Gaining an Operational Edge: Piece-Picking Process Optimization

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SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF ENGINEERING IN LOGISTICS

AT THE

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

JUNE 2016

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May 6, 2016

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Abstract

Order-picking is an integral operation in warehouses and distribution centers (DC), consuming considerable operating resources and expenses. Numerous studies have attempted to optimize the efficiency and reduce the cost of order-picking. In working with a partner company, this thesis evaluates a proposed mechanism for piece-picking that would achieve this end. The company has a shelf-pack number for each SKU, whereby the SKU must be piece-picked in a quantity that is a multiple of the number. The company has proposed to change this number from 1 to 2 to raise the number of units per pick and reduce the number of picks needed for a SKU. In this thesis, simulation is performed on the company's shipment data from DC to store to reveal the merits and demerits of this scheme. SKUs are segmented into different groups based on their suitability for this scheme as a means of mitigating the negative repercussions of the proposal. The scheme can reduce the number of picks and related costs needed, but it causes a shift of inventory from DC to store, thus creating an increase in store inventory. However, SKUs can be allotted into groups suitable or unsuitable for the scheme depending on the amount of savings generated for a given amount of impact on store inventory. The scheme's benefits and impact on store inventory are thoroughly examined, and their implications on DC inventory are also discussed. This thesis offers a novel perspective into piece-picking optimization, and it finds the proposed scheme viable, simple, and flexible.

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Acknowledgments

We would like to thank our thesis advisor, Dr. Bruce C. Arntzen, for his guidance, support, and especially his time throughout the writing of this thesis. He has provided us with a constant stream of inspiration crucial to the way we approached the project. We would also like to thank those we have worked with from our thesis partner company for sharing information, retrieving the data necessary for our analyses, and devoting their time to communicate with us on a weekly basis. Their support and open-minded attitude have been instrumental to the completion of this thesis. They deserve a reward not short of an honorary degree from our advisor. In addition, we would like to thank our classmates, Cyril Khamsi, Renzo Eliseo Trujillo Castaneda, and Peter Shang Ling Tsai Yang, for their support during the early stages of our data analyses for this thesis. Finally, we would like to thank our parents and family for their support and encouragement throughout the completion of our master's program. Thank you.

Stephanie H. Chen & Eunji Han

I would like to thank my best friend, Jennifer Yu, for her constant encouragement. Communications with her provide me with the strengths necessary to persist in the pursuit of knowledge and learning.

Stephanie H. Chen

I would like to express my deep gratitude to my great friends, Jung Ok, Elly, Hyunjin and Sun Young, and my uncle for being there at all times for me. I would not be here without their moral support throughout my life.

Eunji Han

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1. Introduction

Order-picking is an integral operation of a warehouse (WH) or distribution center (DC). It is the "most labour-intensive operation" in a WH with manual picking and a very "capital-intensive operation" (Chackelson, Errasti, Ciprés, & Lahoz, 2013, p. 6079; De Koster, Le-Duc, & Roodbergen, 2007, p. 481) in a WH with automated picking. In fact, it is the most labor-intensive logistics operation even with automation (Weisner & Deuse, 2014), and one of the most time-consuming WH processes (Roodbergen & De Koster, 2001). According to different literatures (Coyle, Bardi, & Langley, 2003; Frazelle, 2002; Henn, Koch, & Wäscher, 2012; Tompkins, White, Bozer, & Tanchoco, 2003, 2010; Weisner & Deuse, 2014), order-picking constitutes 50% to 65% of all WH operating expenses. Its inefficiency can raise costs and lower customer satisfaction (Weisner & Deuse, 2014): order-picking is the "highest-priority area for productivity improvements" (De Koster et al., 2007, p. 481).

Our thesis partner XYZ, a large retailer carrying primarily low-cost daily products, utilizes manual piece-picking[1] in some of its DCs, serving several thousand stores in the US. Naturally, it encounters inefficiency and high costs in the process. Thus, XYZ has proposed an improvement scheme—changing its shelf-pack[2] from 1 to 2 for certain SKUs. This thesis will evaluate the scheme's efficiency improvement and cost reduction opportunities in relation to XYZ's current piece-picking operation. In particular, the thesis will analyze the piece-picking activity in one of XYZ's DCs and 5 stores supplied by it to examine the effects and viability of the scheme. XYZ has provided us with the details of its DC system and operations. Hereafter, any mention of its system and operations will be based on this information.

We first conducted a survey of studies on manual order-picking to mine for possible methods of improvement against which we could benchmark the proposed scheme. Chapter 2's literature review covers studies on the different methods of improving the efficiency and lowering

[1] Piece-picking is order-picking SKUs in pieces while case-picking refers to order-picking SKUs in cases.
[2] XYZ's pickers must piece-pick each SKU in a multiple of *n* pieces. The *n* is the SKU's shelf-pack.

the cost of picking. The survey reveals the proposal of shelf-pack change as a method that has not been studied. Thus, the thesis will analyze the effect of this scheme and determine its applicability for XYZ and beyond.

Chapter 3 details the methodology and hypotheses with which we analyzed the effect of the proposal. We used MySQL simulation to estimate the results of implementing the scheme. Then, we devised a mechanism of SKU segmentation to determine the SKUs suitable for the scheme. XYZ's operational context and the merits and demerits of the scheme are also analyzed. The logic behind the codes for the simulation, the various data analyzed, the variables constructed for such analyses, and the reasons for introducing SKU segmentation are also discussed here.

Chapter 4 presents the results of simulating the scheme's implementation on all or certain selected SKUs. While changing SKUs' shelf-packs can raise picking efficiency and reduce picking cost, the change requires that XYZ picks and ships units of SKUs ahead of their forecasted time of sale to the retail stores (inventory prepositioning). The scheme improves efficiency and reduces cost by shifting inventory from DC to store at the expense of increasing store inventory. Thus, Chapter 4 focuses on presenting the savings and magnitude of inventory impact generated by the scheme in the context of implementing it on all or certain selected SKUs.

Chapter 5 builds on Chapter 4 and discusses the implications of this thesis beyond XYZ. First, it discusses the applicability of shelf-pack change. Next, it presents the different ways the scheme can be implemented, such as implementing a unified shelf-pack for each SKU regardless of the store it is shipped to or a different shelf-pack for the same SKU depending on which store it is shipped to. Meanwhile, the chapter also touches upon the limitations of this thesis and alternative methodologies that could have been conducted but were excluded. This thesis project is conducted with constraints in time and data available: additional data can lead to more in-depth analyses beyond the scope allowed for the project. In fact, future research building on the results of this thesis is likely. Chapter 5 ends with suggestions for several directions of future research on the issue of shelf-pack change and inventory prepositioning.

Finally, Chapter 6 discusses where this thesis stands among order-picking literatures and methods on picking optimization. Shelf-pack change is a simple yet effective way of improving piece-picking and reducing operating expenses. It does not involve the level of precision needed for new systems like dynamic storage and dynamic picking. While shelf-pack change may not have been thoroughly studied, it may have already been implemented in reality. This thesis will shed more light on and entice further research into the method.

2. Literature Review

In examining XYZ's picking activity for improvement, this chapter reviews prior optimization efforts as a benchmark against which we position our research. Since XYZ currently uses manual, discrete,[3] low-level,[4] picker-to-parts[5] order-picking with conventional process optimization methods, our review focuses on additional optimization efforts applicable to this system. They include order-batching, dynamic storage, dynamic picking, and other methods.

2.1 Current XYZ Optimizations

XYZ currently utilizes storage assignment, zone-picking, and wave-picking for picking efficiency. Storage assignment comprises policies that assign product storage locations to reduce pickers' travel time and distance (Chiang, Lin, & Chen, 2011). XYZ uses forward-reserve segmentation, separating bulk and pick stocks into reserve and forward storage. This allows pickers to pick from a small forward area rather than a large reserve area, lowering their travel distance and time (De Koster et al., 2007; Frazelle, 2002). XYZ also implements class-based storage, which usually divides products into classes according to their sales trends by Pareto's method or artificial neural network modeling (Chan & Chan, 2011; De Koster et al., 2007; Li, 2009; Partovi & Anandarajan, 2002). In the case of XYZ, products with the greatest order frequency and quantity are placed at optimal pick locations for smoother picking. Meanwhile,

[3] Picking entire orders instead of breaking orders down by order batching (Section 2.2).
[4] Low-level picking uses low storage racks while high-level picking uses high storage racks.
[5] Pickers travel to the items. In parts-to-picker, an automated system carries the items to the pickers.

XYZ also utilizes zone-picking. This divides the pick area into zones, each with one picker picking all the lines of an order that are located in his zone, one order at a time (Tompkins et al., 2010). Pickers can avoid congestion, familiarize themselves with item locations, traverse only short distances, and handle a large number of SKUs per order (De Koster et al., 2007; Richards, 2011). Moreover, since each of XYZ's zone is a straight aisle, SKUs are simply listed on a pick list in the order they are stored down the aisle without need for picker routing algorithms. Finally, XYZ also uses wave-picking, releasing pick orders to pickers in waves. This is usually done so that orders departing for a common destination, such as with a certain carrier at a fixed time, are released to pickers simultaneously in a wave (De Koster et al., 2007), coordinated with vehicle departures, replenishment cycles, and shift changes (Richards, 2011). Improvements applicable to this existing system are order-batching, dynamic storage, dynamic picking, and other methods.

2.2 Order-Batching

Order-batching can be applied to alter discrete picking for increased efficiency. In batch picking, orders are broken down and then consolidated by item so that a picker picks multiple orders of each item at once (Richards, 2011). By increasing the orders picked per item, batching increases the quantity picked per trip to an item's pick bin and reduces the travel time per unit picked (Frazelle, 2002; Tompkins et al., 2010). Often, orders arriving in the same time window are batched together, forming a time window batching strategy (De Koster et al., 2007). Another strategy is proximity batching, which assigns orders to a batch if their items' pick locations are close to one another (De Koster et al., 2007). In either case, if an order cannot be broken down, pickers can pick batches of complete orders simultaneously, sorting items by order as they pick, constituting a sort-while-picking strategy (De Koster et al., 2007). If an order can be split, pickers may pick broken-down parts of orders that are batched together, whereby each batch is sorted into its respective orders after picking, forming a pick-and-sort strategy (De Koster et al., 2007).

As can be seen, items need to be sorted into their respective orders after picking to maintain order integrity for delivery. Effort to maintain order integrity is significantly increased in order-batching, especially when items from one order are picked by different pickers (Frazelle, 2002; Tompkins et al., 2010). Moreover, since picking and sorting constitute a two-stage process, batching cannot fulfill time-sensitive orders in time (Richards, 2011). Batching also risks pickers omitting items from an order or sorting them erroneously by mistake (Tompkins et al., 2010). Thus, savings from batching must be weighed against sorting costs and human error (Frazelle, 2002). Therefore, while batching is a viable option, it is not in XYZ's immediate consideration.

