RFID-Enabled Visibility and Retail Inventory Record Inaccuracy: Experiments in the Field

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Accurate inventory records are key to effective store execution, affecting forecasting, ordering, and replenishment. Prior empirical research, however, shows that retailer inventory records are inherently inaccurate. Radio Frequency Identification (RFID) enables visibility into the movement of inventories in the supply chain. Using two different field experiments, the current research investigates the effectiveness of this visibility in reducing retail store inventory record inaccuracy (IRI). Study 1 used an interrupted time-series design and involved daily physical counts of all products in one category in 13 stores (8 treatments and 5 controls) of a major global retailer over 23 weeks. Results indicate a significant decrease in IRI of approximately 26% due to RFID-enabled visibility. Using an untreated control group design with pre-test and post-test, Study 2 expands the number of categories to five and the number of stores to 62 (31 treatment and 31 control stores). Results show that the effectiveness of RFID in reducing IRI varies by category (ranging from no statistically significant improvement to 81%). Results also suggest that RFID ameliorates the effects of known determinants of IRI and provide the key insight that the technology is most effective for product categories characterized by these determinants.

Key words: supply chain management; inventory record inaccuracy (IRI); radio frequency identification (RFID); inventory visibility; field experiment

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1. Introduction

Inventory record accuracy is an essential ingredient for efficient and effective supply chain management and store execution (DeHoratius and Raman 2008, Gaur et al. 2005, Heese 2007). Key functions such as forecasting, ordering, and in-store replenishment are based on accurate inventory records. Most retailers rely upon automated ordering and replenishment systems or, at least, information from a system to provide insight into what, when, and how much to order. For these systems to be effective, retailers must have records of their on-hand inventory. Unfortunately, “retailers are not very good at knowing how many products they have in the stores” (Kang and Gershowin 2005, p. 844). There is a discrepancy between retailer inventory records and actual inventory in the store (DeHoratius et al. 2008). Thus, inventory record accuracy is often referred to the “missing link” in retail execution (Heese 2007). Technology in the form of Radio Frequency Identification (RFID), however, provides unprecedented visibility (Delen et al. 2007, Whitaker et al. 2007) into movements of inventory in the supply chain and, therefore, the potential to reduce inventory, save labor cost, and improve supply chain coordination (Lee and Özçer 2007).

Retailers as well as research studies recognize the problem of inventory record inaccuracy (IRI; for a review, see Heese 2007). Studies have found that retailers only have accurate inventory record information, typically known as perpetual inventory (PI, defined as the continuous system record of on-hand store inventory), on about 35% of their products (Raman et al. 2001). The implication is that ordering and replenishment decisions are based on information that is wrong more often than it is correct. Although it is recognized as a major obstacle to successful store execution, retailers have difficulty
determining when, how, and in what magnitude IRI occurs (DeHoratius et al. 2008, Kang and Gershwin 2005). Because of IRI, systems can order product that is unnecessary or fail to order product that is needed (DeHoratius and Raman 2008). The net result is an estimated 10% reduction in profit due to IRI (Heese 2007).

To combat IRI, companies can increase the frequency of physical counts, but this considerably increases labor costs and may not be effective (Millet 1994) due to the sheer volume of differentiated products stocked by retailers. In a busy consumer packaged goods store, serving a sizable population that may stock several variants of a product (e.g., cans of soup with similar labeling), the chances of human error are high. Maintaining additional safety stock is an option to guard against stockouts (Fisher et al. 2000), but this measure increases inventory holding costs (Fisher and Rajaram 2000).

Radio frequency identification can potentially help companies automate the process of identifying and eliminating the source of errors (Bensoussan et al. 2007, Kang and Gershwin 2005, McFarlane and Sheffi 2003, Morey 1985). Delen et al. (2007) show how RFID can provide visibility into inventory movements from the receipt at the distribution center (DC) to intermediate and long-term storage at the DC, through the shipping process to the retail store, all the way to backroom and finally to the sales floor. Although most firms are aware of the technical specifications of RFID, they want to know how this technology will change their business processes (Gittlen 2006, Hozak and Collier 2008). For example, Zipkin (2006) makes the point that the design and management of processes requires not just RFID, but also care, ingenuity, and wisdom. Very few companies would implement a new technology such as RFID based on pure faith, but need value assessments, tests, or experiments (Dutta et al. 2007). In the past several decades, barcode technology changed the way retailers and their suppliers do business, and RFID has the promise to be similarly transformational for the retail industry.

In this article, we demonstrate the utility of RFID in retail store execution by showing that the technology-enabled visibility can be used to reduce IRI, which is vital for efficient store execution. We also examine the effects of RFID on some known factors that influence IRI. Recently, DeHoratius and Raman (2008) gave an understanding of the how and why of IRI by identifying seven determinants of IRI. We build upon their study by investigating the extent to which RFID can ameliorate the influence of these determinants. Finally, we look at the impact of RFID across multiple categories of products. Consequently, the research questions driving this research are:

1. What is the magnitude of the impact of RFID-enabled visibility on IRI?

2. Can RFID-enabled visibility ameliorate the effects of known predictors of IRI?

Despite the seemingly self-evident potential for RFID-enabled visibility to reduce IRI, due to the difficulty of rigorous study design in the field (Dutta et al. 2007), very limited empirical research has demonstrated how RFID can help (Amini et al. 2007, Hardgrave et al. 2009). Until there are empirical estimates of impact, many in the industry will continue to question its business value (Cachon and Fisher 2000, Camderelli 2008, Hozak and Collier 2008, McWilliams 2007, Whitaker et al. 2007) and companies will be unwilling to adopt. The primary reason why it is difficult to quantify the impact of the technology without a controlled field experiment is that the operational environment in which retailers operate is complex, with fallible human intervention, technological, budgetary, and circumstantial constraints, and the impact of other contextual factors.

The rest of this article is organized as follows: section 2 sets the background and justification for the studies; section 3 presents study 1; section 4 presents study 2; and section 5 discusses the results and draws implications for future researchers and for firms implementing RFID.
Delen et al.’s (2007) case study illustrated the role of RFID in the supply chain and showed precisely how RFID can enhance information visibility. Their focus was on the inventory flow from the DC to the retail store, which could be tracked by strategically located read points at the DC receiving dock, by the conveyor belts in the DC, at the DC shipping dock, the store receiving dock, the backroom entrance to the sales floor, and by the box crusher. In the present research, we define inventory visibility as the retailer’s ability to determine the location of a unit of inventory at a given point in time (e.g., in the DC, in the backroom of the store, on the sales floor, in the box crusher). Our purpose is to use this visibility to automate updates to the PI record system and to demonstrate that the technology can improve system accuracy.

