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RFID-ENABLED VISIBILITY AND RETAIL INVENTORY RECORD INACCURACY: EXPERIMENTS IN THE FIELD

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Experiments in the Field

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

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 treatment and 5 control) of a major global retailer over 23 weeks. We compared in-store IRI before and after implementing RFID-enabled auto-adjustment of records for the test stores and between test stores and control stores. Results indicate a significant decrease in IRI of approximately 26% due to RFID-enabled visibility. In study 2, which used an untreated control group design with pre-test and post-test, the number of categories was expanded to five and the number of stores to 62 (31 treatment and 31 control stores); IRI was measured before and after implementing RFID. Results suggest that RFID ameliorates the effects of known determinants of IRI (from DeHoratius and Raman 2008) and that the effectiveness of RFID on reducing IRI varies by category. The results from both studies provide guidance for researchers and practitioners for the deployment of RFID in the retail store by (1) demonstrating that case-level tagging can be effective in reducing IRI with the ecological validity provided by a field experiment, and (2) providing the key insight that the technology is most effective for product categories characterized by known determinants of IRI.

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

1. Introduction

Inventory record accuracy is an essential ingredient for efficient and effective supply chain management and store execution (DeHoratius and Raman 2008; Gaur, Fisher, Raman 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 Gershwin 2005, p. 844). There is a discrepancy between retailer inventory records and actual inventory in the store (DeHoratius, Mersereau, and Schrage 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, Hardgrave, and Sharda 2007; Whitaker, Mithas, and Krishnan 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 Özer 2007).

Retailers as well as research studies recognize the problem of inventory record inaccuracy (IRI) (for a review, see Heese 2007). For example, a recent AMR report identified IRI as one of the top issues for grocery retailers (Landoc, Garf, and Suleski 2006). 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, DeHoratius, and Ton 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).

In order 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, Raman, and McClelland 2000), but this measure increases inventory holding costs (Fisher and Rajaram 2000).

RFID can potentially help companies automate the process of identifying and eliminating the source of errors (Bensoussan, Cakanyildirim, and Sethi 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. While 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, Lee, and Whang 2007). They argue (p. 653) that such empirical-based research requires "*a well-designed sample, with* *appropriate controls and rigorous statistical analysis*." 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. However, RFID adoption is in the early stages and rigorous research studies are needed to test model predictions in the field and, thus, encourage firms to adopt the technology. The objective of the current research is to investigate, via two field experiments with a major retailer in the U.S., the impact of RFID on IRI.

In this paper, we demonstrate the utility of RFID in retail store execution by showing that RFID presents retailers with unprecedented visibility in day-to-day operations. This visibility, in turn, 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 whether or not 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. *Will RFID-enabled visibility reduce IRI? (Study 1)*
2. *Can RFID-enabled visibility ameliorate the effects of known predictors of IRI? (Study 1 and Study 2)*
3. *What are the characteristics of product categories for which RFID-enabled visibility is effective in reducing IRI? (Study 2)*

The answers to the above questions, especially question 1, may appear to be intuitively obvious (e.g., "of course RFID will reduce IRI"). However, despite the seemingly self-evident potential for RFID-enabled visibility to reduce IRI, very limited empirical research has demonstrated how RFID can help (Amini, Otondo, Janz, and Pitts 2007; Ware 2004). Until there is empirical proof, 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 the answers to the questions are not obvious is that the environment in which retailers operate is complex, with fallible human intervention, technological, budgetary and circumstantial constraints, and the impact of other contextual factors. A comprehensive list of potential complexities is difficult to even visualize let alone be incorporated into an analytical model. Therefore, it is necessary to investigate the potential for RFID-enabled visibility to reduce IRI, in the context of normal business processes in the field. Theorizing, laboratory experiments, passive observation, and many of the other methodologies available to researchers may provide insight but are unlikely to provide the ecological validity that can only be provided by a controlled field experiment. Accordingly, we employ such an experimental approach by manipulating visibility-enabled inventory adjustments.

The rest of this paper is organized as follows: Section 2 sets the background and justification for the studies; Section 3 presents study 1; Section 4 focuses on study 2; and Section 5 discusses the results and draws implications for future researchers and for firms which implement RFID to reduce IRI.

2. Literature Review

Our work builds on prior research on RFID (e.g., Delen et al. 2007) and IRI (e.g., DeHoratius and Raman 2008; Raman et al. 2001). Here, we discuss these two streams (RFID and IRI) that are key to our research.

2.1 RFID and Visibility

RFID refers to a wireless system that relies on radio frequency waves to identify objects (Delen et al. 2007). This technology is one example of a family of auto-identification technologies which also includes the ubiquitous barcode, but has numerous advantages relative to barcodes (for a review, see Barratt and Choi 2007). These advantages have prompted many retail companies (e.g., Wal-Mart, Metro) to aggressively pursue RFID as a way to improve the supply chain by reducing costs and increasing sales.

RFID tagging may be at the pallet-level, the case-level, or at the item-level. Pallet-level tagging provides visibility primarily at the receiving doors and is unlikely to give sufficient visibility into in-store movement of goods so as to reduce IRI. Item-level tagging would result in a much more granular view of movements within the store but at the current time is expensive to implement for low-priced products. Therefore, our research investigates case-level tagging which (as we will explain) provides a sufficient view of in-store movements. If our experiments provide evidence that case-level tagging can indeed result in a reduction of IRI, this makes a strong argument for the continuing adoption of 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. They demonstrated that the flow of inventory 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. They showed that with case-level tagging these readers were capable of providing metrics such as descriptive statistics for the time that a product spends in each section of the supply chain. These metrics could compare efficiencies in different stores or in DC-store pairs, and thus pinpoint potential areas for improvement. 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

IRI 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 $\pm$ 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 X 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 or not it was shipped from a retailer-owned DC).