2.3 Dynamic Storage

Dynamic storage is a more recent research development: as of 2010, Yu and De Koster could not find any relevant literature although the concept was broached in De Koster et al. (2007). To reduce pickers' travel distance, dynamic storage makes the forward area very small and brings SKUs from the reserve dynamically just in time for picking (De Koster et al., 2007). Yu and De Koster's (2010) study finds that dynamic storage improves picking throughput and reduces picking time. However, they find that it requires investment in automated storage and retrieval machines to replenish and reshuffle SKUs in the pick area. This optimization method cannot be applied without capital expenditures beyond the scope of this thesis.

2.4 Dynamic Picking and Others

Other factors have also been studied for picking efficiency. First, dynamic picking is another option that studies have explored. Orders are picked in batches, but the pick list is constantly updated with incoming orders by a pick-by-light, pick-by-RFID, handheld terminal, or voice picking system (Gong & De Koster, 2008; Lu, McFarlane, Giannikas, & Zhang, 2016). Next, though human factors of the pickers have been largely neglected in research (Grosse, Glock, Jaber, & Neumann, 2015; Grosse, Glock, & Neumann, 2015), recent studies (Daria, Martina, Alessandro, & Fabio, 2015; Grosse & Glock, 2013, 2015; Weisner & Deuse, 2014) have begun to explore this field. Finally, some studies (Hagspihl & Visagie, 2014; Rao & Adil, 2013; Tarczynski, 2012) also discuss elements like the pick list or order size and the number of pickers in relation to SKU arrangements, routing, and storage policies.

2.5 Conclusion

While relevant existing research focuses on the above methods, this thesis approaches picking improvement from a new perspective, by changing the shelf-pack for certain SKUs from 1 to 2. In doing so, XYZ would pick more units of SKUs for delivery to store than what XYZ's forecast system orders (see Sections 3.1 and 3.2), essentially prepositioning SKU units from DC to store ahead of demand. In effect, this method is raising picking efficiency with inventory prepositioning. We have found no studies with a similar approach. This thesis is novel in being the first research to incorporate the concept of shelf-pack change into picking improvement.

3. Methodology

This chapter presents the context of XYZ's piece-picking operation, the proposed improvement scheme for the operation, and the methods used to analyze the scheme's implementation. The operational context explains the terminologies and processes specific to XYZ. The layout of the improvement scheme reveals its merits and supply chain impact. The methods used—simulation and SKU segmentation—analyze the scheme and its effects on picking cost and efficiency, its impact on inventory, and each SKU's suitability for the scheme. Finally, wherever necessary, preliminary findings of the analyses are discussed to ensure logical cohesion in the thesis. However, actual final results will be presented in Chapter 4.

3.1 Operational Context

XYZ replenishes most of its stores once or twice weekly from its DCs. A replenishment cycle for a store commences at a DC with a demand forecast for each SKU in the store. An order for the store is then placed according to the forecasted quantity for each SKU. The order becomes this store's pick list for the cycle. One store at a time, pickers travel through the pick area, find the bin containing each SKU on the list, and pick the ordered units. Such a trip to a SKU's bin is called a bin trip or a pick. Then, this order, with the picked SKUs, becomes a shipment to the store. In the DC studied, pickers must pick each SKU in a multiple of n units, called "shelf-pack," to fulfill DC-to-store orders. Each SKU uses the same shelf-pack for every store: XYZ has a DC-wide shelf-pack for each SKU. Currently, most piece-picked SKUs use a shelf-pack of 1. This means that if the forecasted quantity for a SKU is 1, a picker will need to travel to the pick bin for this SKU just to pick 1 unit, resulting in inefficient labor cost.

3.2 Improvement Scheme and Hypotheses

XYZ has proposed a scheme to improve picking efficiency and reduce picking cost by reducing pickers' bin trips (picks) through shelf-pack change. Since excessive diversification in shelf-packs can lead to picker confusion and data complications, XYZ is proposing a change of shelf-pack from 1 to 2 on a certain number of SKUs suitable for this change. This thesis will evaluate this proposed scheme.

In the new scheme, pickers would pick an even number of units per SKU. If the forecast generates an odd number of m units for a SKU, the scheme shall pick an even number of units by rounding up to $m+1$. The number is rounded up beyond the forecasted quantity to avoid store stock-out and increase picking efficiency by raising the number of units per pick, which is the units per line in an order. Essentially, the scheme picks and ships 1 unit of a SKU to a store ahead of demand when the forecast generates an odd quantity of m pieces. XYZ uses an integrated forecast system that reviews store and DC inventories together, so the next time it orders that SKU for this store, it will recognize that 1 unit has been moved to the store and generate a new quantity that is 1 unit less. If this quantity is also odd, the pattern repeats itself; if it is even, the pickers will pick the given quantity. Thus, if this next order's original demand before shelf-pack change is 1 unit, the new quantity will be 0 units, eliminating a pick and reducing picking cost. Through shelf-pack change, both efficiency and cost reduction can be achieved.

Despite these merits, the scheme creates repercussions that require analysis. When there is an odd forecast quantity, the scheme prepositions 1 unit of the SKU from a future order to the store. In essence, the store carries 1 extra SKU unit until the week that the unit should originally be shipped. For instance, in Table 3.1, under the scheme, a store holds 1 extra inventory unit from the time it is prepositioned in week 1 through the end of week 2, for two weeks until week 3, when it would originally be shipped. With the scheme, stores' inventory levels will increase.

Table 3.1. *Example: Extra Inventory in Store due to Shelf-Pack Change*

Delivery Week	1	2	3	4	5	6
Store Inventory with a Shelf-Pack of 1						
Forecasted Sales (Units)	1	0	3	1	2	1
Inventory at Beginning of Week	1	1	1	1	1	1
Delivered Quantity During Week	1	0	3	1	2	1
Inventory After Delivery	2	1	4	2	3	2
Units Sold (Forecasted)	1	0	3	1	2	1
Inventory at End of Week	1	1	1	1	1	1
Store Inventory after Shelf-Pack Is Changed to 2						
Forecasted Sales (Units)	1	0	3	1	2	1
Inventory at Beginning of Week	1	2	2	1	2	2
Delivered Quantity During Week	2	0	2	2	2	0
Inventory After Delivery	3	2	4	3	4	2
Units Sold (Forecasted)	1	0	3	1	2	1
Inventory at End of Week	2	2	1	2	2	1

*Pink cells are where the change in inventory after shelf-pack change lies.

Meanwhile, company-wide inventory experiences little change. Granted, as the scheme prepositions 1 unit of each SKU with shelf-pack change from DC to store, the scheme depletes DC inventory ahead of time. This may trigger DC inventory replenishment from suppliers ahead of time while the prepositioned SKUs exist as extra units in the stores, increasing the company inventory. However, since XYZ's system reviews store and DC inventories together to determine replenishments, it will recognize the presence of the supposedly depleted inventory in the stores, obviating the trigger. In addition, only 1-unit quantities of the certain number of SKUs with shelf-pack change are prepositioned, and it is unlikely that the SKUs are prepositioned simultaneously to all stores. Thus, for most SKUs, DC inventory is sufficient to preclude the prepositioning from stocking out the DC and triggering replenishment. As such, the scheme's primary repercussion is its impact on store inventory, whose magnitude must be evaluated against the picks saved.

Nevertheless, the scheme should be implemented because it should not lead to significant increase in store inventory in units. The scheme changes the shelf-packs of only certain SKUs instead of every SKU. Moreover, it is unlikely for a store to have all SKUs with shelf-pack change simultaneously prepositioned from the DC. Thus, store inventory in units should not be significantly impacted. However, when a SKU has a high dollar value, it will pose a greater impact on the store inventory dollar value if it is prepositioned. Meanwhile, SKUs whose original demand pattern has a great length of time in between orders may be unsuitable for change since they are likelier to have 1 extra unit of store inventory for that great length of time, creating greater impact on store inventory (see Table 3.1 and its preceding paragraph). In sum:

Hypothesis 1: Shelf-pack change on certain suitable SKUs can increase pickers' efficiency and reduce picking costs with relatively minimal impact on store and company inventory.

Hypothesis 2: SKUs with lower dollar values are more suitable for change.

Hypothesis 3: SKUs with more closely spaced orders (shorter inter-shipment proximity) are more suitable for change.

3.3 General Research Approach

To test Hypothesis 1, we needed to examine the effect of shelf-pack change. We used recursive MySQL procedures to simulate its implementation on store orders picked and shipped to five XYZ stores from a DC. We then performed calculations and additional MySQL procedures to generate variables that would reflect the pick reduction, inventory impact, and SKU characteristics related to a SKU's suitability for shelf-pack change (Table 3.4).

To test the remaining hypotheses and construct an easily implementable algorithm that XYZ could use to determine SKU suitability for shelf-pack change, we classified SKUs into segments by their characteristics using the above-mentioned variables. The variables were generated from the SKUs' current pre-change order patterns because XYZ needed to determine if a SKU would be currently suitable. We then compared segments by a measure of their savings-to-inventory-impact ratio under the scheme. Segments with high ratios would be suitable for shelf-pack change because they would pose less impact on inventory given the same efficiency increase and cost reduction they bring. In this way, XYZ could segment all the SKUs in the DC according to the same characteristics and determine which SKUs are suitable for change by their segments.

3.4 Data Source and Fields

As already mentioned, at the DC level, each SKU has only one shelf-pack regardless of the store it is picked for, so shelf-pack change will affect the quantities on every pick list, every store order. Thus, the quantities of every SKU on every single order of every store were needed as pre-change data to simulate scheme implementation. However, instead of single-order quantities, the data we could obtain were the weekly shipment quantities for each SKU by store. Therefore, we used this as a proxy for the single-order quantities for the SKUs of each store.

Due to the scope of this thesis, we limited our analysis to 5 stores picked by XYZ and served by one of XYZ's DCs—stores 1111, 2222, 3333, 4444, and 5555. For each store, the data came with the following relevant fields: SKU number and description, SKU unit cost, and the weekly shipment quantities for each SKU under their respective year and week numbers, where 201401 signifies the first week of 2014. Each data row reflects one SKU being shipped to the store, with 74 weeks of weekly shipment quantities per SKU across the row. For example:

Table 3.2. *Example Data Table for One Store*

SKU	Description	Unit Cost	201401	201402	201403	201404	201405
00001	Product A	$2.0	2 units	0 unit	0 unit	1 unit	3 units
00002	Product B	$2.2	3 units	1 unit	0 unit	0 unit	0 unit

*This is not actual data. It is a demonstration of the relevant fields.

While the 74-week shipment data remained our primary analysis target, we also obtained 52 weeks of data on the total inventory levels in the stores. Since XYZ only maintained the most recent 52 weeks of data on inventory, the timespan of this dataset was different from that of the weekly shipment data. Wherever we needed to cross-compare the two datasets week by week, we used the weeks that overlapped between the two datasets. However, for most comparisons, we calculated an aggregate annual measure irrespective of date range, whereby the inventory and weekly shipment datasets could be combined and compared.