2.2. Inventory Record Inaccuracy
Inventory record inaccuracy is defined as the absolute difference between physical inventory and the information system inventory at any given time (see also DeHoratius and Raman 2008, Fleisch and Tellkamp 2005). For example, Kang and Gershwin (2005) found inventory record accuracy (exact match) to be about 51% and only about 75% when relaxed to ± 5 units. Raman et al. (2001), in a study of 370,000 observations across a single retail chain, found 65% inaccuracy, 20% of which differed by six or more units. Likewise, in a study of 166 items from 121 stores, Gruen and Corsten (2007) found IRI to be 55%. As insight into how and why IRI occurs, DeHoratius and Raman (2008) list seven known determinants of IRI—item cost (the retailer’s cost of an individual item), quantity sold (or sales velocity; number of units sold of an item per year preceding the audit of that item), sales volume (item cost × quantity sold), audit frequency (frequency of physical inventory audit), inventory density (the total number of units found in a retailer’s selling area), product variety (the number of different merchandise categories within a store), and the distribution structure (whether it was shipped from a retailer-owned DC).

2.2.2.1. Overstated vs. Understated PI. There are two basic categories of IRI: overstated PI and understated PI. Gruen and Corsten (2007) indicated that about half of the time, PI is overstated (i.e., PI shows more inventory than is actually in the store), and about half the time PI is understated (i.e., PI shows less than what is in the store). Similarly, DeHoratius and Raman (2008) found about 59% of the inaccurate records to be overstated vs. 41% understated. For overstated PI, the most serious and directly related problem is out of stock—the system thinks it has inventory on hand (i.e., phantom inventory), and thus fails to order new inventory. For understated PI, the most pressing problem is excess inventory (i.e., hidden inventory) because the system thinks it does not have as much as it really does, thus ordering unnecessary inventory. This unnecessary inventory potentially results in excess holding costs, excessive markdowns that impact margin, reduced turns, and breakdowns in store execution-related errors (Raman et al. 2001) such as out of stocks (Hardgrave et al. 2008) due to inefficiencies created by extra inventory.

2.2.2. Trigger Events and the Use of RFID. On the basis of existing literature and interviews with managers from the retailer who participated in the study, we enumerate events that may trigger IRI. First, PI can be incorrectly manually adjusted by employees. For example, when an employee believes the product to be out of stock, PI may be mistakenly set to zero when, in reality, product is in the backroom. Conversely, employees could think a case of product is available in the store when it is not (if, for example, they misidentify a product) and incorrectly adjust PI upward. Thus, incorrect manual adjustments can create both under- and overstated PI. Second, products can be stolen, resulting in an overstated PI condition. Third, damaged or spoiled products, when not recorded as such, result in overstated PI. Fourth, returned products that should add inventory back to the system may not be accounted for properly or are accounted for incorrectly (e.g., showing a return of product A when, in fact, product B was returned), thus potentially creating under- or overstated PI. Fifth, a store can receive mis-shipments from the distribution center, resulting in both over- and understated PI (overshorted for products that should have been received, but were not; understated for products received that should not have been received). Sixth, cashier error can cause both over- and understated PI inaccuracy. For example, if a customer is purchasing three items of product A and three items of product B, but the cashier mistakenly enters six items of product A, then the PI for product A will be understated by three units and the PI for product B will be overstated by three units. For more information about triggers of inventory inaccuracy, see DeHoratius and Raman (2008), Raman et al. (2001), and Sahin and Dallery (2005).

In this study, we are interested in RFID’s ability to reduce IRI. With RFID, stores will know what cases have been delivered to the store, taken to the sales floor, or stocked in the backroom. At the store level, there are three RFID read points (see Figure 1): (i) receiving doors have read portals and capture reads from individual cases as they are unloaded from the truck, (ii) the product moving to the sales floor are read by readers placed next to the doors going from...
the backroom to the sales floor and when the empty cartons return through the sales floor doors (another read is captured at this point), and (iii) placed into the box crusher for disposal (the last read point).

This visibility (of the location of a product—backroom or sales floor) enables a much more accurate view of inventory. As product is sold, PI is updated (from the point of sale system). Coupled with the RFID-generated information of product location, the system has an indication of the accuracy of PI and can now make decisions about what to stock. We illustrate the logic used by the RFID system (hereinafter “RFID auto-adjust”) with the following two examples: Suppose the system observes a PI count of 11 for Product A and also shows an RFID read on a box (with a case pack size of 24) at the receiving door, but none at the sales floor door (i.e., indicating the box is still in the backroom). Thus, PI must be incorrect because at least 24 units are in the store and, subsequently, RFID auto-adjust would modify the PI for Product A. A second example: The system observes for Product B a PI of 13, and the RFID reads indicate a box (with a case pack size of 12) had entered the backroom, but was not yet taken to the sales floor. RFID auto-adjust would issue a picklist (instructing store personnel to restock the store shelf from the backroom) for this item, as it would surmise that only one item was on the sales floor (PI = 13 minus 12 in the backroom). However, PI would appear to be accurate and RFID auto-adjust would not trigger a change. RFID auto-adjust made all determinations—whether to adjust or not—automatically, with no human intervention. Overall, stores should have a better view of which cases have been delivered to the store, taken to the sales floor, or stocked in the backroom.

To summarize, RFID is known to provide visibility through the supply chain (Delen et al. 2007), visibility is presumed by analytical models to reduce inventory inaccuracy (Lee and Özer 2007), and inventory inaccuracy has been shown to impact profitability (Fleisch and Tellkamp 2005, Lee and Özer 2007, Meyer 1990). The current research studies the hitherto unexplored linkage between RFID-enabled visibility and inventory inaccuracy (Figure 2).

