our paper seeks to develop an understanding of how inventory errors affect different segments of store inventory and shed light on a key operational question for store managers, i.e., how often should retailers count store inventory?

Theoretical Background

We study inventory errors using the theoretical connection between firm's information system (IS) capability and operational performance as supported by the resource-based view (RBV) of a firm (Wernerfelt, 1984; Barney, 1991). In this context, firms that deploy better IS systems can generate competitive advantage through high quality information that is critical in making operational decisions (Bharadwaj, 2000). We apply the theoretical lens of representation theory to our study that highlights the key purpose of an information system to "*faithfully represent a real world domain, such as the state of firm's inventory*" (Weber, 1997, pg. 73). For an information system to provide the requisite competitive advantage, it must represent the true state of a firm. Thus, any efforts to improve the quality of system's representation of a firm's inventory records would result in increasing the effectiveness of the IS capability (Burton-Jones and Grange, 2013). This improvement would in turn lead to better allocation of firm's resources and help reduce speculative behavior of managers that occurs in the presence of poor inventory information (Rabinovich et al., 2003; Sambamurthy et al., 2003). Hence, correction of inventory errors through routine inventory audits would lead to inventory efficiency (Heese, 2007) and better store performance (Moussaoui et al., 2016).

As per the theoretical setting of our research study, we evaluate the effectiveness of the inventory audit process that is focused on reducing the negative effect of inventory errors and improving the effectiveness of inventory information. Our research efforts are targeted to specifically address the following key research question: **RQ:** *Are frequent inventory audits effective in improving store performance?* We seek to collect and analyze detailed empirical data of inventory errors to identify underlying statistical relationships with relevant product attributes. The analysis seeks to develop a SKU categorization scheme based on different IRI error profiles of store inventory. A key issue relevant to routine store audits is the role of different IRI profiles of store inventory as a moderating factor that may influence the effectiveness of inventory audits. Since the store's replenishment process is an inherent part of the inventory management system, we also explore its effect on the operational outcomes of routine inventory audits.

Our study expands on the extant research literature focused on the issues related to inventory errors that includes Raman et al. (2001) as one of the earliest empirical studies. Their analysis revealed that inventory records in a retail store setting can be incorrect for more than 65% SKUs. In a follow-up study, DeHoratius and Raman (2008) presented a detailed analysis that linked items with high sales prices and sold quantities to a high level of inventory errors. In devising strategies to manage operational issues arising from inventory errors, prior literature offers some remedial actions, e.g., Gumruku et al. (2008) suggested holding additional buffer inventory to improve the in-stock position, whereas Kök and Shang (2007) proposed an audit of store inventory if recorded inventory fell below a threshold value. Agarwal and Sharda (2012) used a numerical simulation study to demonstrate that frequent inventory audits would have a linear effect on reducing inventory errors. Recent studies have provided supporting evidence that internal or third-party audits of store inventory can yield high on-shelf availability (Chuang et al., 2015; Hardgrave et al., 2013). Beyond the previous studies discussed above, we have little empirical insight into how variations in IRI profile of store inventory would impact the effectiveness of firms' actions to correct inventory errors. Our paper focuses on this specific issue and presents an empirically grounded analysis of retailers' approach to incorporate routine inventory audits into their store operations strategy.

Empirical Data

Data for this study was collected from a large U.S. retail firm who is a market leader in the apparel and consumer goods retail segment. This retailer ranks near the top of the list of 100 best retail firms, published by the National Retail Federation and is known for excellence in retail supply chain management. For the purpose of collecting data, a particular retail store location was selected. This site is among the largest stores operated by the retailer and experiences strong sales throughout the year. We mined retail firm's information system to extract transactional data related to sales, store receipts from DCs and inventory records. A widely sold apparel product category (over 10,000 SKUs in this category) was selected for analysis. The weekly sales of this product category were tested to confirm general consistency across the data collection time periods (Mean weekly sales = 1020.6, Std. Dev=178.4, SE mean = 29.3). This setting helped us control for the effect of sales promotions and marketing campaigns.