3.5 Simulation and Data Manipulation

For each store, we simulated shelf-pack change by applying MySQL procedures to the weekly shipment quantities of every SKU row to generate shipment quantities that would result from a shelf-pack change on all SKUs. This allowed for the examination of the effect of the scheme on each SKU by store, especially the number of picks saved throughout the 74 weeks of data. We evaluated the savings against the store inventory increase, and in Section 3.6, we would determine if the savings were sufficient to justify the inventory impact.

3.5.1 Simulation Logic and Relevant Variables

For every SKU in each store, each week's shipment quantity is assumed to be the SKU's order quantity in a single order for that store. It is equivalent to one order line on a pick list, one bin trip, or one pick of the SKU for shipment to store (see explanation in Appendix A). For convenience, hereafter, a "weekly shipment" will represent an "order line," "bin trip," or "pick." With this, we simulated shelf-pack change on every SKU in all 5 stores. Table 3.3 demonstrates our simulation logic using data of an actual SKU from 2015 weeks 1 through 15.

Table 3.3. *Logic Used in MySQL Procedures for Simulation on One Store*

Shipments before Shelf-Pack Change: Weeks 201501~201515															
Wk	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Qty	0	0	2	1	2	5	0	0	4	1	0	0	0	1	0
Preposition & Round Up				2	1	5									
Preposition & Round Up				2	2	4									
														One Bin Trip Saved	
Shipments after Shelf-Pack Change: Weeks 201501~201515															
Qty	0	0	2	2	2	4	0	0	4	2	0	0	0	0	0

As can be seen in Table 3.3, by rounding up an odd order quantity (black arrows), shelf-pack change ultimately prepositions 1 unit from the next odd-quantity order (blue arrows). Instead of the inventory before change, the store now carries 1 extra SKU unit until the week this unit is supposed to have been delivered prior to the change, such as for the 2 weeks spanning week 4 to week 6. These are the logics applied in MySQL to simulate a shelf-pack of two and calculate the total number of weeks across which 1 unit of a SKU is prepositioned, or the total number of weeks with 1 extra unit in store. This is calculated in number of unit*week's prepositioned across the 74 weeks. As was expected, the simulation of shelf-pack change ultimately eliminated some 1-unit shipments.

To every SKU row, we also applied MySQL procedures and Excel functions to generate variables for analysis. More specifically, we operationalized how much we could save from shelf-pack change, how much inventory impact it would create, and how suitable the SKU would be for the scheme based on the SKU's characteristics from its pre-change shipment pattern.

The variables, listed in Table 3.4, are designed to measure the efficiency increase and cost reduction effected by shelf-pack change, the amount of inventory prepositioned or total inventory shipped, and the SKU's shipment pattern prior to change. In particular, multiple variables are constructed to measure the same concept because no single variable can capture each concept's entirety. The table's third column indicates the part of the concept that each variable attempts to capture. The variables are calculated by store for each SKU, each SKU being a row of data with shipment quantities. While some variables yield quantifiable results, others offer insight into preliminary qualitative trends, discussed in Subsection 3.5.2.

Table 3.4. *Variables Used to Operationalize Concepts in Simulation*

Variable	**Variable Meaning and Calculation**	**Operationalized Concept**
Retailer-Generated for Each Row's Weekly Shipment Data		
SKU Cost	Each SKU's unit cost.	Dollar value of inventory. Larger value reduces scheme suitability by Hypothesis 2.
Picking Cost Per Line	Average cost of picking a line item in pick list. Equivalent to cost per bin trip or per pick.	Dollar value per line or per pick in picking. Value hidden for confidentiality.
MySQL-Generated for Each Row's Weekly Shipment Data		
Calculated after simulation as impact from shelf-pack change:		
Unit*Week's Prepositioned	Sum of all the weeks across which 1 unit is prepositioned. It is just the number of weeks 1 extra unit is in the store. E.g. In Table 3.3, a unit is originally scheduled to ship on week 14, but it is prepositioned across 4 weeks to week 10, so for 4 weeks the store has 1 extra unit.	Effect of shelf-pack change on store inventory level. Larger number indicates more weeks across which 1 SKU unit is prepositioned, more weeks with 1 extra unit in store. Can measure inventory increase in store after shelf-pack change.
Excel-Generated for Each Row's Weekly Shipment Data		
Calculated before & after simulation to observe *difference* from shelf-pack change:		
Total Units Shipped	Total number of units picked then shipped in the 74 weeks of data.	Effect of shelf-pack change on total inventory shipped to store. There should be 0-unit difference, or only 1-unit difference due to prepositioning, before and after simulation since total order quantity will not change as forecasted demand remains same.
Total Number of Picks	Obtained by counting the total number of weeks with shipment since a shipment for a SKU is, as explained before, a pick.	Decrease in Number of Picks (further down the table). The greater the decrease after simulation, the more picks saved.

Average Number of Units/Line	Average quantity across all weekly shipments, equivalent to "average number of units/pick." Convention measuring picking efficiency is units/line, so units/line is used. Calculation= (Total Units Shipped)/(Total Number of Picks).	Picking efficiency. Larger number indicates more units picked per bin trip. A rise after simulation means shelf-pack change does increase efficiency.
Total Units Shipped Each Quarter	Total number of units picked each quarter in the 74 weeks. Equivalent to the sum of all shipment quantities every thirteen columns (a column represents one week of shipment).	Effect of shelf-pack change on total inventory units shipped to store per quarter. Values before and after should have 0-unit difference, or only 1-unit difference due to prepositioning, since order quantity will not change as demand remains same.
Calculated before simulation as current SKU characteristics:		
Shipment Frequency	The proportion of weeks among the 74 weeks when shipment occurs. Calculation=(Number of weeks with shipments)/(74 weeks).	Possible measure of inter-shipment proximity. Larger frequency may give more shipments per 74 weeks, less likely to have far-apart shipments or many unit*week's of inventory prepositioned.
Average Number of Units Shipped Per Week	Speed with which a SKU is shipped and sold through the store. Calculation=(Total Units Shipped)/(74 weeks).	SKU velocity. Possible measure of inter-shipment proximity. Faster-moving SKUs may be shipped in closer intervals, less likely to have 1 unit prepositioned across many unit*week's, perhaps less effect on store inventory.
Coefficient of Variation (CV) for Quarterly Shipment Number	Coefficient of variation (CV) for the number of weeks with shipments each quarter. The number of nonzero columns every 13 columns represents quarterly shipment number. Using that, find the standard deviation and average, then divide the former by the latter.	Inter-shipment proximity. SKUs can have seasonality or clusters of shipments with wide gaps between clusters. Larger value captures more seasonality and clusters from quarterly shipment variation, likelier to have sudden spikes of shipments ensued by long gaps without shipment, with inventory prepositioned across many weeks.
Calculated after simulation as impact from shelf-pack change:		
Decrease in Number of Picks	Number of weekly shipments, or picks, reduced for the SKU. Calculation=(Pre-simulation Total Number of Picks) – (Post-simulation Total Number of Picks).	Picking efficiency and cost reduction. Larger number indicates more savings in efficiency and cost.
Picking Cost Saved	Picking cost saved from reducing the number of picks. Calculation=(Decrease in Number of Picks)*(Picking Cost Per Line).	Dollar value of picking cost reduction. Larger number indicates more savings. Used to calculate Picking Cost Saved Per $ Average Inventory Shifted to Store.
Increase in Store's Average Inventory in Units	Total unit*week's prepositioned is the number of weeks with 1 extra unit in store, so increase in average inventory is just unit*week's divided by the 74 data weeks. Calculation= (Unit*Weeks Prepositioned)/(74 Weeks).	Effect of shelf-pack change on store inventory in units. Measures increase of average store inventory. Larger number reflects more increase.
Increase in Store's Average Inventory by Dollars	The dollar value of the extra average inventory shipped to store from DC. Calculation=(Increase in Store's Average Inventory in Units)*(SKU Cost).	Effect of shelf-pack change on store inventory in dollars. Measures increase of average store inventory. Larger number reflects more increase.
Calculated as *measure of suitability* for each SKU's suitability for shelf-pack change:		
Picking Cost Saved Per $ Average Inventory	Ratio of picking cost saved to the dollar value increase in store average inventory, equivalent to the cost saved by shifting $1 average inventory to store from DC. Calculation=	Dollar savings given a set impact on store inventory. Measures tradeoff between picking cost reduction and impact on store inventory. Larger number indicates more

Shifted to Store	(Picking Cost Saved)/(Increase in Store's Average Inventory by Dollars).	savings per inventory impact, thus greater suitability for shelf-pack change.
Picks Decreased Per Average Inventory Unit Shifted to Store	Ratio of the number of picks saved to the unit increase in store average inventory, equivalent to the picks saved by shifting 1 extra unit of average inventory to store from DC. Calculation=(Decrease in Number of Picks)/(Increase in Store's Average Inventory in Units)	Picks reduced given a set impact on store inventory. Measures tradeoff between pick efficiency and impact on store inventory. Larger number indicates more picks reduced per inventory impact, thus greater suitability for shelf-pack change.

3.5.2 Preliminary Findings from Simulation

This subsection presents preliminary findings pertinent to the understanding of the next section on SKU segmentation. According to preliminary analyses, certain trends have emerged on the savings and inventory impact from shelf-pack change. Due to the sheer number of SKUs per store—over 11,000 SKU rows—it is infeasible to present entire rows of findings. Therefore, the preliminary results have been summarized as trends discovered through the variables. An example of pre- and post-simulation data tables can be seen in Appendix B. While the data consist of 74 weeks, whenever necessary, results are multiplied by a factor of 52/74 for adjustment to an annual value so as to create a pragmatic timespan basis.

Efficiency and Savings

This subsection presents the trends observed in two variables measuring the benefits generated through shelf-pack change—Average Number of Units/Line and the Decrease in Number of Picks. They shed light on Hypothesis 1 and SKU suitability for shelf-pack change.

First, the trend in Average Number of Units/Line supports Hypothesis 1. Post-simulation values for most SKUs are higher, raising each store's overall Average Number of Units/Line. In other words, if the scheme is implemented to all SKUs, efficiency will rise by raising the number of units picked per bin trip. As discussed in Section 3.2, this arises since the scheme prepositions single units from future 1-unit picks, eliminating the picks and reducing the denominator of Average Number of Units/Line. Meanwhile, the numerator for a SKU is either unchanged or greater. As seen in Section 3.2, XYZ's system reduces 1 unit from a future pick whenever 1 unit has been prepositioned. The number of units shipped in the 74 weeks remains constant except for when the scheme prepositions 1 unit from a future pick outside the data range. This occurs when the final weekly shipments for a SKU are odd-quantity shipments requiring the prepositioning of units outside the data range. In sum, the numerator, the Total Units Shipped, remains constant for some SKUs and increases by 1 unit for other SKUs, raising the overall numerator for the store. With lower denominator and higher numerator for each store, the efficiency measure rises.