2.2.1 Overstated versus 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, also known as phantom inventory), and about half the time PI is understated (i.e., PI shows less than what is in the store, also known as hidden inventory).

Similarly, DeHoratius and Raman (2008) found about 59% of the inaccurate records to be overstated versus 41% understated. Each of these two types of IRI has a detrimental effect on the retailer. 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), 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 which impact margin, reduced turns, and breakdowns in store execution (which can lead to execution-related errors such as out of stocks) due to the inefficiencies created by the extra inventory.

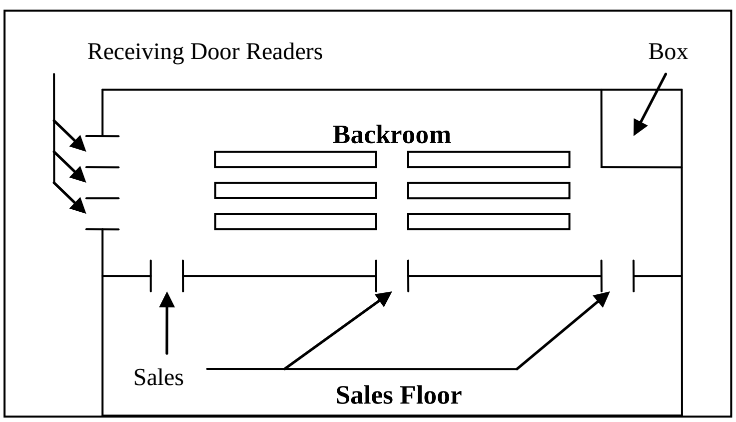
2.2.2 Trigger Events and the Use of RFID

Based on existing literature and interviews with managers from the retailer who participated in the study, we enumerate events which may trigger IRI. We discuss some issues related to both understated and overstated PI in order to give an idea of the general scope of the problem. 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, an employee could think a case of product exists when it does 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 (e.g., the system thinks there are 10 items on hand, but three were stolen leaving a true on hand of only seven). 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 are occasionally not 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 (overstated 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).

To compensate for IRI, companies can do a variety of things (for a review, see Kang and Gershwin 2005; Morey 1985). First, increasing safety stock helps avoid out of stocks by keeping 'extra' inventory on hand (Waller, Nachtmann, and Hunter 2006). RFID may help reduce this extra, and unnecessary, inventory. Second, the company can perform frequent manual inventory counts which can be disruptive to store execution, vary in accuracy, and are very costly (Millet 1994). Because of the onerous nature of manual inventory counts, most large retailers only perform enterprise-wide manual counts once or twice per year. RFID-enabled IRI improvement may be a cost effective alternative with the further advantage of a much more vigilant monitoring system with more frequent adjustments than is possible with manual counts. Third, to offset overstated PI, the company can build in a constant decrement equal to the amount of stock loss one thinks is occurring. The visibility enabled by RFID may result in greater accuracy than current methods of estimating stock loss. Finally, the company can try to eliminate the source of errors by better inventory management, reducing theft, etc. Kang and Gershwin (2005) suggest an automatic product identification system (such as RFID) as one method to help firms eliminate the source of errors -- though this function of RFID is outside the scope of the current research.

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): (1) receiving doors have read portals and capture reads from individual cases as they are unloaded from the truck; (2) 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 (3) placed into the box crusher for disposal (the last read point).

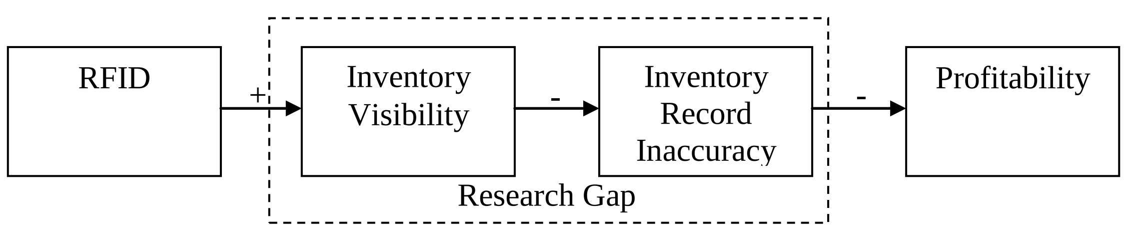
Figure 1 Retail Store Read Points



This visibility (of the location of a product – backroom or sales floor) provides 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. Now consider 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, with RFID, 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 Ozer, 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).

Figure 2 Research Model



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[1]. All stores in the study were RFID-enabled. Control stores were equipped with RFID equipment (readers), but data from the system was 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 arrived at each store between 4PM and 8PM and followed the same counting path (e.g., begin at bottom left shelf and work way to top right) 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 the act of measurement changing what is being measured).

[1] We did not use a balanced design for two reasons: (1) Our primary test was the within-store comparison, and therefore it was more desirable to have a larger sample of test stores, and (2) the retailer wanted to observe more test stores for their own internal process improvement purposes.

In the test stores in the treatment period, using a system of logic based on the RFID reads[2], the system made adjustments to PI automatically when triggered by the reads (as described earlier). In this particular field trial, the retailer was interested in studying the impact of RFID-enabled visibility on understated PI as a means to reduce inventory costs. Therefore, study 1 focuses on understated PI only. The retailer had good reason to look at understated PI initially. First, this retailer has an ongoing concerted effort to reduce its inventory-to-sales ratio. In the past 10 years, the percentage of inventory to sales decreased from 12.4% to 8.2% while increasing net profit margin by 30 basis points (Wal-Mart 2010). By making their supply chain leaner (as illustrated by the aforementioned ratio), the importance of inventory record accuracy increased. As suggested by Kang and Gershwin (2005), IRI wreaks "far greater havoc on lean systems" (p. 851). Second, the retailer had undertaken a previous study examining the impact of RFID on out of stocks (Hardgrave, et al. 2008). As out of stocks are a primary outcome of overstated PI, the retailer felt they had initial insight into overstated PI.