Table 1: Data description and summary statistics

Variable	Description	Mean	St. Dev	Min	Max
PRICE	Unit sale price	$59.99	$17.00	$4.99	$199.99
SALES	Weekly sales (units)	1.12	0.27	1.00	12.00
POPULAR	SKU popularity	14%	11%	2%	72%
SKU_INV	Avg. weekly inventory (units)	1.93	1.40	0.00	19.49
REPL_QTY	Weekly receipt quantity (units)	1.50	1.50	0.00	18.00
REPL_FRQ	Replenishment frequency	9%	7%	0%	51%
IRI_ERROR	Average IRI error	12%	28%	0.%	100%

The dataset comprises of 248,000 weekly transactional records covering 10,099 SKUs. The dataset includes information about SKU description, sales price, weekly sales, quantity and dates of receipts from DCs, and weekly inventory records. A preliminary review of the dataset showed that it contained SKUs that were not stocked for the entire length of time (items discontinued through the data collection phase or new items that were introduced during this time) or had no sales. After removing information for such SKUs, the final dataset comprised of 199,807 records covering 7,260 SKUs. The description of data variables and summary statistics are presented in Table 1. Note that SKU popularity is coded in the dataset as the proportion of weeks in which a SKU had sales and replenishment frequency variable records the proportion of weekly store shipments that replenished a particular SKU.

The information about errors in the store inventory was gathered from multiple RFID scans of store inventory. These scans were done at the end of the first week of each month during the data collection phase. The *physical inventory* counts obtained from these scans where compared with the *system inventory* record for each SKU. This comparison provided data on whether store inventory records were incorrect (captured by binary variable IRI_ERROR) and by how much. The mean of IRI_ERRORs from multiple RFID scans was used as the average IRI_ERROR value for that SKU. We also recorded the numerical difference between the system inventory record and the physical inventory count.

Research Methodology

We analyzed this data using a multi-method approach. In the first method, we use Cluster Analysis to identify underlying structures of inventory errors and various independent variables. This technique is especially useful for knowledge extraction from large datasets (McCallum et al., 2000). In the second method, we evaluate the effectiveness of inventory audits to manage inventory errors through a simulation model using a factorial design study. We applied the clustering technique on the SKU-level store inventory data through SAS Enterprise Miner platform, using the WARD method. In this method the distance between two clusters is determined by conducting an Analysis of Variance (ANOVA) for all variables in the dataset (Anderberg, 2014; Ward, 1963). The iterations in cluster generation combines sub-clusters until stable final clusters are achieved. We used the RADIUS measure to observe the spread of observations within a cluster. The other measure used in the analysis was the root mean square of error values (RMSSTD) with smaller values indicating homogenous observations within a cluster. The results of this technique identified three clusters of SKUs with distinct ranges of price, sales, popularity, inventory levels and replenishment frequency. The mean values of these variables are listed in Table 2. The results show that clusters IRI_1, IRI_2 and IRI_3 consist of 16%, 72% and 12% of SKUS in the dataset, respectively. Using SAS Miner, we used values shown in Table 2 to assign a unique CLUSTER_ID to each SKU in the dataset.

Table 2: SKU clusters in store inventory

	Cluster ID		
Variables (Normalized Mean)	**IRI_1**	**IRI_2**	**IRI_3**
Sales Price Sales Quantity Product Popularity Avg. Inventory Level Avg. Weekly Receipts Repl. frequency	\$56.49 1.39 30.96% 3.27 2.96 16.95%	\$60.49 1.07 10.58% 1.49 1.23 7.45%	\$57.99 1.11 12.74% 2.68 1.08 7.62%
IRI Error	10.8%	1.5%	81.8%
Radius	15.780	9.154	18.683
Observation Frequency	1,188	5,211	861
Root Mean Square Std.Dev (RMSSTD)	1.199	0.611	0.976

Table 3: Confirmatory ANOVA test

	Sum of Squares	DF	Mean Square	F-value	p-value
Between Groups	476.707	2	238.353	14950.76	0.000
Within Groups	115.695	7257	0.016		
Total	592.402	7257			