In the meantime, there are SKUs whose denominator remains unchanged: no picks are eliminated. They are SKUs with only one shipment during the 74 weeks, SKUs with only even-quantity shipments, SKUs whose shipment quantities are all greater than 1 unit, and SKUs with shelf-pack already greater than 1. Their commonality lies in having no prepositioning of 1-unit shipments within the 74 weeks, so no pick elimination is recorded. This reveals the importance of the number of 1-unit shipments per year for a SKU in determining SKU suitability for the scheme: a lack of pick elimination will lead to low picking cost reduction and low suitability.

In particular, the Decrease in Number of Picks measures the number of picks saved in the 74 weeks. Multiplying this value for each store by 52/74 yields about 20,000 picks saved per store each year, as will be presented in Subsection 4.1.1. In addition, with picks eliminated, store shelving trips are reduced by the same number since store employees must visit a SKU's shelf and refill it whenever there is a delivery. It is clear the scheme generates efficiency and savings, especially for suitable SKUs whose picks are eliminated by shelf-pack change.

Inventory

Despite its benefits, the scheme creates a concomitant increase in store inventory. As already explained in Subsection 3.5.1 and Table 3.3, to make an odd-number order quantity even, the scheme prepositions 1 unit from the next order that would have been an odd number in the original forecast. In between these two orders, there is 1 extra inventory unit in store since it is shipped to store ahead of demand for that length of time. For instance, in Table 3.5, the scheme prepositions 1 unit across 2 weeks for a SKU (2 unit*week's prepositioned), increasing the store inventory by 1 unit for 2 weeks. The store inventory for this SKU resumes pre-change level after

2 weeks because that is when the 1 unit would have arrived in store prior to shelf-pack change.

Some findings in the inventory-related variables support Hypothesis 1 while others do not. As is expected, for each SKU, the Total Units Shipped Each Quarter shows that the scheme ships only 1 additional unit per quarter to a store when a unit is prepositioned from a later quarter, and 1 fewer if a unit has been prepositioned to a prior quarter. Meanwhile, for the reasons in the *Efficiency and Savings* subsection, the Total Units Shipped either remains unchanged or increases by only 1 unit, prepositioned from outside the data range. In this regard, the scheme's effect on store inventory seems small, supporting Hypothesis 1.

However, the Unit*Week's Prepositioned variable offers other insight. If 55 unit*week's of a SKU are prepositioned in the 74 weeks of data, it can be interpreted as an increase in average store inventory of 55/74 units for the SKU. If the SKU Cost is $3.5, with $3.5*55/74, there is $2.6 extra average inventory in store shifted from the DC for that SKU. Along with enough SKUs of high cost or enough Unit*Week's Prepositioned, come a high Increase in Store's Average Inventory by Dollars and/or a high Increase in Store's Average Inventory in Units. Meanwhile, a SKU's Unit*Week's Prepositioned seems correlated with its shipment pattern, as will be discussed in Section 3.6 and Chapter 4. In short, the prepositioning leads to an increase in store inventory, whose magnitude depends on SKU characteristics. This creates periodic one-unit increases in store inventory for SKUs changed by the scheme and a permanent, higher average store inventory. As presented in Chapter 4, the inventory level will remain in the range created by the scheme as the new picking mechanism becomes the norm.

Initial analysis shows that the ramifications of such an increase support Hypothesis 1. First, the scheme would actually raise a store's average inventory by much less than 1 unit per SKU since this scheme changes shelf-packs only for the SKUs determined suitable through SKU segmentation, and since there is 1 extra unit in store for a SKU only during the weeks prepositioned. Second, with these conditions, a store would most likely have enough space to house the extra units. Third, the increase in store inventory is caused by the shift of inventory from DC to store, so the DC inventory decreases by the same amount from its original pre-scheme level. As long as the normal DC target inventory level is not small (about 200 units or less), this decrease usually will not trigger the DC to replenish from its suppliers because XYZ's system will recognize the presence of the shifted inventory in the stores. Consequently, XYZ's company-wide inventory is unlikely to rise significantly.

Although the preliminary findings support Hypothesis 1, they have also shown that more expensive SKUs will generate higher Increase in Store's Average Inventory by Dollars, leading to lower Picking Cost Saved Per $ Average Inventory Shifted to Store. Therefore, high-cost SKUs are not suitable for change, supporting Hypothesis 2.

SKU Suitability

As revealed above, some SKU characteristics surface as probable factors determining the magnitude of pick and cost reduction while others as the ones determining the magnitude of impact on store inventory. For instance, in the analysis of Average Number of Units/Line in the *Efficiency and Savings* subsection, there seems to be a positive correlation between a SKU's number of 1-unit shipments and the number of picks reduced by the scheme. Meanwhile, SKUs with high unit cost can have higher impact on store inventory because the prepositioning of such SKUs will shift more dollar values of inventory to store. In addition, SKUs with larger gaps between shipments are likelier to have more Unit*Week's Prepositioned because a unit can be prepositioned across large gaps of many weeks (Tables 3.5 vs. 3.6). The store would have 1 extra SKU unit for a greater number of weeks, with higher Increase in Store's Average Inventory in Units, leading to fewer Picks Decreased Per Average Inventory Unit Shifted to Store. This supports Hypothesis 3: SKUs with far-apart shipments create more inventory impact compared with savings, making them less ideal for the scheme. In this regard, SKU 0001 in Table 3.5 would be ideal for the scheme while SKU 0002 in Table 3.6 would not be. However, if SKUs with many Unit*Week's Prepositioned and high Increase in Store's Average Inventory in Units have low SKU Cost, they may have very low Increase in Store's Average Inventory by Dollars, leading to high Picking Cost Saved Per $ Average Inventory Shifted to Store, making the SKUs ideal for the scheme.

Table 3.5. *Shipment Quantities before & after Shelf-Pack Change for SKU 0001 in 2015 in Store 4444, Smaller Inter-Shipment Gap*

Week	27	28	29	30	31	32	33	34	35	36	37	38	39	40
Qty Before	1	1	3	1	0	2	0	0	0	0	0	0	0	3
Qty Sfter	2	0	4	0	0	2	0	0	0	0	0	0	0	4

Table 3.6. *Shipment Quantities before & after Shelf-Pack Change for SKU 0002 in 2015 in Store 4444, Larger Inter-Shipment Gap*

Week	30	31	32	33	34	35	36	37	38	39	40	41	42	43
Qty Before	1	0	0	0	0	0	0	0	0	0	0	0	1	0
Qty After	2	0	0	0	0	0	0	0	0	0	0	0	0	0

As can be seen, many SKU characteristics and their variables appear to determine if a SKU can have large savings with small inventory impact. Moreover, a SKU may appear unsuitable for the scheme, with low Shipment Frequency that may lead to large shipment gaps or very few 1-unit picks for potential elimination. However, it may generate very high Picking Cost Saved Per $ Average Inventory Shifted to Store due to low SKU Cost. In other words, SKU characteristics interact with one another to determine a SKU's savings-to-inventory-impact ratio and scheme suitability: it is difficult to predict which SKUs generate higher ratios by merely observing individual characteristics. Therefore, as laid out in Section 3.3, we proceeded to determine pre-change SKU characteristics variables correlated with the ratios and used them to allot SKUs into segments suitable and unsuitable for the scheme.

3.6 SKU Segmentation

For the scheme to be worth implementing, it needs to generate large savings in picks and picking cost relative to its inventory shift in units and dollar value. In other words, the scheme needs to be applied to SKUs that can generate high values for both Picking Cost Saved Per $ Average Inventory Shifted to Store and Picks Decreased Per Average Inventory Unit Shifted to Store. For convenience, they will hereafter be referred to as "Cost Saved/$ Inventory Shifted" and "Picks Decreased/Unit Shifted." We sought to construct a mechanism that determined a SKU's scheme suitability by categorizing all the SKUs in our data into segments according to their pre-scheme characteristics variables and identifying the segments that could create high values for both savings-to-inventory-impact ratios, ideal for shelf-pack change. This way, XYZ could segment their SKUs according to the same variables and determine SKU suitability.

3.6.1 Data Cleaning and Combination of All 5 Stores

Since the scheme's impact is tied to shipment patterns, the SKU characteristics variables are calculated from the weekly shipment data for each SKU by store. SKUs whose shelf-pack is greater than 1 are eliminated because the scheme will not apply to them. Finally, the new shelf-pack policy needs to be DC-wide, in line with XYZ's mechanism, so all data rows from the 5 stores are combined into one table for unified analysis, with variable values for each row. For distinction, each row is labeled by SKU-store instead of SKU number (Figure 3.1).

Data Table Appearance Before: Separate Stores

SKU	Store	Description	Unit Cost	201401	201402	201403	SKU Variable 1	SKU Variable 2
1234	1111	Product A	$5	2 units	0 unit	0 unit		

SKU	Store	Description	Unit Cost	201401	201402	201403	Variable 1	Variable 2
1234	2222	Product A	$5	0 unit	1 unit	0 unit		

Data Table Appearance Now: All Stores Combined

SKU-Store	Description	Unit Cost	201401	201402	201403	Variable 1	Variable 2
1234-1111	Product A	$5	2 units	0 unit	0 unit		
1234-2222	Product A	$5	0 unit	1 unit	0 unit		

Figure 3.1. Illustration of SKU-store data combined from 5 stores. SKU 1234 is a hypothetical SKU.

3.6.2 Variable Selection

The two savings-to-inventory-impact ratios, Cost Saved/$ Inventory Shifted and Picks Decreased/Unit Shifted, are derived from four variables—Decrease in Number of Picks, Picking Cost Saved, Increase in Store's Average Inventory in Units, and Increase in Store's Average Inventory by Dollars. Therefore, to find SKU characteristics predictive of the ratios, we searched for SKU characteristics variables likely correlated with these four. We knew that SKUs with large shipment gaps might produce more Unit*Week's Prepositioned, leading to greater Increase in Store's Average Inventory in units and dollars. We also knew from Subsection 3.5.2 that more 1-unit shipments would generate more Decrease in Number of Picks while a higher SKU Cost would create a higher Increase in Store's Average Inventory by Dollars. Hence, we examined the variables in Table 3.4 relevant to inter-shipment proximity and SKU cost. We also constructed a new variable, Number of 1-Unit Shipments Per Year. However, we excluded MySQL-generated variables to ensure that segmentation was operations-friendly with easy calculations. Final variables considered for segmentation are in Table 3.7.

Table 3.7. *Final List of Variables Considered for SKU Segmentation*

Variable	Concept Being Measured
SKU Cost	Dollar value of inventory. Larger value reduces scheme suitability by Hypothesis 2.
Shipment Frequency	Possible measure of inter-shipment proximity. Larger frequency may give more shipments per 74 weeks, less likely to have far-apart shipments or many unit*week's of inventory prepositioned.
Average Number of Units Shipped Per Week	SKU velocity. Possible measure of inter-shipment proximity. Faster-moving SKUs may be shipped in closer intervals, less likely to have 1 unit prepositioned across many unit*week's, perhaps less effect on store inventory.
Coefficient of Variation (CV) for Quarterly Shipment Number	Inter-shipment proximity. SKUs can have seasonality or clusters of shipments with wide gaps between clusters. Larger value captures more seasonality and clusters from quarterly shipment variation, likelier to have sudden spikes of shipments ensued by long gaps without shipment, with inventory prepositioned across many weeks.
Number of 1-Unit Shipments Per Year	Possibility of a pick being eliminated through shelf-pack change. A pick can only be eliminated when 1 unit is prepositioned from a 1-unit shipment, so with more 1-unit shipments, more picks can be saved.