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 versus post increase in test stores' overstated PI was not more than the pre versus post increase in control stores' overstated PI (0.38% for the test stores; 0.91% for control stores).

3.2 Study Design

To investigate research question 1 (*will RFID-enabled visibility reduce IRI?*), we use an interrupted time-series design which is "one of the most effective and powerful of all quasi-

[2] The exact set of business rules used by the retailer in making a determination of whether or not 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.

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 pretest 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 or not 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.

Table 1 Descriptive Statistics and Correlations

Variable	Mean	Std. Dev.	1	2	3	4	5
1. Velocity	1.13	1.18					
2. Item Cost	1.72	0.76	-0.305**				
3. Sales Volume	21.78	20.26	0.650***	0.125***			
4. Variety	294.08	74.15	0.078***	0.146***	0.160***		
5. Treatment	0.52	0.50	-0.038	0.001	-0.076**	0.059***	
6. IRI	5.01	8.38	0.076***	-0.080***	0.121***	0.182***	0.03

Notes: *** $p < .001$, ** $p < .01$

Velocity = Number of units sold per day; Item Cost = Cost of an item; Sales Volume = Item Cost X 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

3.3.1 Comparison of IRI: Pre and Post Auto-adjust Implementation

We used a discontinuous growth model as described by Bliese, McGurk, Thomas, Balkin, and Wesensten (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). Even curvilinear models may not present an accurate picture because higher-order terms in nonlinear models are likely to miss the distinct transition phase (Bliese et al. 2007) masking the true change in the IRI over time. Therefore, discontinuous growth models serve as a framework to accurately measure the transition of the dependent variable (IRI) over time. Further, repeated measures and the multi-level nature of the data made it necessary for us to use linear-mixed effects instead of simple regression. Regression assumes that observations are independent. However, IRI on a given day is carried forward to the next day unless there is an adjustment. Also, inaccuracy of SKUs in a given store may not be independent. Given these challenges, we followed Bliese and Ployhart (2002) and used discontinuous growth linear-mixed effects model.

We used the actual date when a given SKU was adjusted by RFID auto-adjust. Although the total duration of the study was several 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).

Our discontinuous growth equation is represented by:

$$IRI_{ijk} = \theta_0 + STORE_{00k} + \alpha_1{*}PRE_{00k} + \alpha_2{*}TRANS_{00k} + \alpha_3{*}\,POST_{00k} + \beta_{01}{*}(Velocity_{jk}) + \beta_{02}{*}(Item\_Cost_{jk}) + \beta_{03}{*}(Sales\_Volume_{jk}) + \gamma_{001}{*}(Variety_k) + \varepsilon_{ijk} \quad \text{.................................}(1)$$

IRI_{ijk} is the inventory record inaccuracy in period i (i=1,2,...,40), for SKU j (j=1,2,..,337), in store k (k = 1,2,..,8). The fixed intercept parameter is denoted θ_0, and the term $STORE_{00k}$ denotes the random main effect of store k. Here, three variables (i.e., PRE_{00k}, $TRANS_{00k}$, $POST_{00k}$) represent three different phases – i.e., 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 refers to the time periods after a SKU was adjusted. The coding of these variables is presented in Table 2. The variables $Velocity_{jk}$, $Item\ Cost_{jk}$, $Sales\_Volume_{jk}$ are second level (SKU) variables. Finally, $Variety_k$ is a third level (store) variable.

Table 2 Variable Coding

PRE	***POST***	***TRANS***
1	0	0
2	0	0
⋮	⋮	⋮
20	0	0
21	1	0
22	1	1
⋮	⋮	⋮
39	19	1
40	20	1

Notes: 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

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

$IRI_{ijk} = b_0 + b_1{*}PRE_{00k}$ ……………………………………………………………………..(2)

With the transition dummy variable $TRANS_{00k}$, we model a change in the intercept at day 21. After day 21, equation (1) is given by:

$IRI_{ijk} = b_0 + b_1{*}PRE_{00k} + b2{*}TRANS_{00k}$ ………………………………………………..(3)

Based on the extant IRI literature (e.g., DeHoratius and Raman 2008; Neely 1987) and the RFID literature (e.g., Delen et al. 2007), we expect the following effects to be true: (1) IRI increases over time; therefore, the coefficient of the variable *PRE* should be positive (test 1); and (2) IRI will decrease immediately after RFID auto-adjustment (research question 1). This decrease can be tested by the variable *TRANS* such that if its value is negative and significant it will indicate RFID auto-adjust decreased IRI (test 2). While 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 (PRE=0.138, $p<.01$; test 1). More importantly, we found that the overall IRI decreased during the transition period (TRANS = -1.875, $p<.001$; test 2), as expected and, thus, we have evidence that RFID resulted in a decrease in IRI. To quantify the percentage improvement, we substituted the value of PRE and 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 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<.001).