3. Study 1
3.1. Sample and Procedure
Study 1 included 13 retail stores in a metropolitan area, ranging from approximately 40,000 square feet to approximately 220,000 square feet. Eight of the 13 stores were designated test stores, and the remaining five stores served as control stores. All stores in the study were RFID-enabled. Control stores were equipped with RFID equipment (readers), but data from the system were not captured. Only test stores used RFID auto-adjust to update their inventory records. This approach, of RFID-enabling test and control stores, ensured that the mere installation of RFID equipment could not be a reason for any improvement in store execution (a placebo effect).

The category selected for the study was aircare products (air fresheners, candles, sprays, etc.) and was selected by the retailer. All products in this category were shipped from the same distribution center to all stores included in the study. The category was physically counted daily for 23 weeks by an independent firm specializing in counting inventory. Each day, personnel from the independent firm followed the same counting path (e.g., begin at bottom left shelf and work way to top right) between 4 P.M. and 8 P.M. to ensure consistency.

After approximately 12 weeks of daily inventory counts, all cases of products in the category being shipped to all 13 stores were RFID tagged by the suppliers. We conducted this extended baseline counting period so that store personnel (in both test and control stores) would be accustomed to the daily count, thus guarding against a change in behavior during the window of the experiment (Roth 2007 warns against this as a threat to external experimental validity).

In the test stores in the treatment period, using a system of logic based on the RFID reads, the system made adjustments to understated PI automatically when triggered by the reads (as described earlier). In this particular field trial, the retailer was only interested in studying the impact of RFID-enabled visibility on understated PI as a means to reduce inventory costs.
In adjusting only one side of the problem (i.e., understated PI), there is a danger of over-correcting one side and making the other side (i.e., overstated PI) worse. In this case, an analysis of overstated PI from both the control and test stores suggests that the pre- vs. post-increase (0.38%) in test stores’ overstated PI was not more than the pre- vs. post-increase (0.91%) in control stores’ overstated PI.

3.2. Study Design
To investigate research question 1 (What is the magnitude of the impact of RFID-enabled visibility on IRI?), we use an interrupted time-series design that is “one of the most effective and powerful of all quasi-experimental designs” (Shadish et al. 2002, p. 159). This is especially true when supplemented by design elements such as the nonequivalent internal comparison group chosen to have maximum pre-test similarity to the treatment group. Specifically, we use a within-store comparison of time series before and after the implementation of the RFID auto-adjust. We perform an additional test using a post-test only comparison using internal controls (Shadish et al. 2002) between test and control stores. Here, we conduct a between-store comparison of a set of (RFID-enabled) stores that use RFID to auto-adjust PI records and a set of (also RFID-enabled) control stores that do not use RFID to auto-adjust PI records.

Consistent with prior studies (e.g., DeHoratius and Raman 2008), IRI was measured as the absolute difference between actual on-hand and PI (what the system thinks is on hand). Herein, we are interested in the magnitude of the error (as indicated by the absolute difference) and not merely whether the record was accurate. In addition to being consistent with other studies, case pack size and shelf quantity were consistent (on a stock keeping unit [SKU] basis) across all stores used in this study. Thus, the absolute difference (e.g., two units) was the same as the relative difference because the case pack size was fixed across the stores for each product.

3.3. Results—Research Question 1: Impact of RFID on IRI
Table 1 presents descriptive statistics and correlations for the stores in the experiment, pooled across the baseline and treatment periods.

3.3.1. Comparison of IRI: Pre- and Post-Auto-adjust Implementation. We used a discontinuous growth model (see Bliese et al. 2007) in a linear mixed effects model as specified in Bliese and Ployhart (2002) to test for the effect of the RFID auto-adjust within stores. Use of these methodologies allowed us to examine change in the IRI of a SKU over time by modeling discontinuities (i.e., transitions) when the stores implemented RFID auto-adjust. Such change over time cannot be modeled by linear models (Singer and Willett 2003) or even curvilinear models (Bliese et al. 2007). Further, repeated measures and the hierarchical nature of the data made it necessary for us to use linear-mixed effects instead of OLS regression, which assumes independence of observations. IRI on a given day is carried forward to the next day unless there is an adjustment. Also, IRI across SKUs in a given store may not be independent due to execution practices in that store.

We centered our analysis around the actual date when a given SKU was adjusted by RFID auto-adjust. Although the total duration of the study was 23 weeks, a 40-day window around the adjustment was used at the SKU level to investigate the before and after effects of the RFID auto-adjust (20 days before the adjustment and 20 days after the adjustment). Following this, we had a total sample of 2184 observations. Although the 40-day window is somewhat arbitrary, we wanted to choose a time period long enough to generate a pattern of inventory inaccuracy before a change and then observe the effects after the change. On the other hand, a very long time period increases the likelihood that extraneous events may be confounded with the effects of the experimental manipulation (Roth 2007).

Table 1: Descriptive Statistics and Correlations

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Velocity</td>
<td>1.13</td>
<td>1.18</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Item cost</td>
<td>1.72</td>
<td>0.76</td>
<td>-0.305**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Sales volume</td>
<td>21.78</td>
<td>20.26</td>
<td>0.650***</td>
<td>0.125***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Variety</td>
<td>294.08</td>
<td>74.15</td>
<td>0.076***</td>
<td>0.146***</td>
<td>0.160***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Treatment</td>
<td>0.52</td>
<td>0.50</td>
<td>-0.038</td>
<td>0.001</td>
<td>-0.076**</td>
<td>0.059***</td>
<td></td>
</tr>
<tr>
<td>6. IRI</td>
<td>5.01</td>
<td>8.38</td>
<td>0.076***</td>
<td>-0.080***</td>
<td>0.121***</td>
<td>0.182***</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Velocity = Number of units sold per day; Item cost = Cost of an item; Sales volume = Item cost × velocity; Variety = Number of unique SKUs carried in a store; Treatment = Dummy variable coded 1 for RFID auto-adjust switched on, and 0 otherwise; IRI = |PI — actual count| if PI < actual count, and 0 otherwise.