Next, we evaluated these variables' predictability of Cost Saved/$ Inventory Shifted and Picks Decreased/Unit Shifted. As discussed in *SKU Suitability* under Subsection 3.5.2, variables interact with one another in such a way that they cannot be distinctly identified as predictive of the ratios by observation. In addition, the 5 stores constitute over 60,000 data rows. Therefore, we used a correlation matrix to evaluate each variable's correlation with the ratios. In addition, we observed the weekly shipment quantities in each data row to understand if a correlation was explainable by shipment pattern. The matrix is in Table 3.8, with variable names abbreviated. Hereafter, the abbreviated names will be used to refer to the variables.

Table 3.8. *Correlation Matrix of Variables Considered for SKU Segmentation*

	SKU Cost	Units Shipped/ Week	1-Unit Shipments/ Year	Shipment Frequency	CV Quarterly Shipment	Picks Decreased/ Unit Shifted	Cost Saved/ $ Inventory Shifted
SKU Cost	1	-0.086	-0.041	-0.139	0.113	-0.003	-0.221
Units Shipped/ Week	-0.086	1	0.135	0.769	-0.470	-0.063	0.040
1-Unit Shipments/Year	-0.041	0.135	1	0.606	-0.525	0.378	0.289
Shipment Frequency	-0.139	0.769	0.606	1	-0.708	0.120	0.185
CV Quarterly Shipment	0.113	-0.470	-0.525	-0.708	1	-0.006	-0.078
Picks Decreased/ Units Shifted	-0.003	-0.063	0.378	0.120	-0.006	1	0.584
Cost Saved/$ Inventory Shifted	-0.221	0.040	0.289	0.185	-0.078	0.584	1

*Each cell contains a coefficient of correlation between two variables. Pink represents a highly positive correlation, and green represents a highly negative correlation. CV is the abbreviation of the "coefficient of variation," as introduced in Table 3.4.

Units Shipped/Week should correlate highly with the savings-to-inventory-impact ratios since faster-moving items should be shipped with smaller inter-shipment gaps. This would mean fewer unit*week's prepositioned with less inventory shift. However, Table 3.8 shows otherwise. The fact is that some SKUs have very high Units Shipped/Week from very few shipments in high quantities, with large gaps and very few 1-unit shipments for elimination. Other SKUs have very low Units Shipped/Week from many shipments in low quantities, with many 1-unit shipments. This variable has no consistent relationship with savings from pick elimination or inventory shift from unit*week's prepositioned. It is also highly correlated with Shipment Frequency, which is more correlated to the ratios. Therefore, Units Shipped/Week is excluded for collinearity, and Shipment Frequency is retained.

The CV Quarterly Shipment is designed to capture possible gaps between clusters of shipments. If a quarter of few or no shipment is situated between quarters with many shipments, the CV (coefficient of variation) will be high, reflecting large gaps between dense quarters and a high number of unit*week's prepositioned. However, the CV is highly correlated with Shipment Frequency and not correlated with the two ratios, so it is excluded. Shipment Frequency is kept.

SKU Cost, 1-Unit Shipments/Year, and Shipment Frequency will be the variables used to create segments categorizing the SKUs.

3.6.3 SKU Segmentation Process

To create segments practical for operation, we divided the SKUs into simplistic high, medium, and low categories with respect to the three variables. By each SKU's value for SKU Cost, 1-Unit Shipments/Year, and Shipment Frequency, we labeled the SKU as high, medium, or low for each respective variable. Meanwhile, it was well known that 10%, 20%, and 70% represented plausible segregation points among SKU groups, especially in ABC analysis. Such segregation would also distribute enough data rows for analysis into each of the high, medium, and low categories. Consequently, we decided to create the categories with this method. We arranged all SKU-store data rows from the highest to the lowest value for each variable. Then, we searched for cutoff variable values that segregated the data into the top 10%, middle 20%, and lower 70%, building 9 categories, 3 under each variable (Table 3.9).

Table 3.9. *Cutoffs Grouping SKUs into High, Medium, and Low Categories by Variable*

	Top 10% of Data	Middle 20% of Data	Lower 70% of Data
SKU Cost	Cost $\geq$ 11.4	5.99 $\leq$ Cost < 11.4	Cost < 5.99
1-Unit Shipments/Year	Shipments $\geq$ 8.4	4.9 $\leq$ Shipments < 8.4	Shipments < 4.9
Shipment Frequency	Frequency $\geq$ 0.31	0.18 $\leq$ Frequency < 0.31	Frequency < 0.18
Category	High	Medium	Low

We grouped different combinations of high, medium, and low categories into segments. For instance, SKUs with high SKU Cost, high Shipment Frequency, and high 1-Unit Shipments/ Year and SKUs with high SKU Cost, high Shipment Frequency, and low 1-Unit Shipments/Year would constitute two different segments. This formed 27 segments from 3 combinations of the 3 categories under each of the 3 variables.

3.6.4 Determining Segment Suitability for Shelf-Pack Change

The segments needed to be marked as suitable or unsuitable for shelf-pack change. Some segments had thousands of SKU-store rows while others had only 32. A unified way to evaluate segment suitability would be calculating the SKU-store rows' average Cost Saved/$ Inventory Shifted and average Picks Decreased/Unit Shifted within each segment. To evaluate the average's robustness, we also calculated the coefficient of variation for the two respective ratios of all members in each segment and a 95% confidence interval for the average. Results of these analyses are reported in Chapter 4 and Table C-2 of Appendix C. They offer insight into the final SKU variables pertinent to segmentation and into the kinds of segments suitable for change.

4. Results and Analyses

While Subsections 3.5.2 and 3.6.2 summarily discuss trends surrounding the hypotheses, this chapter offers more in-depth results and analyses. Section 4.1 presents results from Section 3.5 for the pre-segmentation simulation on all SKUs. Although the simulation reduces picks and increases picking efficiency, it leads to an inventory increase, mainly in the stores. Thus, Section 4.2 ensues with results from SKU segmentation to ascertain the SKUs that offer large savings with minimal inventory increase. Section 4.3 gives the results of applying shelf-pack change only to SKUs in suitable segments. It generates more savings given the same inventory impact, demonstrating the efficacy of segmentation. Finally, Section 4.4 adds to this revelation. It shows that instead of instituting a DC-wide uniform shelf-pack for each SKU, the use of segmentation on store-specific shelf-pack change can achieve proportionally larger savings. In sum, this chapter presents the scheme's effect in more exact terms, especially its influence on the stores.

4.1 Simulation Results on All SKUs before Segmentation

In this section, the simulation of shelf-pack change on all SKUs offers preliminary insight into the scheme's benefits and inventory impact. The picks and store shelving trips for most SKUs are reduced while their inventories increase in the stores. These findings partially support Hypothesis 1, suggesting that shelf-pack change is a viable method in piece-picking optimization.

4.1.1 Efficiency and Savings

First, with shelf-pack change simulated on all SKUs in the 5 stores, there is considerable picking improvement. In particular, the variables Total Number of Picks and Decrease in Number of Picks capture a significant number of picks reduced, as seen in Table 4.1.

Table 4.1. *Savings on Picks and Store Shelf Visits under Shelf-Pack Change on All SKUs, Annual*

Store	1111				2222			
(Annual)	Before Change	After Change	Change (Δ)	Reduction %	Before Change	After Change	Change (Δ)	Reduction %
Total Picks	106,838	84,224	22,614	21%	94,053	74,695	19,357	21%
Store Shelf Visits	106,838	84,224	22,614		94,053	74,695	19,357	
Store	3333				4444			
(Annual)	Before Change	After Change	Change (Δ)	Reduction %	Before Change	After Change	Change (Δ)	Reduction %
Total Picks	100,445	80,259	20,186	20%	102,774	81,408	21,366	21%
Store Shelf Visits	100,445	80,259	20,186		102,774	81,408	21,366	
Store	5555							
(Annual)	Before Change	After Change	Change (Δ)	Reduction %				
Total Picks	109,725	88,435	21,290	19%				
Store Shelf Visits	109,725	88,435	21,290					

The picks in the DC, the store shelf visits, and the costs they incur are reduced by approximately 20% for each store (recall Subsection 3.5.2, where every pick leads to a store shelf visit). Figure 4.1 below uses stores 4444 and 5555 to demonstrate the size of the savings.

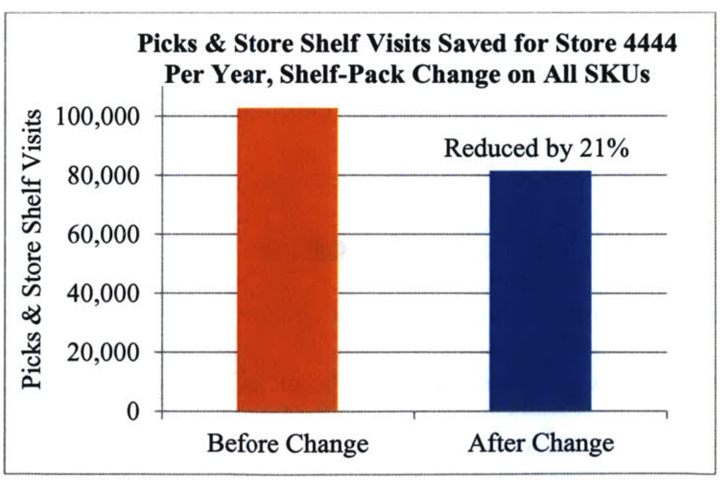

Figure 4.1a. Picks & store shelf visits saved for store 4444 per year, shelf-pack change on all SKUs. Here, 21,366 picks and store shelving trips are saved. Data adopted from Table 4.1.

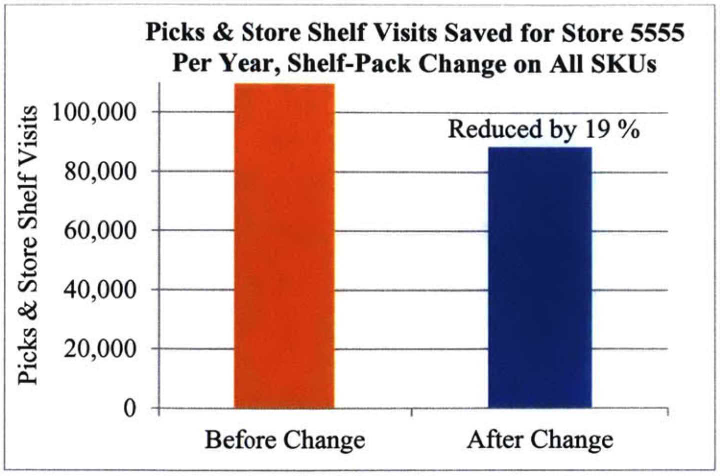

Figure 4.1b. Picks & store shelf visits saved for store 5555 per year, shelf-pack change on all SKUs. Here, 21,290 picks and store shelving trips are saved. Data adopted from Table 4.1.