Next, we conducted a confirmatory Analysis of Variance (ANOVA) test to confirm that the difference in the mean values of the dependent variables in each cluster are statistically significant across the clusters. The ANOVA test checks whether mean values of dependent variables in the clusters are significantly different. The null hypothesis H_0 is stated as follows: *Mean value of IRI error variables in each cluster are equal* ($\mu_1 = \mu_2 = \mu_3$). The alternate hypothesis H_a states that not all μ_i are equal. First, we conducted the Analysis of Variance (ANOVA) for the dependent variable (IRI_ERROR) that measures the chance that a SKU's inventory records are incorrect. The results (see Table 3) show the *F* test-statistic is significantly greater than 1 (*p*-value of *F* statistic is less than 0.05); thus the null hypothesis of equal means is rejected and we conclude that the mean IRI_ERROR of at least one cluster is different from the other clusters. To identify how the means of the cluster differ from each other, we used the GAMES-HOWELL p*ost hoc* test (Kerlinger and Lee, 1999). This test is used to identify the exact pattern of differences among variable means that is not sensitive to unequal groups or heterogeneous variances (Shadish et al., 2001). The results finally confirm that the pairwise differences of mean values of IRI_ERROR variable in the three clusters are statistically different.

Table 5: IRI rating of store inventory

CLUSTER_ID	IRI_RATING	N	Mean	Std. Dev.	Std. Err. Mean
1	MID	1,188	11.0%	21.5%	0.6%
2	LOW	5,211	2.0%	5.7%	0.1%
3	HIGH	861	82.0%	22.5%	0.8%

The robust statistical tests discussed above confirmed that the identified clusters have different IRI error profiles and the weights used for identifying clusters are statistically valid. Thus, we assigned each SKU in the dataset to a particular cluster based on the values of IRI variables. We designated the identified clusters based on the descriptive statists of the IRI_ERROR variable (see Table 5). The results for CLUSTER_ID 2 shows SKUs with small mean values for the IRI error variable (i.e., IRI_ERROR= 2.0%). Thus, we describe this group of SKUs as LOW IRI error group. On the other hand, CLUSTER_ID 3 shows SKUs with large mean values for the IRI error variable, i.e., IRI_ERROR= 82.0%, which is designated the HIGH IRI group. Similarly, CLUSTER_ID 1 is designated as the MID IRI group of SKUs. We use these IRI profiles of store inventory to analyze the effectiveness of store inventory audits.

Simulation Study

To manage the operational issues caused by inventory errors, retailers often incorporate an inventory audit program that routinely counts inventory in the store. Key managerial questions in setting up such a program are: how frequently should we do inventory audits and how effective are these routine audits in improving retail store performance? The following analysis explores these questions in terms of the impact of different audit intervals on in-shelf availability of store inventory. We developed a systems-dynamics model of store operations that simulates the interactions among the sales process, inventory management system and store replenishment process (see Table 6). The simulation approach is useful for this analysis as it helps with incorporating the non-linear effects among different store processes. This element of the analysis is also useful due to the stochastic nature of demand and inventory errors. We sample values for related variables from the best-fit probability distributions obtained from the empirical dataset collected for this study. This sampling is done at a single-SKU level with hundreds of SKUs included in the analysis.

The demand data for each SKU was extracted from the point-of-sale (POS) records. The proportion of demand filled from store inventory was recorded as sales, whereas unfilled demand due to stock out is logged as lost sales. Note that demand for an item would result in a sale (or lost sale) based on its physical inventory in the store which may be different from the system inventory record (due to inventory errors). Hence, stock outs would occur even if the system inventory records indicated that units were available in the store. The store receives replenishments from its designated distribution warehouse on a fixed schedule (e.g., every Thursday). Store replenishments consist of quantities requested by the store at the start of each replenishment cycle. The model implements the periodic inventory review system used by the focal retail firm. The replenishment quantities are ordered to completely fill the corresponding shelf space allocated to each SKU.