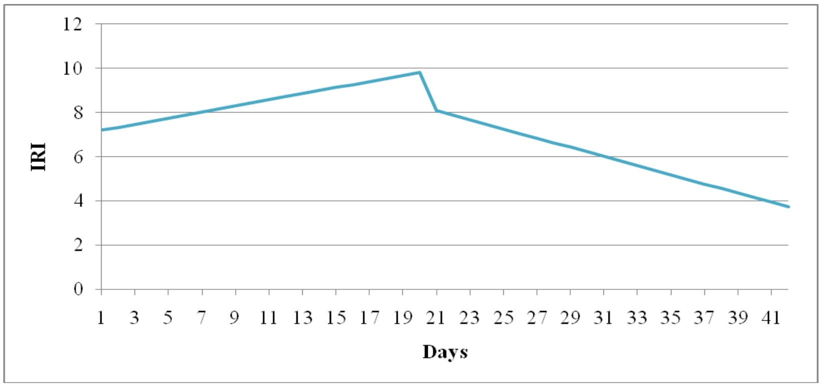
Table 3 Results of Linear Mixed Effects

Variables	Effect
(Intercept)	8.004***
Velocity	-0.953**
Variety	-0.003
Item cost	-0.040*
Sales Volume	0.000
PRE	0.138**
TRANS	-1.875***
POST	-0.345***

*Notes: *p < .05, **p < .01, ***p < .001*

Velocity = Number of units sold per day; Item Cost = Cost of an item; Sales Volume = Item Cost X 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

Figure 3 Linear Growth Model for IRI



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. If we considered a more inclusive sample than only those SKUs that were auto-adjusted, we would potentially be subject, in some degree, to gradual rather than abrupt interventions (Shadish et al. 2002) since the adjustments would be dispersed over time. The consequence would be that the coefficient of the variable TRANS is then underestimated while some of this decrease (diffused over time) is captured by the slope of the POST variable. Therefore, to substantiate the robustness of our findings, we extended our analysis to two additional supersets of SKUs: (1) the dataset with all inaccurate SKUs (regardless if they were adjusted or not[3]), and (2) the dataset with all SKUs (accurate or inaccurate). Using these two more inclusive, and ever broader, data sets, we found the same pattern of results, i.e., for *all inaccurate* SKUs, *TRANS* = -1.37, $p<0.01$ and for *all* SKUs, *TRANS* = -1.25, $p<0.01$. Therefore, regardless of the view, RFID decreased IRI, as suggested by research question 1.

[3] Recall that the retailer used the RFID data and a set of decision rules to determine whether or not 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.

3.3.2 Comparison of Test versus 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. Furthermore, the number of SKUs is not the same across stores, and linear mixed effects allows for unbalanced data.

We conjectured that the presence of RFID would decrease IRI over time. In order to test this, 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:

$$IRI_{ijk} = \theta_0 + STORE_{00k} + \alpha_1 * PERIOD_{00k} + \beta_{01} *(Velocity_{jk}) + \beta_{02} *(Item\_Cost_{jk}) + \beta_{03} *(Sales\_Volume_{jk}) + \gamma_{001} *(Variety_k) + \gamma_{002} *(Treatment_k) + \varepsilon_{ijk}$$

IRI_{ijk} is the inventory record inaccuracy in period i (i=1,2,...,40), for SKU j (j=1,2,..,337), in store k (k = 1,2,..,8). The fixed intercept parameter is denoted θ_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 $Velocity_{jk}$, $Item\ Cost_{jk}$, $Sales\_Volume_{jk}$ are second level (SKU) variables. Finally, $Variety_k$ and $Treatment_k$ are third level (store) variables.

As shown in Table 4, the level of IRI was significantly lower (-1.630, $p < .01$) for the test stores than for the control stores.

Table 4 Linear Mixed Model for Comparison of Test versus 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

*Notes: *** p < .001, ** p < .01*

Velocity = Number of units sold per day; Item Cost = Cost of an item; Sales Volume = Item Cost X 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.

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). In order to test the influence of RFID on these predictors, we created interaction terms by multiplying these predictors with the treatment dummy variable (0 = baseline period; and 1 = treatment period). The results of the linear mixed effects model are presented in Table 5.

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

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	8.794***	8.961***	8.578***	8.509***	8.632***
Treatment	-2.385***	-1.932***	-1.964***	-1.606***	-1.899***
Item Cost	-0.003	-0.002	-0.003	-0.004	-0.005
Velocity	-0.858*	-1.044**	-0.571**	-0.991**	-1.186**
Variety	-0.022	-0.025	-0.021	-0.021	0.023
Sales Volume	0.000	0.002	0.000	0.000	0.002
Treatment X Item Cost		0.002***			
Treatment X Velocity			-0.087		
Treatment X Variety				-0.157***	
Treatment X Sales Volume					-0.005

Note: **p < .05, **p < .01, ***p < .001*

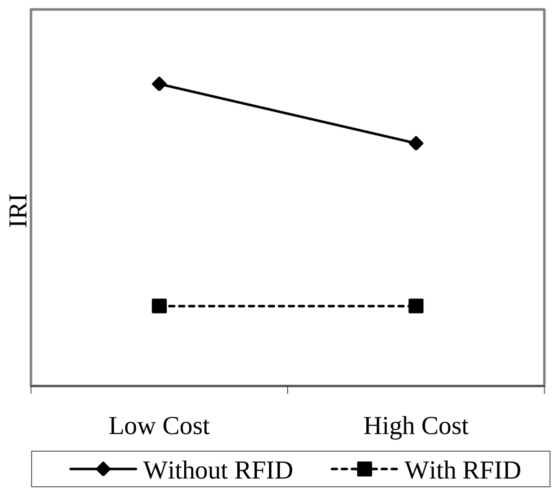
Velocity = Number of units sold per day; Item Cost = Cost of an item; Sales Volume = Item Cost X Velocity; Variety = Number of unique SKUs carried in a store; Treatment: Numbered 0 before the adjustment, numbered 1 after

We found that the interaction terms with item cost and variety were significant (p < .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 increases, IRI decreases. 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 to low variety items, in an RFID-enabled environment. While this is counter to DeHoratius and Raman (2008) who found variety to be positively related to IRI, it is most likely an interesting artifact of our sample. Because we were looking at a single category (aircare), variety was only found between store types (large format vs. small format). Specifically, small format stores had smaller backrooms to store inventory. Thus, for the smaller stores, RFID would be less helpful because of the smaller backrooms;