**p < 0.001.
*p < 0.01.
Our discontinuous growth equation is represented by

\[ IRI_{ijk} = \theta_0 + \text{STORE}_{00k} + \alpha_1^i \text{PRE}_{00k} + \alpha_2^i \text{TRANS}_{00k} + \beta_3^k \text{POST}_{00k} + \beta_{01}^k (\text{Velocity}_{jk}) \\
+ \beta_{02}^k (\text{Item Cost}_{jk}) + \beta_{03}^k (\text{Sales Volume}_{jk}) + \gamma_{001}^i (\text{Variety}_{jk}) + e_{ijk}. \]  

(1)

\[ IRI_{ijk} \] is the inventory record inaccuracy in period \( i \) for SKU \( j \) in store \( k \) \((i = 1, 2, \ldots, 40, j = 1, 2, \ldots, 337, k = 1, 2, \ldots, 8)\). The fixed intercept parameter is denoted \( \theta_0 \), and the term \( \text{STORE}_{00k} \) denotes the random main effect of store \( k \). Here, three variables (i.e., \( \text{PRE}_{00k}, \text{TRANS}_{00k}, \text{POST}_{00k} \)) represent three different phases—that is, the pre-test phase, the transition phase, and the post-test phase. The pre-test phase refers to the time periods before a SKU was adjusted, the transition phase refers to the time period when the SKU was adjusted by RFID auto-adjust, and the post-test phase refers to the time periods after a SKU was adjusted. The coding of these variables is presented in Table 2. The variables \( \text{Velocity}_{jk}, \text{Item Cost}_{jk}, \text{Sales Volume}_{jk} \) are second (SKU) level variables. Finally, \( \text{Variety}_{jk} \) is a third (store) level variable.

For the pre-test phase, because \( \text{POST} = \text{TRANS} = 0 \), the slope of the equation during the pre-test phase is represented by the coefficient of the \( \text{PRE} \) variable and Equation (1) can be presented as

\[ IRI_{ijk} = b_0^i + \beta_1^i \text{PRE}_{00k}. \]  

(2)

With the transition dummy variable \( \text{TRANS}_{00k} \), we model a change in the intercept at day 21. After day 21, Equation (1) is given by

\[ IRI_{ijk} = b_0^i + \beta_1^i \text{PRE}_{00k} + \beta_2^i \text{TRANS}_{00k}. \]  

(3)

On the basis of the extant IRI literature (e.g., DeHoratius and Raman 2008, Neely 1987) and the RFID literature (e.g., Delen et al. 2007), we expected that (i) IRI would increase over time, and therefore, the coefficient of the variable \( \text{PRE} \) would be positive (test 1), and (ii) IRI would decrease immediately after RFID auto-adjustment (research question 1). This decrease can be tested by the variable \( \text{TRANS} \) such that if its value is negative and significant, it will indicate RFID auto-adjust decreased IRI (test 2). Although prior research suggests that IRI will increase over time if left unchecked, with the activation of the RFID-enabled system we have no basis for assuming what will happen to PI after the adjustment is made (post-RFID).

The results of the discontinuous growth linear mixed effect model are presented in Table 3 and Figure 3. Consistent with the prior IRI literature, we found that IRI was increasing before the RFID auto-adjustment (\( \text{PRE} = 0.138, \ p < 0.01; \) test 1). More importantly, we found that IRI decreased during the transition period (\( \text{TRANS} = -1.875, \ p < 0.001; \) test 2), as expected. To quantify the percentage improvement, we substituted the value of \( \text{PRE} \) and \( \text{TRANS} \) in Equations (2) and (3). On day 20 (before the implementation of RFID auto-adjust), the IRI is 7.146. On day 21 (after the implementation of RFID auto-adjust), the IRI is 5.271. This shows that the percentage

Table 2. Variable Coding

<table>
<thead>
<tr>
<th>Pre</th>
<th>Post</th>
<th>Trans</th>
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<tbody>
<tr>
<td>1</td>
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<td>0</td>
</tr>
<tr>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>⋮</td>
<td>⋮</td>
<td>⋮</td>
</tr>
<tr>
<td>20</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>21</td>
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<td>0</td>
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<tr>
<td>22</td>
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<td>1</td>
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<tr>
<td>⋮</td>
<td>⋮</td>
<td>⋮</td>
</tr>
<tr>
<td>39</td>
<td>19</td>
<td>1</td>
</tr>
<tr>
<td>40</td>
<td>20</td>
<td>1</td>
</tr>
</tbody>
</table>

PRE, Periods numbered consecutively for 40 day window around the adjustment; POST, Periods numbered 0 for 20 days before the adjustment, numbered consecutively after; TRANS, Numbered 0 before the adjustment, numbered 1 after.

Table 3. Results of Linear Mixed Effects

<table>
<thead>
<tr>
<th>Variables</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>8.004***</td>
</tr>
<tr>
<td>Velocity</td>
<td>-0.953**</td>
</tr>
<tr>
<td>Variety</td>
<td>-0.003</td>
</tr>
<tr>
<td>Item cost</td>
<td>-0.040</td>
</tr>
<tr>
<td>Sales volume</td>
<td>0.000</td>
</tr>
<tr>
<td>PRE</td>
<td>0.138***</td>
</tr>
<tr>
<td>TRANS</td>
<td>-1.875***</td>
</tr>
<tr>
<td>POST</td>
<td>-0.345***</td>
</tr>
</tbody>
</table>

Velocity = Number of units sold per day; Item cost = Cost of an item; Sales volume = Item cost \( \times \) velocity; Variety = Number of unique SKUs carried in a store; PRE: Periods numbered consecutively for 40 day window around the adjustment; POST: Periods numbered 0 for 20 days before the adjustment, numbered consecutively; TRANS: Numbered 0 before the adjustment, numbered 1 after.

* \( p < 0.05 \)

** \( p < 0.01 \)

*** \( p < 0.001 \)
reduction in IRI after the implementation of RFID auto-adjust is about 26% (i.e., \([7.146 - 5.271]/7.146\)). We did not have a basis to conjecture a positive, negative, or zero slope in the post-adjustment period, but we found that IRI continued to decrease after the intervention (\(POST = -0.345, p < 0.001\)).

Recall that for the results presented in Table 3 and Figure 3, we used a restricted data set consisting only of those SKUs that were RFID auto-adjusted. To substantiate the robustness of our findings, we extended our analysis to two additional supersets of SKUs: (i) the data set with all inaccurate SKUs (regardless if they were adjusted or not), and (ii) the data set with all SKUs (accurate or inaccurate). Using these two more inclusive, and ever broader, data sets, we found the same pattern of results, that is, for all inaccurate SKUs, \(TRANS = -1.37, p < 0.01\) and for all SKUs, \(TRANS = -1.25, p < 0.01\).