Table 6: Simulation Model and Flow

Process	**Simulation Step**
Initialize	Initialize system variables.
Sales Process	Sample demand data and generate weekly demand (D) IF physical inventory (PI > D} THEN Sales (S) = D ELSE S = PI Lost Sales (LS) = *max* {0, D - PI}
Inventory Process	Update PI and system inventory (SI): PI = PI – S and SI = SI - S
Replenishment Process	Review inventory: IF SI < ROP THEN Place replenishment order Q = Shelf Space - SI Store receives Q units. Update inventory: SI = SI + Q and PI = PI + Q
IRI Process	Sample IRI data and generate inventory errors (IRI QTY) Update PI = PI ± IRI QTY
Error correction	At scheduled inventory audit interval set SI = PI

Each SKU's starting inventory level was set at fully-stocked shelf. Store inventory is reviewed at a pre-set replenishment interval. If the inventory level is found to be sufficient (above the reorder threshold) no action is taken. Note that store's inventory system may not trigger a replenishment order even when there are no items on the shelf because (erroneous) system records may show sufficient number of items in stock. The replenishment quantity is determined to bring the inventory position to fully stock the shelf space allocated to each SKU. The replenishment order is received at the store in the next scheduled delivery from retailer's distribution facilities.

To account for inventory errors, physical inventory in the simulation model was adjusted using the sampled IRI error rate. The IRI error probability distributions were estimated from the empirical data using the same approach as discussed above for the demand data. For each SKU, the IRI error data was used to replicate inventory errors as a percentage of in-stock inventory. The errors between system inventory records and physical counts were reconciled in the simulation model through scheduled inventory audits. For the duration of time between two successive audits, inventory errors would degrade system inventory records based on each SKU's IRI error profile. Using empirical data for IRI errors helped us incorporate error data unique to each SKU instead of using a generalized IRI error rate that ignores item-specific attributes, such as price, popularity, replenishments, and sales velocity.

The analysis is based on a factorial research design in which four independent variables (factors) are set at multiple levels (Box et al., 2005). These factors include: *audit interval* (Factor: A), *replenishment interval* (Factor B), *sales velocity* (Factor C), and *IRI rating* (Factor D). The test levels for factors were set as follows: Factor A = {1, 2, 3, 4, 5, 6} weeks, Factor B = {twice a week, weekly, bi-weekly} interval, Factor C = {low, mid, high} sales velocity and Factor D = {low, mid, high} IRI rating. These factor levels were selected in consultation with the retailer that facilitated the collection of data, and validated through a panel of retail supply chain executives at a forum organized by one of the authors. The main effects and interaction effects were analyzed from the results using the Analysis of Variance approach (Montgomery, 2012).

Results and Analysis

Different combinations (162 independent scenarios) in the factorial design were each simulated for 365 days with 30 replications of sample data. A warm-up period of 31 days was added to each simulation run for initialization purpose. A larger number of replications ($n \geq 20$) is necessary to avoid sampling bias and to obtain a sufficient number of data points for the statistical validity of the outcome variables (Fleisch and Tellkamp, 2005; Agarwal and Sharda, 2012). The analysis of the results discussed below is based on average values of the output variables over 30 replications. The following outcome variables (time averages) were recorded for each SKU in each replication; in-stock position, inventory record accuracy, physical inventory, system inventory, number of replenishment orders, and replenishment quantity per order.

We divided the dataset into ten groups, where each group represents SKU sales as a decile of total sales. A subset of 100 SKUs were randomly selected from the 90th percentile (Group A: HIGH sales velocity), 75th percentile (Group B: MID sales velocity) and 50th percentile (Group C: LOW sales velocity). These percentiles were selected to keep sufficient sales differences across groups at the SKU-level while ensuring sufficient number of data points (weeks with non-zero sales) for parameter estimation. The SKUs within each group were further classified by their IRI rating. The percentages of SKUs identified by IRI rating (HIGH, MID, LOW) in each group are as follows: Group A (35%, 38%, and 27%), Group B (31%, 25%, and 44%), and Group C (44%, 24%, and 32%). Note that SKUs were randomly selected in each group, thus the corresponding IRI ratings were not controlled according to any specific criterion and each IRI sub-group has a somewhat different number of SKUs. However, each sub-group is sufficiently large to ensure proper interpretation of the results.