Meanwhile, picking efficiency has been raised with increased average number of units per pick, as measured by Average Number of Units/Line, hereafter referred to as Average Units/Line. This measure has increased on average across the 5 stores by 0.67 units/line (Table 4.2 and Figure 4.2). The efficiency has risen because pickers are picking two weeks of orders in a single week whenever the scheme prepositions a future to a current pick. In addition, as discussed in Subsection 3.5.2, since the scheme prepositions SKU units from outside the data range for certain SKUs, the total number of units shipped for each store has increased with the reduction in picks, reinforcing the increase of Average Units/Line. This also occurs in the cases of Sections 4.3 and 4.4, where the scheme prepositions units from outside the data range for certain selected SKUs under shelf-pack change.

Table 4.2. *Picking Efficiency with Shelf-Pack Change on All SKUs, 74 Weeks*

Store	1111		2222		3333		4444		5555	
Shelf-Pack Change	Before	After	Before	After	Before	After	Before	After	Before	After
Total Units Shipped	349,747	356,816	329,273	335,736	339,906	346,192	336,785	343,330	410,755	417,374
Total Picks	152,038	119,857	133,844	106,297	142,941	114,215	146,256	115,850	156,147	125,850
Average Units/Line	2.30	2.98	2.46	3.16	2.38	3.03	2.30	2.96	2.63	3.32
Change (Δ)		0.68		0.70		0.65		0.66		0.69

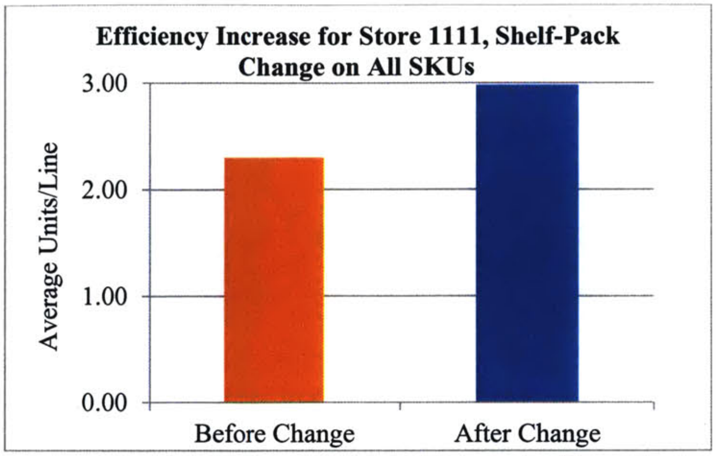

Figure 4.2. Efficiency increase for store 1111, shelf-pack change on all SKUs. This is an example illustration of what efficiency increase appears like for each store. Here, the efficiency has increased by 0.68 units/line, as given in Table 4.2.

4.1.2 Impact on Inventory

In prepositioning SKUs to make odd-quantity picks even, shelf-pack change on all SKUs raises each store's average inventory for the 74 weeks of data (Table 4.3). The DC experiences a concomitant decrease in inventory units that are now extra units in the stores. In this regard, the inventory impact is really an inventory shift from DC to store. However, unlike the premise of selective shelf-pack change in Section 3.2 and Subsection 3.5.2-*Inventory*, this all-SKU change is likelier to preposition enough units to deplete DC inventory for some SKUs, triggering a DC replenishment that increases the company inventory level. Nonetheless, the real scheme proposed involves selective shelf-pack change that mitigates this issue. Thus, Table 4.3 and Figure 4.3 will put aside the issue of DC replenishment to focus on demonstrating the shift from DC to store.

Table 4.3. *A Shift of Company Inventory Units from DC to Store*

Store	Avg. Inventory Before Change	Avg. Inventory After Change	Increase in Store Avg. Inventory
2222	129,675	134,645	4,970
3333	107,260	112,272	5,013
4444	139,891	144,957	5,066
5555	121,170	126,423	5,254
Total Increase	20,303		
DC	Avg. Inventory Before Change	Avg. Inventory After Change	Decrease in DC Avg. Inventory
	30,154,757	30,175,059	20,303

*Store 1111 is not included because its inventory data is unavailable. Note that Avg. is the abbreviation of "average," and DC replenishment and company inventory are not in the consideration of this table.

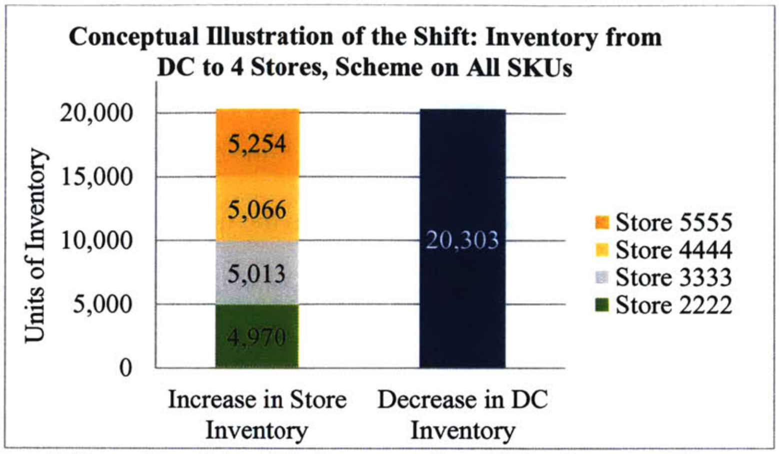

Figure 4.3. Conceptual illustration of the shift: inventory from DC to 4 stores, scheme on all SKUs. DC replenishment and company inventory are not in the consideration of this figure.

The prepositioning also affects in-store material handling. As mentioned in Subsection 3.5.2-*Inventory*, it creates a permanent rise in store inventory that remains steady at a level customary of a shelf-pack of 2. Excessive prepositioning can increase this inventory to an extent that requires unexpectedly more backroom storage or material-handling man-hours. It is necessary to examine the scheme's effect on store inventory. Thus, the net change of total inventory level by store is calculated for this case of shelf-pack change on all SKUs (Figure 4.4).

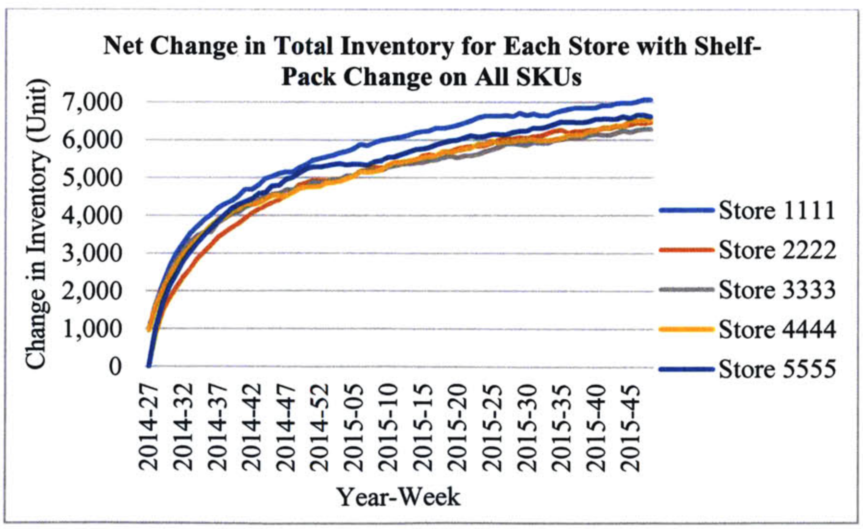

Figure 4.4. Net change in total inventory for each store with shelf-pack change on all SKUs. See Appendix C for data used.

Figure 4.4 shows the net change in total inventory for each store seemingly plateauing just as is expected: a one-off change in store inventory level will occur and remain steady afterwards. However, even at the 74th week of the data, the net change has not plateaued. More time is necessary for it to plateau, and the net increase extrapolated from the graph for each store may be as high as 7,600 to 8,600 units. This means the increase in each store's average inventory should be within this range, unlike in Table 4.3. However, the data consist of only 74 weeks, during which the inventory increase has not plateaued, so the final net increase in average inventory cannot be ascertained. Thus, Table 4.3 is calculated to represent the increase over only the data range, dividing the Unit*Week's Prepositioned for each SKU—the number of weeks a store has 1 extra unit of that SKU—by the total 74 weeks for each store. This yields the increase in average inventory over the 74 weeks for each SKU by store. The sum of all the SKUs' increase within each store equals that store's average inventory increase in Table 4.3. Though this fails to give the accurate net increase for each SKU, it gives a value for the calculation of the SKU's Picks Decreased/Unit Shifted and Cost Saved/$ Inventory Shifted. These ratios allow us to benchmark SKUs against one another and determine the list of SKUs, through segmentation, that can bring great savings with minimal inventory impact.

The extrapolated rise in store inventory reveals the effect of all-SKU shelf-pack change on the store material handling we have set out to explore. Given XYZ's averages of 18 units/case and 60 cases/pallet, the 7,600~8,600 units amount to 7~8 pallets of extra store inventory shifted from DC, requiring more backroom storage and material handling than what stores can manage.

4.1.3 Hypothesis 1 and the Need for Selective Shelf-Pack Change

It is true that shelf-pack change on all SKUs may increase company inventory by DC replenishment and create an excessive level of store inventory. However, it also generates savings and increases picking efficiency. Shelf-pack change is a viable picking optimization method. It just needs to be selectively implemented, supporting Hypothesis 1's point on the necessity of selective shelf-pack change to create savings with minimal inventory impact. Hence, SKU segmentation is introduced to exclude SKUs with low savings-to-inventory-impact ratios.

4.2 Results of SKU Segmentation

As explained in Subsection 3.6.3, SKU segmentation first divides all 5 stores' SKU-store data rows into high, medium, and low categories by the values of each row's SKU Cost, 1-Unit Shipments/Year, and Shipment Frequency, forming the 9 categories in Table 3.9. Then, it places the SKU-store items into 27 segments by different combinations of the categories. It also calculates the respective average of the two savings-to-inventory-impact ratios for all the SKU-store rows in each segment. This section presents the 27 segments formed and the criteria of the segments suitable for the scheme. The calculation results and the 27 segments are in Table 4.4.