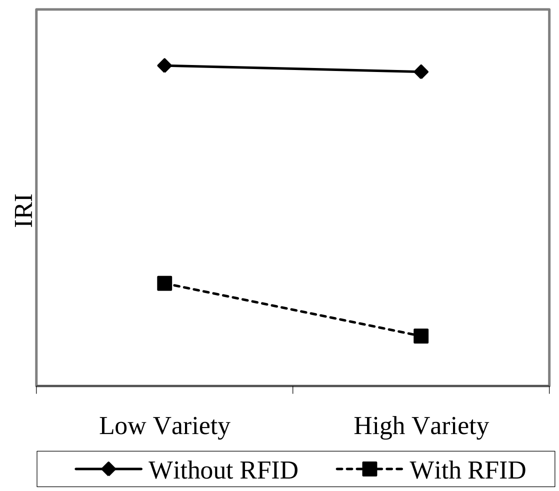
conversely, it would be more useful in larger stores with larger backrooms. Thus, although RFID was useful in both formats, it was more useful in the large stores.

Figure 4 Interaction Plots for Study 1

4A: Interaction Plot for RFID and Cost



4B: Interaction Plot for RFID and Variety



3.5 Study 1 Discussion

Study 1 investigated the effectiveness of RFID-enabled visibility in reducing retail store IRI. The results of our field experiment demonstrated that RFID does reduce IRI. First, we compared pre and post in-store IRI for the test stores. 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.

Finally, we also confirmed the findings of our study on more inclusive datasets that not only included the SKUs that were adjusted by the RFID auto-adjust, but also two more datasets which included (1) all inaccurate SKUs—regardless if they were adjusted or not, and (2) the dataset with all SKUs—accurate or inaccurate. Our substantive finding was robust as we found that all the more inclusive datasets showed an overall decrease (shift in the intercept) in IRI with the implementation of RFID auto-adjust. The analysis we performed on these datasets was subject to some noise because not all PI adjustments were synchronized with the date which we used in our model for the transformation. The tests we conducted on these datasets, however, were conservative, as the intercept shift was likely to be underestimated since the effects of RFID auto-adjust was delayed for some SKUs.

3.6 Study 2 Prologue

The results from study 1 provide several useful insights. First, for the retailer, it demonstrated the ability of case-level RFID to reduce IRI. Second, from a research perspective, the results from the discontinuous growth model are convincing in answering research question 1, and beginning to answer research question 2. The biggest limitation to study 1, though, was the use of a single category. Therefore, based on the success of study 1, the retailer decided to extend the study to five additional categories. This extension allows the study to expand its scope and research questions explored, as described in the next section.

4. Study 2

4.1 Sample and procedure

Study 2 included 62 stores from the same retailer in study 1. These stores were spread all across the United States and represented various store formats. Of the 62 stores, 31 were categorized as test stores and 31 were categorized as control stores. These test and control stores were 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 for the experiment. These categories were aircare products (e.g., air fresheners, candles, sprays), floorcare (e.g., vacuums, 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 to 48), prices (from less than a dollar to several hundred dollars), and sales velocities (from tens of units per day to one per week). In all, the five categories included in our study had a total of 1,268 unique SKUs.

All the SKUs in the five categories were physically counted at two separate points in time. The first count was conducted one week before the implementation of the RFID auto-adjust. The second count was conducted two months after the first count, approximately seven weeks after the implementation of the RFID auto-adjust. This was done to ensure that both physical counts were conducted in the first week of the respective months.

Physical counts were conducted by an independent firm (same firm as study 1) that specializes in counting inventory. Because of the large number of SKUs involved in this study, physical counts for a store were typically completed in a five day window. Physical counts at all 62 stores were conducted during the same five day window.

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 also used measures for the DeHoratius and Raman (2008) factors known to influence inventory inaccuracy. We operationalized these measures as follows: Sales velocity was the number of units of a SKU sold for two 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 two months preceding the count across all stores; Category variety was the total number of unique SKUs in a category; and Category density was the total number of units in a category divided by linear feet of shelf space for that category.

4.2 Study Design

We employed an untreated control group design with pretest and posttest (Shadish et al. 2002). In order to determine the influence of the treatment in our experiment, we first conducted a within-store comparison before and after the implementation of RFID auto-adjust for both test and control stores. This within store comparison provided us with the differences in the levels of IRI before and after the implementation of RFID auto-adjust. To provide additional support, we examined between store differences by conducting a difference of differences test.

4.3 Results

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

Table 6 Descriptive Statistics and Correlations

	Variable	Mean	Std. Dev.	1	2	3	4	5
1	**IRI**	3.16	11.38					
2	**Item Cost**	47.99	11.96	-.049**				
3	**Variety**	795.31	464.01	.015**	-.198**			
4	**Velocity**	52.4	184.95	.400**	-.032**	-.037**		
5	**Sales Volume**	735.31	2786.83	.201**	.356**	-.177**	.648**	
6	**Density**	100.84	93.1	.159**	-.217**	.263**	.170**	-.114**

Notes: *** $p < .001$, ** $p < .01$

Velocity = Quantity of item sold for two month preceding measurement; Item Cost =Cost of an item to the retailer; Sales Volume = Item Cost X Velocity; Variety = Total number of unique SKUs in a category; Density: Total number of units in a category divided by linear feet of shelf space for that category; IRI = |PI – actual count|

4.3.1 Comparison of IRI: Pre and Post Auto-adjust Implementation

The goal of study 2 was to examine the influence of the treatment—i.e., implementation of RFID auto-adjust—on the IRI of different categories. In order to examine this influence, we conducted within store comparisons for both test stores and control stores by categories. We used a linear mixed effects model where items were grouped within stores. Therefore (simplifying notation and showing fixed effects only), IRI was given by the model $IRI = \beta_0 + \beta_1 * Treatment$, where *Treatment* was a dummy variable coded 1 for RFID auto-adjust switched on, and 0 otherwise. The results for the linear mixed effects model are presented in Table 7.