Table 7: ANOVA Results (In stock position)

Analysis of Variance: In stock Position

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	53	27574.3	520.27	90.43	0.000
Linear	11	23007.2	2091.57	363.52	0.000
Audit Interval	5	3038.6	607.72	105.62	0.000
Replenishment Interval	2	3043.2	1521.58	264.46	0.000
IRI Rating	2	10992.7	5496.36	955.29	0.000
Sales Velocity	2	5932.8	2966.40	515.57	0.000
2-Way Interactions	42	4567.1	108.74	18.90	0.000
Audit Interval*Replenishment Interval	10	451.7	45.17	7.85	0.000
Audit Interval*IRI Rating	10	1999.5	199.95	34.75	0.000
Audit Interval*Sales Velocity	10	68.9	6.89	1.20	0.300
Replenishment Interval*IRI Rating	4	111.0	27.75	4.82	0.001
Replenishment Interval*Sales Velocity	4	199.0	49.75	8.65	0.000
IRI Rating*Sales Velocity	4	1737.0	434.25	75.47	0.000
Error	108	621.4	5.75		
Total	161	28195.7			

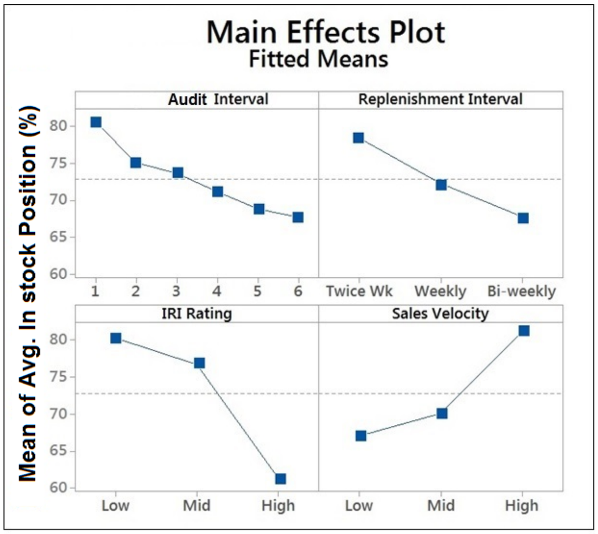

Figure 1: Main Effects Plots

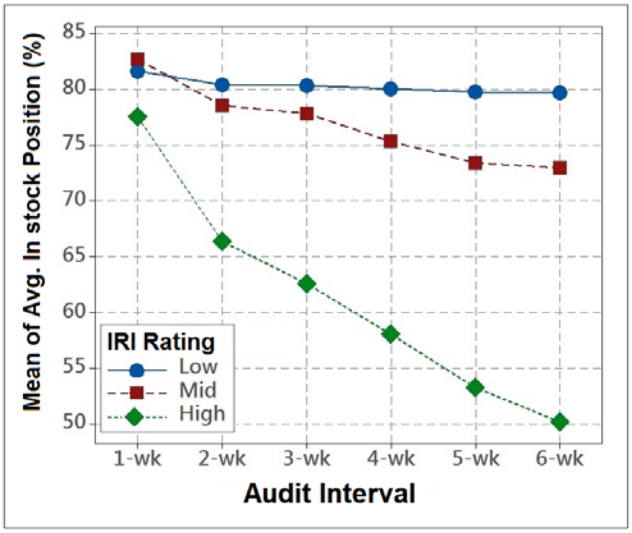

Figure 2: Interactions Effect Plot

Table 8: ANOVA Results (Average inventory)