Table 4.4. *Segments Formed from Different Combinations of SKU Categories by Variable Value*

	Combinations of SKUs by Categories of Variable Values			Ratio: Picks Decrease/ Units Shifted			Ratio: Cost Saved/ $ Inventory Shifted		
Segment	Shipment Frequency	1-Unit Shipments/ Yr	SKU Cost	Ratio Average	Good or Not	Ratio CV	Ratio Average	Good or Not	Ratio CV
1	H	H	H	17.52	G	0.33	0.06	N	0.45
2	H	H	M	17.20	G	0.33	0.13	N	0.36
3	H	H	L	17.12	G	0.34	0.55	G	0.95
4	H	L	H	2.95	N	1.21	0.01	N	1.33
5	H	L	L	2.96	N	1.25	0.13	N	1.55
6	H	L	M	3.26	N	1.01	0.02	N	1.06
7	H	M	H	8.80	G	0.38	0.03	N	0.45
8	H	M	L	10.26	G	0.41	0.39	G	0.99
9	H	M	M	11.46	G	0.43	0.08	N	0.48
10	L	H	H	14.29	G	0.34	0.05	N	0.44
11	L	H	L	15.71	G	0.40	0.42	G	1.08
12	L	H	M	15.21	G	0.51	0.11	N	0.44
13	L	L	H	6.27	N	1.83	0.02	N	1.90
14	L	L	L	6.30	N	1.85	0.17	N	2.43
15	L	L	M	6.92	N	1.79	0.05	N	1.84
16	L	M	H	10.47	G	0.55	0.03	N	0.67
17	L	M	L	11.01	G	0.65	0.29	G	1.12
18	L	M	M	10.39	G	0.61	0.07	N	0.63
19	M	H	H	15.81	G	0.34	0.06	N	0.45
20	M	H	L	15.97	G	0.39	0.45	G	1.02
21	M	H	M	15.63	G	0.36	0.11	N	0.40
22	M	L	H	3.93	N	1.47	0.01	N	1.67
23	M	L	L	3.56	N	1.32	0.12	N	1.81
24	M	L	M	4.19	N	1.10	0.03	N	1.16
25	M	M	H	11.25	G	0.52	0.04	N	0.61
26	M	M	L	11.42	G	0.55	0.35	G	1.09
27	M	M	M	11.40	G	0.50	0.08	N	0.54

*H=high, M=medium, L=Low. A more comprehensive version of this table can be found in Appendix C.

In Table 4.4, for Cost Saved/$ Inventory Shifted, there is a marked difference in ratio average between low-cost and medium- or high-cost SKUs. Only low-cost SKUs yield large enough ratios to be considered suitable for shelf-pack change regardless of the SKUs' shipment frequency or 1-unit shipments. Given the same increase in store inventory, larger SKU Cost generates a larger denominator for and a lower value of Cost Saved/$ Inventory Shifted, so SKU Cost is the dominant variable that determines suitability here. SKUs with higher unit cost are unsuitable for the scheme, supporting Hypothesis 2.

For Picks Decreased/Unit Shifted, 1-Unit Shipments/Year is the dominant variable determining a segment's suitability. As long as a segment has a high or medium number of 1-unit shipments per year, it has a large enough Picks Decreased/Unit Shifted to be considered suitable. This is plausible because 1-Unit Shipments/Year determines the numerator of the ratio. A 1-unit shipment can be prepositioned to make a previous shipment's quantity even. Once prepositioned, it is eliminated as a pick. The more 1-unit shipments there are, the more picks can be eliminated. In fact, it also contributes to the numerator of Cost Saved/$ Inventory Shifted since the numerator is a product of Decrease in Number of Picks and Picking Cost Per Line. Therefore, suitable segments should have high and medium 1-Unit Shipments/Year. Albeit 1-Unit Shipments/Year is not a measure of the inter-shipment proximity or SKU Cost relevant to the hypotheses, it appears more directly correlated to pick reduction than inter-shipment proximity.

An interesting phenomenon is the absolute dominance of SKU Cost. A low-cost segment has high values for both savings-to-inventory-impact ratios, but a segment with high or medium 1-Unit Shipments/Year does not necessarily have a high Cost Saved/$ Inventory Shifted. This is plausible. The Picking Cost Per Line is lower than most SKUs' unit cost. Given a Picks Decreased/Unit Shifted, if we multiply it by (Picking Cost Per Line)/(SKU Cost) to convert it to Cost Saved/$ Inventory Shifted, the process will significantly amplify the magnitude of the denominator. Therefore, for a segment to be suitable for shelf-pack change by the standard of both ratios, we must first select only low-cost SKU segments, then pick from them the segments that also have a high or medium number of 1-unit shipments per year.

Shipment Frequency seems to have become an unnecessary variable despite its correlation with both ratios. A higher frequency represents a larger number of shipments in a time period, creating a higher probability of 1-unit shipments and picks saved. This resonates with Table 3.8, where a high, positive correlation exists between Shipment Frequency and 1-Unit Shipments/Year. In other words, higher Shipment Frequency should be correlated with higher numerator for both Cost Saved/$ Inventory Shifted and Picks Decreased/Unit Shifted. In the meantime, higher frequency should theoretically come with smaller shipment gaps, with lower Unit* Week's Prepositioned. It should be negatively correlated with Unit*Week's Prepositioned and the two ratios' denominator. If this were so, Shipment Frequency should be highly positively correlated with the ratios. However, it has low coefficients of correlation with the two ratios. In fact, Shipment Frequency is positively correlated with Unit*Week's Prepositioned at a coefficient of 0.23, likely because more frequent shipments allow for more chances of prepositioning even though the gaps of unit*week's prepositioned are smaller. Therefore, Shipment Frequency is much less correlated with the ratios than SKU Cost and 1-Unit Shipments/Year. Thus, it is unnecessary for segmentation, especially because it is already highly correlated with 1-Unit Shipments/Year, which can better predict the ratios. SKU Cost and 1-Unit Shipments/Year are the dominating factors to be used for SKU suitability segmentation.

The elimination of Shipment Frequency as a variable for segmentation does not undermine Hypothesis 3. Shipment Frequency itself does not directly measure the actual size of inter-shipment gaps. The fact remains that larger gaps do lead to more unit*week's prepositioned and inventory impact. Hypothesis 3 remains supported by the findings in Subsection 3.5.2.

Given these analyses, segments suitable for shelf-pack change are segments 3, 8, 11, 17, 20, and 26, as highlighted in Table 4.4. They are the segments whose SKU-store items have low unit cost and a high or medium number of 1-unit shipments per year.

The segment suitability analysis relies on the respective average of the two ratios for each segment, but the coefficients of variation for the ratios in each segment are high. Nonetheless, the average seems most plausible for evaluating segment suitability since the segments contain widely different numbers of SKU-store items, rendering it difficult to perform other cross-comparisons. For the purpose of this thesis, the average-based analysis appears sufficient.

4.3 Shelf-Pack Change on All SKUs in Segments 3, 8, 11, 17, 20, and 26

The previous section concludes with segments 3, 8, 11, 17, 20, and 26 as "good" segments. This section now presents the effect of shelf-pack change on all the SKUs in the good segments. For instance, if a SKU-store item 1234-1111 (SKU 1234 in store 1111) is in a good segment for store 1111, we will apply the scheme to SKU 1234 for all the stores even if 1234-4444 is not in a good segment for store 4444. This is done to replicate XYZ's current DC-wide shelf-pack policy, where a single shelf-pack is applied for each SKU across every store.

4.3.1 Impact on Inventory

SKU segmentation should eliminate SKUs with small savings-to-inventory-impact ratios yielding minimal savings with large increases in store inventory by units or dollars. A reduction in inventory increase after segmentation will support the necessity of SKU segmentation and the process with which it is conducted. The three examples in Figure 4.5 exhibit significant reduction in the net increase of store inventory once shelf-pack change is applied only to SKUs in good segments. This gives ground to SKU segmentation: it curbs the increase in store inventory from shelf-pack change. Data for Figure 4.5 can be found in Appendix C Tables C-1 and C-3.

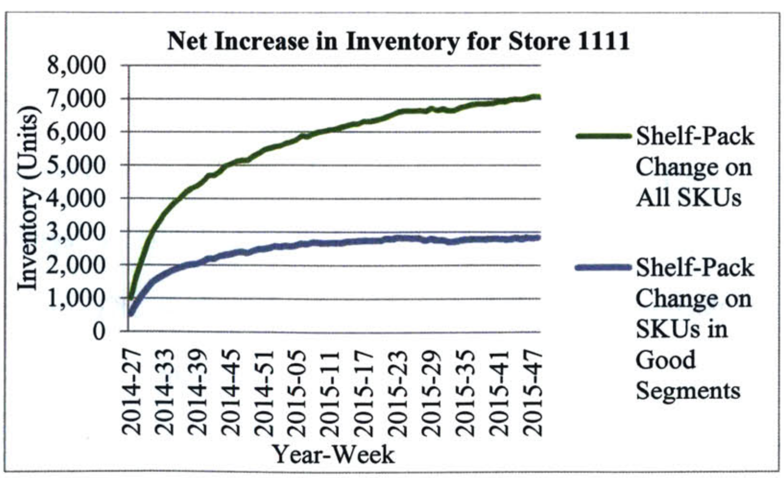

Figure 4.5a. Net increase in inventory for store 1111.

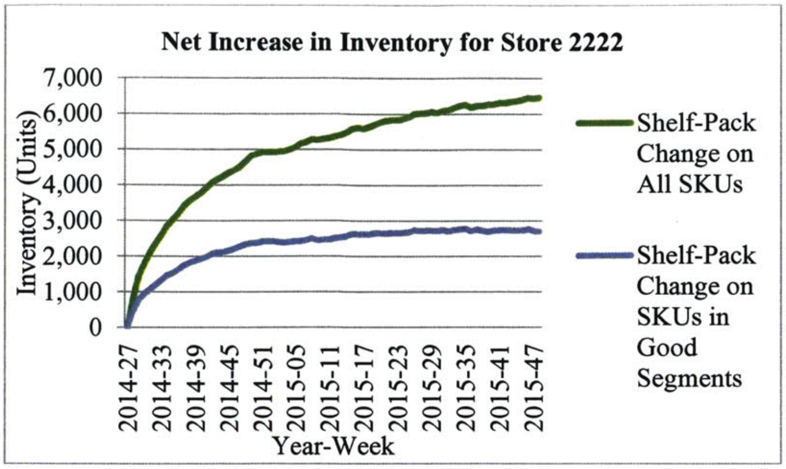

Figure 4.5b. Net increase in inventory for store 2222.

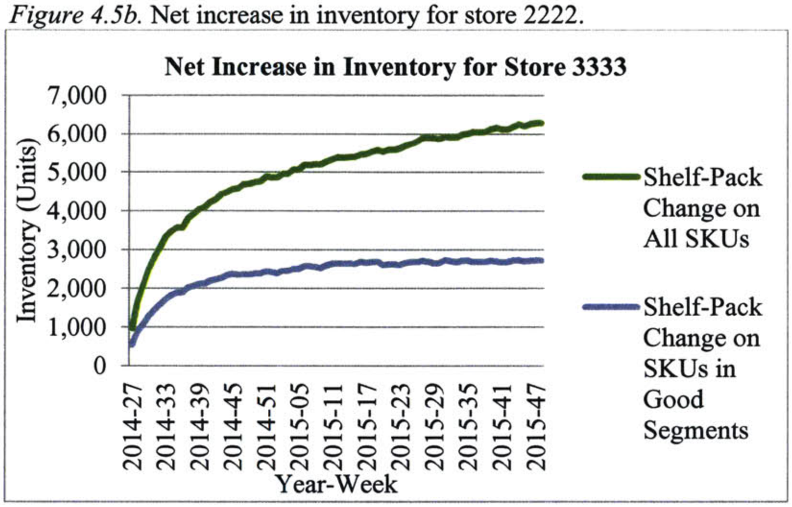

Figure 4.5c. Net increase in inventory for store 3333.