Table 7 also presents 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 versus post differences in control stores were significantly different from the pre versus 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): $IRI = \beta_0 + \beta_1{*}Treatment + \beta_2{*}Group + \beta_3{*}Treatment\ X\ Group$, where *Group* was a dummy variable coded 1 for test stores, and 0 otherwise.

Table 7 Effect Size for Treatment, Linear Mixed Effects Model

Category	**Control Stores**	**Test Stores**	**Difference**
Floorcare	-0.208*	-0.899***	0.691**
Aircare	-1.099*	-2.729***	1.630***
Furniture	-0.061	0.168	-0.229
Formula	0.894	-2.004***	2.898***
Quick Cleaners	1.692**	1.319**	0.373**

Notes: *** $p < .001$, ** $p < .01$; * $p < .05$; *Significance of difference assessed by interaction term of treatment (pre-post) and group (test-control)*

The results of the linear mixed effects model show that for all the categories except ready to assemble furniture pre versus 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.

4.3.2 Results - Research Question 2: The Ameliorating Effect of RFID on Predictors of IRI

To enhance our understanding of the influence of RFID on 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. In order 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). The results of the linear mixed effects model are presented in Table 8.

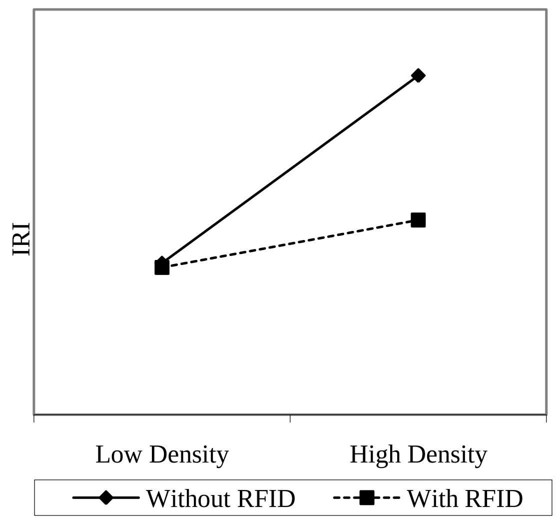
Table 8 Influence of RFID-enabled Visibility on Known Predictors of Inventory Inaccuracy

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.759***	1.833***	1.167***	1.651***	0.606	1.221**
Treatment	-1.977***	-2.177***	-0.806***	-1.682***	-0.840**	-0.817**
Item Cost	0.001	0.001	0.002	0.001	0.002	0.001
Velocity	0.021***	0.021***	0.028***	0.021***	0.021***	0.021***
Sales Volume	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Density	0.010***	0.010***	0.011***	0.010***	0.017***	0.010***
Variety	0.000	0.000	0.000	0.000	0.000	0.001*
Treatment X Cost		0.005*				
Treatment X SalesVol			-0.014***			
Treatment X Velocity				-0.0004***		
Treatment X Density					-0.013***	
Treatment X Variety						-0.001**

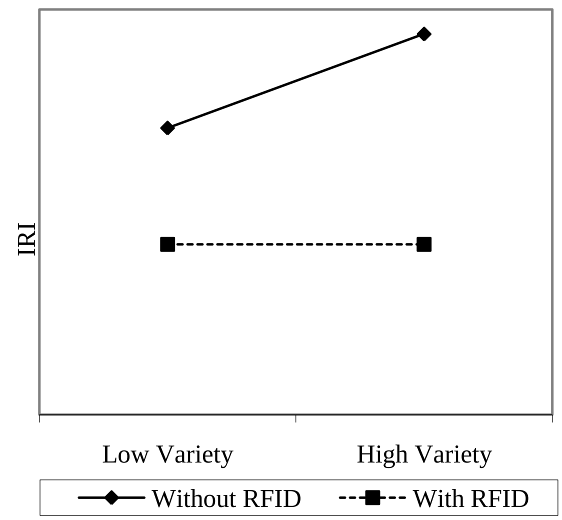
The interaction plots are shown in Figure 5 (graphs A through E). In Figures 5A, 5B, 5C, and 5E, consistent with DeHoratius and Raman (2008), we find that RFID appears to ameliorate the effect of inventory density, variety, sales volume and velocity on IRI. The interaction plot (Figure 5D) suggests that without RFID, cost has no effect on IRI; with RFID, high cost items have higher IRI. DeHoratius and Raman (2008) argued that higher cost is negatively associated with the IRI. Thus, this finding is counter to DeHoratius and Raman and with our own findings from study 1. The reason we believe is due to differences in the product categories and is explored in more detail in the next section.