### 3.3.2. Comparison of Test vs. Control Stores.

As SKUs are grouped within stores, which are in turn grouped within treatment conditions, we used a linear mixed effects model to analyze our data. Again, regression is not appropriate, as the assumption of independent observations fails. To test our conjecture that RFID would decrease IRI we ran a hierarchical linear mixed effects model including \(Velocity, Variety, Item\ Cost\), and \(Sales\ Volume\) as fixed effects, since they are known determinants of IRI (DeHoratius and Raman 2008) that we did not experimentally control:

\[
IRI_{ijk} = \theta_0 + STORE_{00k} + \alpha_i^{PERIOD}_{00k} \\
+ \beta_{01}^{P}(Velocity_{ijk}) + \beta_{02}^{P}(Item\ Cost_{ijk}) \\
+ \beta_{03}^{P}(Sales\ Volume_{ijk}) + \gamma_{01}^{P}(Variety_{ijk}) \\
+ \gamma_{02}^{P}(Treatment_{ijk}) + \epsilon_{ijk}.
\]

\(IRI_{ijk}\) is the inventory record inaccuracy in period \(i\) (\(i = 1, 2, \ldots , 40\)), for SKU \(j\) (\(j = 1, 2, \ldots , 337\)), in store \(k\) (\(k = 1, 2, \ldots , 8\)). The fixed intercept parameter is denoted \(\theta_0\), and the term \(STORE_{00k}\) denotes the random main effect of store \(k\). The variable \(PERIOD_{00k}\) denotes the repeated measure of IRI for an individual level SKU and is a first level variable. The variables \(Velocity_{ijk}\), \(Item\ Cost_{ijk}\), and \(Sales\ Volume_{ijk}\) are second level (SKU) variables. Finally, \(Variety_{ijk}\) and \(Treatment_{ijk}\) are third level (store) variables. Table 4 shows that the level of IRI was significantly lower \((-1.630, p < 0.01)\) for test stores than for control stores.

### 3.4. Results—Research Question 2: The Ameliorating Effect of RFID on Predictors of IRI

Research question 2 asks: Can RFID-enabled visibility ameliorate the effects of known predictors of IRI? Of the seven known predictors found by DeHoratius and Raman (2008), we experimentally controlled for three of the determinants (density, audit frequency, and distribution method) and statistically controlled for the remaining four (velocity, item cost, variety, and sales volume). To test the influence of RFID on these predictors, we created interaction terms by multiplying these predictors with the treatment dummy variable \(\{0 = \text{baseline period and 1 = treatment period}\). The results of the linear mixed effects model are presented in Table 5.

We found that the interaction terms with item cost and variety were significant \((p < 0.05)\). The interaction plots for these two variables are shown in Figure 4. For cost per item, consistent with DeHoratius and Raman (2008), we found that without RFID, as cost per item increased, IRI decreased. With RFID, however, cost per item did not have a significant effect on IRI (i.e., no difference between low and high cost items on IRI). For product variety, we did not find a difference between low variety and high variety in the absence of RFID. However, we found that high variety items exhibited less IRI, compared with low variety items, in an RFID-enabled environment. Although this is counter to DeHoratius and Raman (2008), who found variety to be positively related to IRI, it is most likely due to a confound with store format in our sample. As we were looking at a single category (aircare), variance in variety was only found between store types (large format vs. small format). As small format stores had smaller backrooms to store inventory, RFID would be less helpful because of the smaller backrooms; conversely, it would be more useful in larger stores with larger backrooms. Thus, although RFID was useful in both formats, it was more useful in the large stores.

### 3.5. Study 1 Discussion

Study 1 investigated the effectiveness of RFID-enabled visibility in reducing retail store IRI. First, we compared pre- and post-in-store IRI for the test stores.

| Table 4 Linear Mixed Model for Comparison of Test vs. Control Stores |
|-----------------------------|-----------------------------|
| Variables                   | Fixed effects               |
| (Intercept)                 | 5.654***                    |
| Velocity                    | 2.356***                    |
| Variety                     | 0.000                       |
| Item cost                   | 0.001                       |
| Sales volume                | -0.002                      |
| Test                        | -1.630**                    |
| Period                      | -0.008                      |

Velocity = Number of units sold per day; Item cost = Cost of an item; Sales volume = Item cost \times\ velocity; Variety = Number of unique SKUs carried in a store; Test: Dummy variable coded 1 for test stores and 0 for control stores; Period: Day 1 starting when RFID auto-adjust was made available in test store.

*** \(p < 0.001\). ** \(p < 0.01\).
The hierarchical discontinuous growth model showed that RFID-enabled visibility results in a significant decrease in IRI. One way to view this decrease is to examine the shift in intercept pre- and post-auto-adjustment as illustrated earlier in Figure 3. Using the data from Figure 3, the percentage decrease is 26%. Interestingly, we found that IRI continued to decline after the auto-adjustment. An ad hoc analysis of the number of manual adjustments, a key cause of IRI, revealed a 41% decline in the number of manual adjustments after RFID auto-adjust was installed. As we observed from our discussion with the store managers, these (often incorrect) manual adjustments are a key trigger for IRI. We believe this decline in manual adjustments, attributed to the system making auto-adjustments, is likely to lead to fewer incorrect adjustments to PI (and, thus, one less source of error).

Second, we conducted a between-store comparison of the eight test and five control stores. The results of this comparison showed that RFID auto-adjust decreased IRI as we found that the test stores had significantly lower IRI than the control stores.

Overall, the discontinuous growth model from study 1 provides evidence for the impact of case-level RFID to reduce IRI. However, the use of a single category limits the generalizable insights that may be drawn, and, therefore, we broaden the scope of this research with Study 2.

4. Study 2

4.1. Sample and Procedure

Study 2 included 62 stores representing various store formats spread all across the United States from the retailer in study 1. Of the 62 stores, 31 were categorized as test stores and 31 were categorized as control stores, matched by the retailer on a set of characteristics, such as annual sales.

Unlike study 1, which used only a single category, study 2 used five categories with 1268 unique SKU’s.