Analysis of Variance: Avg. Inventory

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	53	77.8364	1.4686	182.21	0.000
Linear	11	69.6574	6.3325	785.66	0.000
Audit Interval	5	1.9777	0.3955	49.07	0.000
Replenishment Interval	2	6.2926	3.1463	390.36	0.000
IRI Rating	2	11.0823	5.5411	687.48	0.000
Sales Velocity	2	50.3049	25.1524	3120.62	0.000
2-Way Interactions	42	8.1790	0.1947	24.16	0.000
Audit Interval*Replenishment Interval	10	0.3875	0.0387	4.81	0.000
Audit Interval*IRI Rating	10	1.0822	0.1082	13.43	0.000
Audit Interval*Sales Velocity	10	0.3968	0.0397	4.92	0.992
Replenishment Interval*IRI Rating	4	0.5585	0.1396	17.32	0.000
Replenishment Interval*Sales Velocity	4	2.5972	0.6493	80.56	0.000
IRI Rating*Sales Velocity	4	3.1567	0.7892	97.91	0.000
Error	108	0.8705	0.0081		
Total	161	78.7069			

The ANOVA results for response variable: *in-stock position* is shown in Table 7, which presents *F*-values and *p*-values for main and interaction effects of the four factors. The results show that all tested factors affect values of the response variable. The main effects as well as all interaction effects are statistically significant, under the 0.05 significance level, except for the interaction (*sales velocity* × *audit interval*). The main effects plot (see Figure 1) confirms that in stock position improves with frequent audits. A similar improvement of in stock position is also seen in the main effect plot of variable: *replenishment interval*. These plots indicate that frequent replenishments improve the in-stock position at approximately same scale as frequent inventory audits. The plot for *IRI rating* shows the highest effect on *in-stock position* of all variables in the study (*F*-value= 955.29; *p*-value <0.0001). This result shows that average *in-stock position* of items with high IRI errors is much lower than items with low IRI errors (by approx. 20%). The results also show a significant association between the *in-stock position* and *sales velocity* variables in that better in-stock positions are recorded for higher demand items.

Next, we analyzed the interaction effect of *audit interval* and *IRI rating* on the *in-stock position* variable (see Figure 2). The top plot shows changes in the average *in-stock position* for items with low IRI errors under different audit interval settings. The *in-stock position* for items in this category is not affected by IRI errors, as much as for items which have a mid to high rate of IRI errors. The biggest improvement of *in-stock position* due to frequent inventory audits is seen for items with a high IRI rating. For these items, the average *in-stock position* increased from 50% to 77% for the *audit interval* of 6-week and 1-week, respectively. For the mid IRI rating, a modest gain in the average *in-stock position* (up to 10%) was recorded.

The ANOVA results for the *average inventory* variable (see Table 8) show that all main effects and interaction effects are statistically significant. The ANAOVA results and main effect plots confirm that inventory availability in the store depends on the IRI rating of the items. The (*IRI rating* × *sales velocity*) interaction effect has the most significant effect in the ANOVA results (*F*-value = 97.91). The items that have a high rate of IRI errors have the lowest inventory availability. These results show that items with a high IRI rating are exposed to a higher chance of stock out. The post-hoc analysis of *average inventory* variable confirmed that a major cause of stock out is lower inventory availability of such items. These results also indicate that the current practice of keeping low inventory of slow moving items (i.e., low sales velocity) contributes to stock outs especially for items with high IRI errors.

Conclusions

This study addressed the issue of inventory errors and focused on the use of inventory audit process to correct such errors. The corresponding empirical analysis identified statistical relationships between product attributes such as SKU popularity, price, sales velocity, store’s replenishment process and items’ IRI error profiles. These statistical relationships are shown to provide sufficient information to devise a SKU classification scheme for store inventory. The study identified tradeoffs between different inventory audit and replenishment intervals and evaluated the usefulness of frequent inventory audits. The results show that items with low IRI rating and high sales velocity will see small improvements in the in-stock position with frequent inventory audits. Conversely, items with a high IRI rating would benefit the most (e.g., the average in-stock position for high IRI items increased from 50% to 77% when inventory errors were corrected weekly as compared to a 6-week interval). The results also demonstrated that the replenishment process moderates the effect of inventory audits. For example, in the twice-weekly replenishment scenario, the focal retail firm was able to use information gained from inventory audits to replenish store inventory effectively. This action resulted in better in-stock position and higher sales.

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