Figure 5. Interaction Plots for Study 2

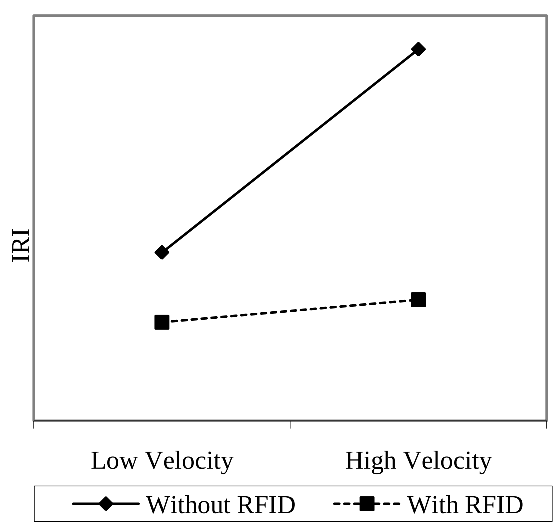
5A: Interaction Plot for RFID and Density



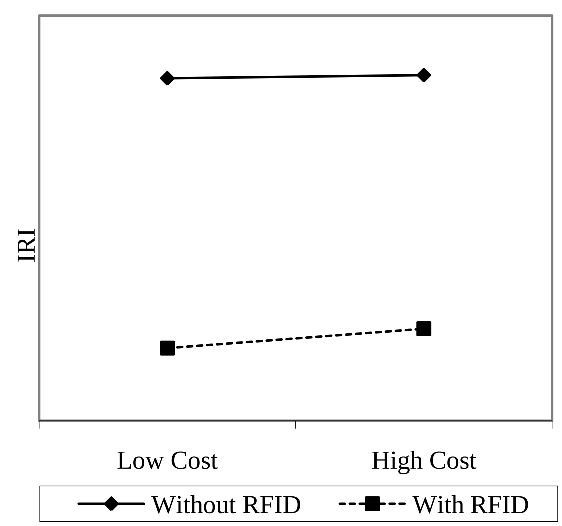
5B: Interaction Plot for RFID and Variety



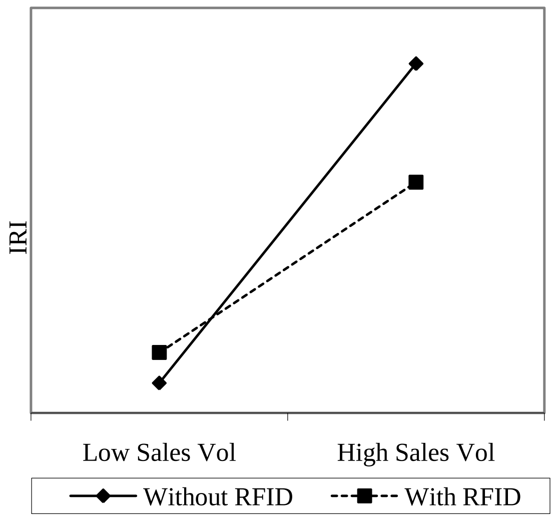
5C: Interaction Plot for RFID and Velocity



5D: Interaction Plot for RFID and Cost



5E: Interaction Plot for RFID and Sales Volume



4.3.3 Results - Research Question 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. The percentage improvement in aircare, a category common to both studies 1 and 2, provides some validation to both our studies. Recall, in study 1, we found that the RFID implementation improved the inventory accuracy of aircare category by about 26%. Slightly better improvement of 30% in study 2 can be attributed to the inclusion of overstated in the IRI evaluation. It is important to note that the ready to assemble furniture, a category with low sales velocity, high cost, low sales volume, 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 suggests 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.

Table 9 Characterization of Categories

Category	Velocity	Item Cost	Sales Volume	Variety	Density	% Improve
Floorcare	16.06	20.21	366.52	736	24	45.15%**
Aircare	91.47	2.59	232.14	1123	224	29.56%***
Furniture	9.69	51.94	586.32	384	4	-60.64%
Formula	127.53	10.46	1499.14	282	130	81.60%***
Cleaners	80.46	6.14	559.47	120	72	16.86%**

Notes: *** $p < .001$, ** $p < .01$; * $p < .05$

Let us now revisit one finding from the previous section – the ameliorating effect of RFID on cost. As discussed, although the interaction was significant, neither the 'without RFID' nor the 'with RFID' relationship were as expected. However, the explanation appears to be straightforward. In this case, the IRI for furniture – the highest cost category – was not positively affected by RFID. In fact, IRI seemed to get worse over time (i.e., no effect of RFID as IRI would get worse naturally). This category, because of its high cost (more than double the cost of the next highest category and almost 25 times the lowest cost category), appears to have attenuated the effect of cost in the overall interaction.

4.4 Study 2 Discussion

In study 2, consistent with study 1, we found that RFID with case-pack tagging significantly improved IRI. 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 items (i.e., low density), such as ready to assemble furniture, were not influenced by RFID while small and fast moving items (i.e., high density, high velocity), such as formula, were influenced the most. This categorical breakdown of both IRI and the effects thereof provide important information for both practice and research as we continue to seek insight into how to control IRI.

5. Discussion

In two separate field studies with a major retailer, we examined three important research questions: (1) will RFID-enabled visibility reduce IRI? (2) can RFID-enabled visibility ameloriate the effects of known predictors of IRI? and (3) what are the characteristics of product categories of which RFID-enabled visibility is effective in reducing IRI? Study 1 addressed question 1 (primarily) with some insight into question 2. Because of the success of RFID in the first field study, the retailer expanded the study by increasing the number of categories and stores involved, leading to study 2. Study 2 provided insight into the effects of RFID on the known predictors of IRI and the effects of category differences on the ability of RFID to reduce IRI.