Table 5 Influence of RFID-enabled Visibility on Known Predictors of Inventory Inaccuracy

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>8.794***</td>
<td>8.961***</td>
<td>8.578***</td>
<td>8.509***</td>
<td>8.632***</td>
</tr>
<tr>
<td>Treatment</td>
<td>-2.385***</td>
<td>-1.932***</td>
<td>-1.964***</td>
<td>-1.606***</td>
<td>-1.899***</td>
</tr>
<tr>
<td>Item cost</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.003</td>
<td>-0.004</td>
<td>-0.005</td>
</tr>
<tr>
<td>Velocity</td>
<td>-0.858*</td>
<td>-1.044**</td>
<td>-0.571**</td>
<td>-0.991**</td>
<td>-1.186**</td>
</tr>
<tr>
<td>Variety</td>
<td>-0.022</td>
<td>-0.025</td>
<td>-0.021</td>
<td>-0.021</td>
<td>0.023</td>
</tr>
<tr>
<td>Sales volume</td>
<td>0.000</td>
<td>0.002</td>
<td>0.000</td>
<td>0.000</td>
<td>0.002</td>
</tr>
<tr>
<td>Treatment × item cost</td>
<td>0.002***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × velocity</td>
<td>-0.087</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × variety</td>
<td>-0.157***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × sales volume</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.005</td>
</tr>
</tbody>
</table>

Velocity = Number of units sold per day; Item cost = Cost of an item; Sales volume = Item cost × velocity; Variety = Number of unique SKUs carried in a store; Treatment: Numbered 0 before the adjustment, numbered 1 after.

*p < 0.05.

**p < 0.01.

***p < 0.001.

Figure 4 Interaction Plots for Study 1

(a) Interaction Plot for RFID and Cost

(b) Interaction Plot for RFID and Variety
for the experiment. These categories were air-care products (e.g., air fresheners, candles, sprays), floor-care (e.g., vacuum cleaners, carpet spot remover), formula (e.g., infant nutritional products, canned soy milk), ready to assemble furniture (e.g., computer cart, executive chair), and quick cleaners (e.g., fabric cleaner, microfiber pads). These categories represented products from across the store in a variety of sizes (from baby formula to furniture), case pack sizes (from case pack sizes of 1–48), prices (from less than a dollar to several hundred dollars), and sales velocities (from tens of units per day to one per week).

All the SKUs in the five categories were physically counted at two separate points in time. The first count was 1 week before the implementation of the RFID auto-adjust, and the second was 2 months after the first, approximately 7 weeks after the implementation of the RFID auto-adjust. This ensured that both physical counts were conducted in the first week of the respective months. Physical counts were conducted by the same independent firm as study 1 and because of the large number of SKUs involved in this study, took approximately 5 days to complete.

In contrast to study 1, where we only examined understated IRI, we examined both understated and overstated IRI in study 2 (using the same dependent variable as study 1: absolute difference between actual on-hand inventory and PI). We operationalized measures for factors known to influence IRI as follows: Sales velocity was the number of units of a SKU sold for 2 months preceding the count across all stores; Item cost was the cost of an item to the retailer; Sales volume was the total dollar amount of a SKU sold for 2 months preceding the count across all stores; Variety was the total number of unique SKUs in a category; and Density was the total number of units in a category divided by linear feet of shelf space for that category.

We used an untreated control group design with pre-test and post-test (Shadish et al. 2002). We conducted a within-store comparison before and after the implementation of RFID auto-adjust for both test and control stores.

Table 6 presents descriptive statistics and correlations for the 62 stores in the experiment.

### 4.2. Results

Table 6 presents descriptive statistics and correlations for the 62 stores in the experiment.

#### 4.2.1. Study 2 Research Question 1: Impact of RFID on IRI

The goal of study 2 was to examine the influence of RFID auto-adjust on IRI across categories. We conducted within-store comparisons for both test stores and control stores by categories, using linear mixed effects models where items were grouped within stores. Simplifying notation and showing fixed effects only, $IRI = \beta_0 + \beta_1 \ast Treatment$, where Treatment was a dummy variable coded 1 for RFID auto-adjust switched on and 0 otherwise. The results for the linear mixed effects models are presented in Table 7, along with the differences in the effect size of the treatment between test and control stores. We assessed the statistical significance of these differences by conducting a difference of differences test to see if the pre- vs. post-differences in control stores were significantly different from the pre- vs. post-differences in the test stores. Following the procedure suggested by Cohen et al. (2003), we introduced an interaction term in our linear mixed effects model. Therefore, IRI was now given by (again simplifying notation): $IRI = \beta_0 + \beta_1 \ast Treatment + \beta_2 \ast Group + \beta_3 \ast Treatment \times Group$, where Group was a dummy variable coded 1 for test stores and 0 otherwise.

The results of the linear mixed effects model show that for all the categories except ready to assemble furniture, pre- vs. post-decrease in the level of IRI was significantly higher for test stores than control stores. For ready to assemble furniture, we did not find any significant differences between test stores and control stores.

#### 4.2.2. Study 2 Research Question 2: The Ameliorating Effect of RFID on Predictors of IRI

We examined the moderating influence of RFID-enabled visibility on the DeHoratius and Raman (2008) predictors of IRI. With the inclusion of five general merchandise categories of products in study 2,
we were able to examine the influence of RFID on the known effects of product density, velocity, item cost, variety, and sales volume. To test the influence of RFID on these predictors, we created interaction terms by multiplying these predictors with the treatment (dummy variable coded 1 for RFID auto-adjust switched on and 0 otherwise). Table 8 shows the linear mixed effects models.

In the interaction plots in Figure 5a–c and e, consistent with DeHoratius and Raman (2008), we find that RFID appears to ameliorate the effect of inventory density, variety, sales volume, and velocity on IRI. The interaction plot (Figure 5d) suggests that without RFID, cost has no effect on IRI; with RFID, high cost items have higher IRI. This is counter to DeHoratius and Raman (2008), who show that higher cost is negatively associated with IRI and counter to our own findings from study 1. We believe this is due to the profile of product category attributes and we revisit this issue in the next section.