There are two questions worthy of discussion: (1) why was a study necessary to answer these research questions? and (2) is RFID necessary to reduce IRI? This research answers the call by prior research (e.g., Dutta et al. 2007, Lee and Ozer 2007) to investigate the impact of RFID via empirical-based research with a well-designed sample and rigorous controls. We may assume that RFID will reduce IRI, but until now, without rigorous empirical testing, the question remained open (Amini et al., 2007). Was RFID necessary to achieve the results herein? It is theoretically possible for a retailer to individually barcode scan every box entering the receving door, going to the sales floor, returning from the sales floor, etc. as a means of providing visibility into product location. There are, however, two issues with this theoretical possiblity. First, the cost is prohibitive. This method would require additional human resources to scan the boxes. Second, and perhaps the bigger issue, is it requires diligence (i.e., perfect execution) by the employees to provide the necessary visibility. The likelihood that employees will diligently scan every box entering the backroom, leaving the backroom, going to the box crusher, etc.is not very high. An examination of the carefully constructed rationales for *why* DeHoratius and Raman (2008) theorized their predictors would impact IRI is informative. A broad generilization 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 The ROI for RFID

The results of this study, as suggested earlier, prodded the retailer to expand the scope of the study and investigate additional categories where RFID might be beneficial. Overall, this research provides insight into the potential business value of RFID, although it is not within the scope of our study to explicitly quantify the discovered benefits. However, an examination of these benefits can provide research and practice insight and information needed to start developing ROI models. An interesting question for future research is: what is the resulting value in sales/profit/etc. of a 1% improvement in IRI?

Several financial considerations can be gleaned from this research. First, understated PI, if left unchecked, can cause the system to order unnecessary inventory. This unnecessary inventory, in the form of safety stock ordered to cover the uncertainties in the supply chain, increases costs to suppliers and retailers, thus decreasing the efficiency of the supply chain. Excess inventory leads to inefficient use of capital (i.e., the inventory holding costs), excessive markdowns due to aged products or the need to reduce inventories, and increased amounts of spoilage (for date sensitive products). For this particular retailer, the reduction of inventory is a huge benefit and is a goal they have pursued for years. For example, 10 years ago, the company held $19 billion in inventory for sales of $150 billion. During the past 10 years, sales have increased $250 billion, while only adding $14 billion in inventory (Wal-Mart 2010). Second, RFID auto-adjusted PI can reduce the labor costs required for manual adjustments, as in the absence of RFID store employees would have to conduct regular physical counts of store inventory. As our ad hoc analysis revealed, manual adjustments were reduced by 41% while simultaneously reducing IRI due to the system removing the burden of having to do manual counts and adjustments. Third, a reduction in out of stocks, driven by the RFID visibility, increases sales. As demonstrated in an earlier study with this retailer, Hardgrave et al. (2008) found a significant reduction in out of stocks and estimates a potential sales increase of 0.7% as a result. Finally, an interesting outcome of this study is that the benefits can vary by category. The drivers of these benefits, such as SKU density, sales velocity, etc., can be used by retailers to help make the decision as to what categories of products to RFID-enable using a prioritization approach.

On the other side of the ROI equation is the cost of the technology. Costs will vary by retailer and by business problem addressed. In this study, the RFID architecture was driven by the retailer's desire to have visibility into the location of cases; thus, this desire drove the technology layout discussed earlier (i.e., readers at receiving door, sales floor door, etc.). The investment in RFID infrastructure is rather straightforward to calculate after deciding on the problem to address. The key here is to let the business problem drive the need for the technology, rather than the technology drive the search for a business problem.

There is also the issue of "benefit to whom" and "cost to whom"; that is, who pays for RFID and who benefits from RFID? On the surface, it would appear that the retailer would benefit more from store-level RFID than the supplier. Also, the retailer is likely to have more fixed costs (i.e., from the RFID readers installed in DCs, stores, etc.) and the suppliers would have more variable costs (i.e., the cost per tag). The allocation of benefits and costs, unfortunately, are not this straightforward. When out of stocks are reduced, for example, the retailer obviously benefits, but so does the supplier. How much benefit does each one receive? Should the variable costs (of tags) be allocated based on the benefits received? The questions of costs and benefits are yet to be adequately explored in the literature. We are hopeful that the results of our study can yield additional insight into these important questions.

5.2 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 understanding of the study context … *(and)* control for firm-specific factors that influence IRI" (p. 638). Because this retailer is very large and successful, the results may have suffered from a 'ceiling' effect. That is, compared to other retailers, this retailer may already be very good. In this case, though, our results would underestimate RFID's true potential. The improvement brought about by RFID was also based on tagging cases only. As RFID moves to item-level, the effect of RFID would be expected to be stronger. An investigation of this benefit, at the item-level would yield further insight into the benefit of RFID

As expected, we found that RFID did reduce IRI. Specifically, in study 1, IRI grew until RFID was used to make an adjustment. The adjustment resulted in a significantly lower inaccuracy point. We found inaccuracy to *continue* to decline after the auto-adjustment. While we speculate that it may be due to fewer manual adjustments, we have no firm evidence to confirm this linkage. This finding raises two interesting questions that should be explored in future research: (1) what caused inventory inaccuracy's continued decline and (2) is this steady-state or is it out-of-equilibrium performance (how long will it decline before it levels out or increases again)?

Although we studied the effects of RFID on inventory inaccuracy in a retail environment, it is likely that the same pattern of improvements can be obtained in other environments. For example, hospitals must track and account for assets such as defibrillators and inventory such as pharmaceuticals that could be improved with the use of RFID (Buyurgan, Hardgrave, Lo, and Walker 2009). RFID could also be used to improve inventory accuracy in manufacturing and other parts-intensive environments (Gaukler and Hausman 2008; Gaukler, Seifert, and Hausman 2007; Sheppard, George, and Brown 1993; Vijayaraman and Osyk, 2006).

6. Conclusion

Inventory inaccuracy has plagued retailers for many years. Using two different field experiments which provide ecological validity, this research investigated the impact of RFID-enabled perpetual inventory 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 1,268 SKUs from the same retailer. We first examined whether RFID will improve IRI. We then investigated the ameliorating effects of RFID on known causal predictors of inventory inaccuracy. Finally, we explored 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 does reduce inventory inaccuracy. The results also suggest that RFID does ameliorate the effects of known predictors of inventory inaccuracy and the impact of RFID on inaccuracy varies by category. 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.

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