4.2.3. Differences between Categories. Table 9 presents average characteristics of different categories along with the percentage change in the accuracy improvement. We found that the accuracy improvement varied from 16% to 81% depending on the category. It is important to note that the ready to assemble furniture, a category with low sales velocity, high cost, and low density, was not influenced by RFID. More interestingly, we found that formula, a category with high sales velocity, low cost, high sales volume, and high density benefited the most with the presence of RFID. Informal discussions with various retailers suggest this category to be “high theft,” thus most likely experiencing high overstated PI and corresponding high IRI. This provides further evidence that RFID is more effective in reducing inventory inaccuracy in product categories that have higher sales volume, higher dollar sales, greater SKU variety, and greater inventory density.

Revisiting the ameliorating effect of RFID on cost, as discussed, although the interaction was significant, neither the “without RFID” nor the “with RFID” relationship was as expected. However, the explanation appears to be straightforward. The IRI for furniture—the highest cost category—was not positively affected by RFID, perhaps due to its profile of other characteristics (low velocity and low density). This category, because of its high cost (more than double the cost of the next highest category and more than 20 times the lowest cost category), appears to have attenuated the effect of cost in the overall interaction.

4.3. Study 2 Discussion

Study 2 used a completely different sample of stores and was conducted more than a year after study 1. The analysis featured a cross-sectional snapshot of data before and after the intervention, unlike study 1, which examined the period before and after the intervention with some considerable detail. The consistency in the aircare category that found an improvement of 26% in study 1 compared with 30% for study 2 is some evidence for robustness of estimates. The slightly better improvement of 30% in study 2 may be attributed to the inclusion of

Table 7 Effect Size for Treatment, Linear Mixed Effects Model

<table>
<thead>
<tr>
<th>Category</th>
<th>Control stores</th>
<th>Test stores</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floorcare</td>
<td>-0.208**</td>
<td>-0.899***</td>
<td>0.691**</td>
</tr>
<tr>
<td>Aircare</td>
<td>-1.099**</td>
<td>-2.729***</td>
<td>1.630***</td>
</tr>
<tr>
<td>Furniture</td>
<td>-0.061</td>
<td>0.168</td>
<td>-0.229***</td>
</tr>
<tr>
<td>Formula</td>
<td>0.894</td>
<td>-2.004***</td>
<td>2.898***</td>
</tr>
<tr>
<td>Quick cleaners</td>
<td>1.692**</td>
<td>1.319**</td>
<td>0.373**</td>
</tr>
</tbody>
</table>

Significance of difference assessed by interaction term of treatment (pre-post) and group (test-control).

***p < 0.001.
**p < 0.01.
*p < 0.05.

Table 8 Influence of RFID-enabled Visibility on Known Predictors of Inventory Inaccuracy

<table>
<thead>
<tr>
<th>Variables</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.759***</td>
<td>1.833***</td>
<td>1.167***</td>
<td>1.651***</td>
<td>0.606</td>
<td>1.221***</td>
</tr>
<tr>
<td>Treatment</td>
<td>-1.977***</td>
<td>-2.177***</td>
<td>-0.806***</td>
<td>-1.682***</td>
<td>-0.840***</td>
<td>-0.817***</td>
</tr>
<tr>
<td>Item cost</td>
<td>0.001</td>
<td>0.001</td>
<td>0.002</td>
<td>0.001</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>Velocity</td>
<td>0.021***</td>
<td>0.021***</td>
<td>0.028***</td>
<td>0.021***</td>
<td>0.021***</td>
<td>0.021***</td>
</tr>
<tr>
<td>Sales volume</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
</tr>
<tr>
<td>Density</td>
<td>0.010***</td>
<td>0.010***</td>
<td>0.011***</td>
<td>0.010***</td>
<td>0.017***</td>
<td>0.010***</td>
</tr>
<tr>
<td>Variety</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
<td>Treatment × cost</td>
<td>0.005*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × salesvol</td>
<td></td>
<td>-0.014***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × velocity</td>
<td></td>
<td></td>
<td></td>
<td>-0.004***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment × density</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.013***</td>
<td></td>
</tr>
<tr>
<td>Treatment × variety</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.001***</td>
</tr>
</tbody>
</table>

***p < 0.001.
**p < 0.01.
*p < 0.05.
overstated in the IRI evaluation. We also found that RFID ameliorated the influence of known predictors of IRI. With the exception of cost, RFID reduced or eliminated the effect of the known predictors—density, variety, velocity, sales volume—on IRI. This may be the most important outcome of study 2, as it provides additional insight into these predictors and the ability to influence their effect on IRI. Moreover, we found the influence of RFID on IRI varied by product category. The differences across categories reinforce the results of the ameliorating effects of RFID on the known predictors of IRI. For example, larger (i.e., low density), low velocity items such as ready to assemble furniture were not influenced by RFID, whereas small, fast moving items (i.e., high density, high velocity) such as formula were influenced the most. This categorical breakdown provides some predictive insight for both theory and practice as to what product categories are likely to show the greatest improvement with case-level tagging.
In two separate field studies with a major retailer, we
examined two research questions: (i) What is the mag-
nitude of the impact of RFID-enabled visibility on
IRI? (ii) Can RFID-enabled visibility ameliorate the
effects of known predictors of IRI? Study 1 addressed
question 1 in detail with some insight into question 2.
Study 2 provided insight into the effects of RFID on
the known predictors of IRI and on the effects of cate-
gory differences on the ability of RFID to reduce IRI.

This research answers the call by prior research
e.g., Dutta et al. 2007, Lee and Özer 2007) to investi-
gate the impact of RFID via empirical-based research
with a well-designed sample and rigorous controls.
Although it may be theoretically possible for a retailer
to individually barcode scan every box entering the
receiving door, going to the sales floor, returning from
the sales floor, etc., the cost is prohibitive. It also
requires diligence (i.e., perfect execution) by employ-
ees (diligently scanning every box entering the back-
room, leaving the backroom, going to the box
 crusher) that is not realistic. An examination of the
carefully constructed rationales for why DeHoratius
and Raman (2008) theorized their predictors would
impact IRI is informative. A broad generalization
would characterize many of these rationales to be
based on the finite capacity of human agents to deal
with environmental and task complexity. Thus, it is
unlikely that a solution based on human intervention
will solve the problem unless environmental and task
complexity are reduced. RFID provides an automated
zero human intervention solution to the problem.

5. Discussion

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examined two research questions: (i) What is the mag-
nitude of the impact of RFID-enabled visibility on
IRI? (ii) Can RFID-enabled visibility ameliorate the
effects of known predictors of IRI? Study 1 addressed
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Study 2 provided insight into the effects of RFID on
the known predictors of IRI and on the effects of cate-
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requires diligence (i.e., perfect execution) by employ-
ees (diligently scanning every box entering the back-
room, leaving the backroom, going to the box
 crusher) that is not realistic. An examination of the
carefully constructed rationales for why DeHoratius
and Raman (2008) theorized their predictors would
impact IRI is informative. A broad generalization
would characterize many of these rationales to be
based on the finite capacity of human agents to deal
with environmental and task complexity. Thus, it is
unlikely that a solution based on human intervention
will solve the problem unless environmental and task
complexity are reduced. RFID provides an automated
zero human intervention solution to the problem.

5.1. Research Limitations and Future Directions

In this study, we investigated IRI across multiple
stores from a single retailer. Thus, the results may not
generalize across all retailers. However, as noted by
DeHoratius and Raman (2008), the “advantages of
field research within one organization include the use
of detailed, firm-specific data and a deep understand-
ing of the study context … [and] control for firm-spe-
cific factors that influence IRI” (p. 638). As this retailer
is very large and successful, the results may have
suffered from a “ceiling” effect as compared to other
retailers; this retailer may already be very good. In
this case, therefore, our estimates may be conserva-
tive. The improvement brought about by RFID was
also based on tagging cases only. With item-level tag-
ging becoming the standard in the apparel industry,
the impact of RFID may be greater. Therefore, future
research should investigate the influence of item-level
RFID on retail store execution.

In study 1, IRI increased until RFID was used to
make an adjustment and resulted in a significantly
lower inaccuracy point. We found inaccuracy to con-
tinue to decline after the auto-adjustment. Although
we speculate that it may be due to fewer manual
adjustments, which are a source of human error, we
have no firm evidence to confirm this linkage. A pro-
cess analysis that identifies what caused the contin-
ued decrease in IRI is an avenue for future research.

It was not within the scope of our study to explicitly
quantify the return on investment (ROI) resulting
from the reduction in IRI. However, typically, the
retailer bears the brunt of the fixed costs (i.e., from
the RFID readers installed in DCs, stores, etc.) and
the suppliers incur greater variable costs (i.e., the cost per
tag). Camdereli and Swaminathan (2010) show that
there is misalignment of incentives for the retailer and
the supplier to invest when there is a fixed cost of
investment. Further, reducing out of stocks is benefi-
cial to the retailer because of store switching, but ben-
eficial to the supplier because of brand switching
(Corsten and Gruen 2004). An empirical investigation
that quantifies the benefits from RFID to retailers and
to suppliers may be the subject of future research.

6. Conclusion

Inventory inaccuracy has plagued retailers for many
years. Using two different field experiments that pro-
vide ecological validity, this research investigated
the impact of RFID-enabled perpetual inventory

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Table 9 Characterization of Categories

<table>
<thead>
<tr>
<th>Category</th>
<th>Velocity</th>
<th>Item cost</th>
<th>Sales volume</th>
<th>Variety</th>
<th>Density</th>
<th>% Improve</th>
</tr>
</thead>
<tbody>
<tr>
<td>Floorcare</td>
<td>1.66</td>
<td>7.80</td>
<td>1.58</td>
<td>6.13</td>
<td>6.00</td>
<td>45.15%***</td>
</tr>
<tr>
<td>Aircare</td>
<td>9.44</td>
<td>1.00</td>
<td>1.00</td>
<td>9.36</td>
<td>56.00</td>
<td>29.56%***</td>
</tr>
<tr>
<td>Furniture</td>
<td>1.00</td>
<td>20.05</td>
<td>2.53</td>
<td>3.20</td>
<td>1.00</td>
<td>–60.64%</td>
</tr>
<tr>
<td>Formula</td>
<td>13.16</td>
<td>4.04</td>
<td>6.46</td>
<td>2.35</td>
<td>32.50</td>
<td>81.60%***</td>
</tr>
<tr>
<td>Cleaners</td>
<td>8.30</td>
<td>2.37</td>
<td>2.41</td>
<td>1.00</td>
<td>18.00</td>
<td>16.86%***</td>
</tr>
</tbody>
</table>

Cell values (except % improve) have been re-scaled to protect information deemed confidential by the retailer. Cell values were re-scaled by dividing each number in a column by the smallest number in the column and, thus, providing a relative value. For example, in the Item cost column, Furniture is 20.05 times the value of Aircare (the lowest cost item).

***p < 0.001.
**p < 0.01.
auto-adjustments on inventory record inaccuracy. Study 1 used a sample of 13 stores from a major retailer and daily counts (for 23 weeks) of 337 SKUs in a single category (aircare products). Study 2 used a much larger sample of 62 stores, five different categories, and 1268 SKUs from the same retailer. We first examined the impact of RFID on IRI. We then investigated the ameliorating effects of RFID on known causal predictors of inventory inaccuracy. Finally, we drew inferences about the characteristics of product categories for which RFID is effective in reducing inventory inaccuracy. Using one of the largest samples of stores and SKUs of its kind with longitudinal data across two separate experiments, our findings suggest that the visibility provided by RFID is a viable intervention to reduce inventory inaccuracy. The insight that the product categories most likely to benefit from RFID may be characterized by predictors of inventory inaccuracy is key. These results inform future research as to ways in which IRI can be further reduced. For the practitioner, this is further evidence that RFID can be used successfully, thus reducing excess inventory and improving store execution.

Acknowledgments

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Notes

1We did not use a balanced design for two reasons: (i) Our primary test was the within-store comparison, and therefore, it was more desirable to have a larger sample of test stores, and (ii) the retailer wanted to observe more test stores for their own internal process improvement purposes.

2The exact set of business rules used by the retailer in making a determination of whether to adjust PI are considered proprietary and cannot be shared. In essence, the system used the visibility provided by the RFID read points to determine the location of product (backroom or sales floor), combined with the information from point of sale, to determine the accuracy of PI, as prior examples have illustrated.

3Recall that the retailer used the RFID data and a set of decision rules to determine whether to automatically adjust PI. There were several instances in which PI was wrong, but did not match the criteria as determined by the retailer and was, thus, not adjusted. This extended data set included these records.

References