Instead of Figure 4.4's continuously rising net increase in store inventory, the net increase now plateaus before the 74th week, demonstrating clearly a one-time, permanent increase in store inventory under the proposed scheme. This is a much smaller increase in each store's average inventory level, calculated from the average of the net increase during the weeks of plateau (Appendix 3 Table C-3). The increase in the stores' average inventory ranges from 2,685 to 2,819 units, most of which less than 0.5 standard deviations of each store's total inventory (Table 4.5). Given 18 units/case and 60 cases/pallet, this is a 2.5- to 2.6-pallet increase, requiring much fewer handling man-hours than universal shelf-pack change and almost no extra storage as the increased units may fit right on the store shelves. Each store's end-of-week inventory experiences a relatively small increase, no more than 2.8%, as illustrated by the three stores in Figure 4.6. Data for Figure 4.6 are in Appendix C Table C-5.

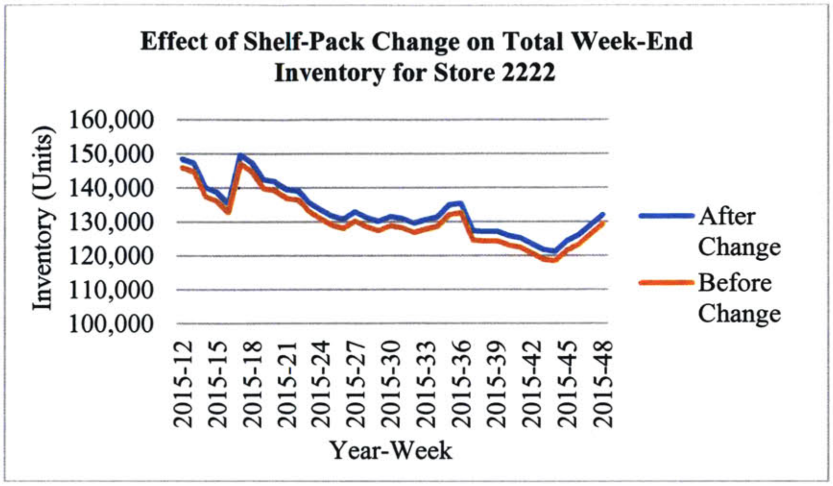

Figure 4.6a. Effect of shelf-pack change on total week-end inventory for store 2222.

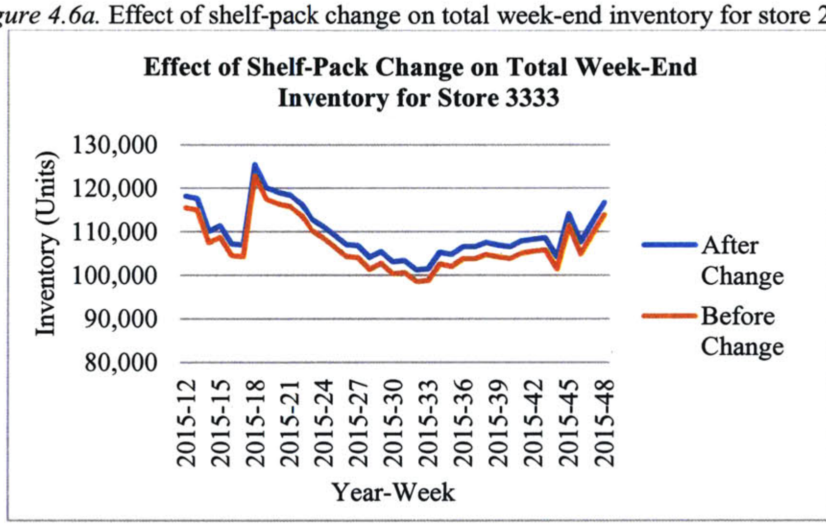

Figure 4.6b. Effect of shelf-pack change on total week-end inventory for store 3333.

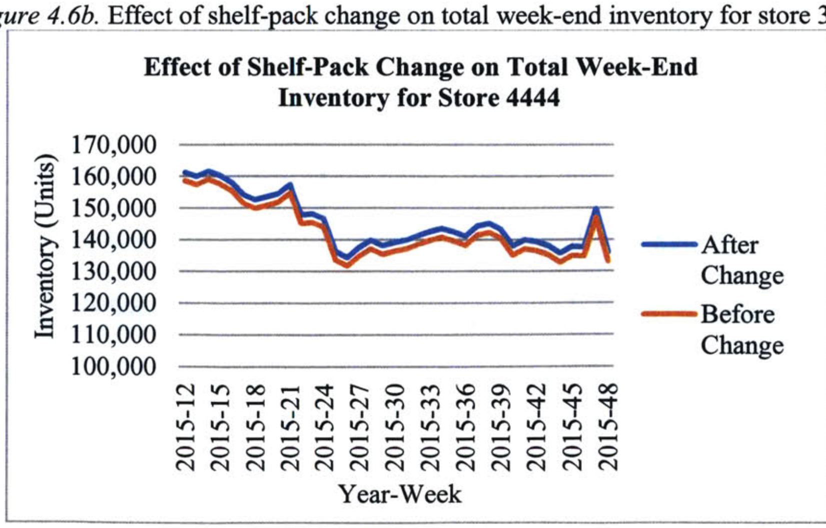

Figure 4.6c. Effect of shelf-pack change on total week-end inventory for store 4444.

Finally, as discussed in Subsection 4.1.2, the DC will experience an inventory decrease parallel to the increase in store inventory, an inventory shift to the stores. Meanwhile, since the scheme is now applied only to about 44% of the SKUs (Table 4.5), occasions when the scheme's prepositioning triggers DC replenishments will be significantly reduced. As a result, company inventory will witness very little change.

4.3.2 Savings from Shelf-Pack Change

Although bypassing less suitable SKUs through segmentation forgoes the opportunity of saving 1-unit picks for these SKUs, the segmentation actually reduces the inventory increase without sacrificing too much savings in picks and costs. As seen in Table 4.5, when shelf-pack change is applied only to SKUs in good segments, the net increase in a store's inventory is 2,685 to 2,819 units, which is at least 60% less than the 7,600 to 8,600 units extrapolated for universal shelf-pack change in Subsection 4.1.2. Moreover, segmentation excludes about 56% of SKUs. However, the store savings are only reduced by about 39% from the savings under universal shelf-pack change. For example, store 1111 sees a 21.2% savings if the change is applied to all SKUs, but it still has a 13% savings if the change is applied only to SKUs in good segments.

Table 4.5. *Pick Reduction & Savings in Shelf-Pack Change on All SKUs in Good Segments, Annual*

	Before Change		Shelf-Pack Change on All SKUs				Shelf-Pack Change on SKUs in Good Segments			
Store	Standard Deviation of Store Inventory (Units)	Number of Picks	Pct. of SKUs Changed	Picks Saved	Pct. of Savings	Net Increase in Average Inventory Units, **Extrapolated**	Pct. of SKUs Changed	Picks Saved	Pct. of Savings	Net Increase in Average Inventory Units
1111	No data	106,838	100%	22,614	21.2%	8,600	42.2%	13,924	13.0%	2,788
2222	7,912	94,053	100%	19,357	20.6%	7,900	44.0%	11,812	12.6%	2,735
3333	5,174	100,445	100%	20,186	20.1%	7,600	45.2%	12,391	12.3%	2,685
4444	8,711	102,774	100%	21,366	20.8%	8,300	45.2%	13,473	13.1%	2,819
5555	6,752	109,725	100%	21,290	19.4%	8,300	42.8%	12,536	11.4%	2,742

*For shelf-pack change on all SKUs, the Net Increase in Average Inventory Units is the extrapolated plateau from Figure 4.4. For shelf-pack change on all SKUs in good segments, it is calculated by averaging the net increase each week for the weeks when net increase has plateaued in Appendix C Table C-3.

Figure 4.7 uses store 2222 to demonstrate this trend. When shelf-pack change is limited to SKUs in good segments, the number of SKUs changed and the increase in inventory created actually decrease by an amount proportionally larger than the savings lost from limiting the scope of the scheme. SKU segmentation has eliminated the SKUs that create large increases in store inventory while preserving much of the savings: SKUs in good segments offer larger savings per inventory impact. The segmentation performed is viable for selecting SKUs fit for the scheme.

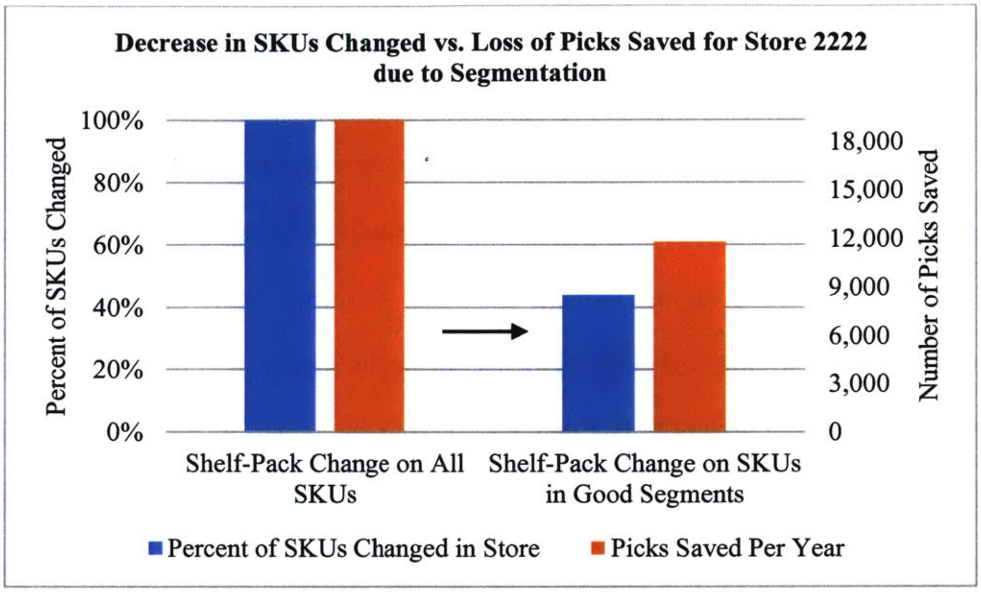

Figure 4.7a. Decrease in SKUs changed vs. loss of picks saved for store 2222 due to segmentation. Adopted from data in Table 4.5 to compare the **proportion** of decrease in SKUs changed and picks saved between two schemes.

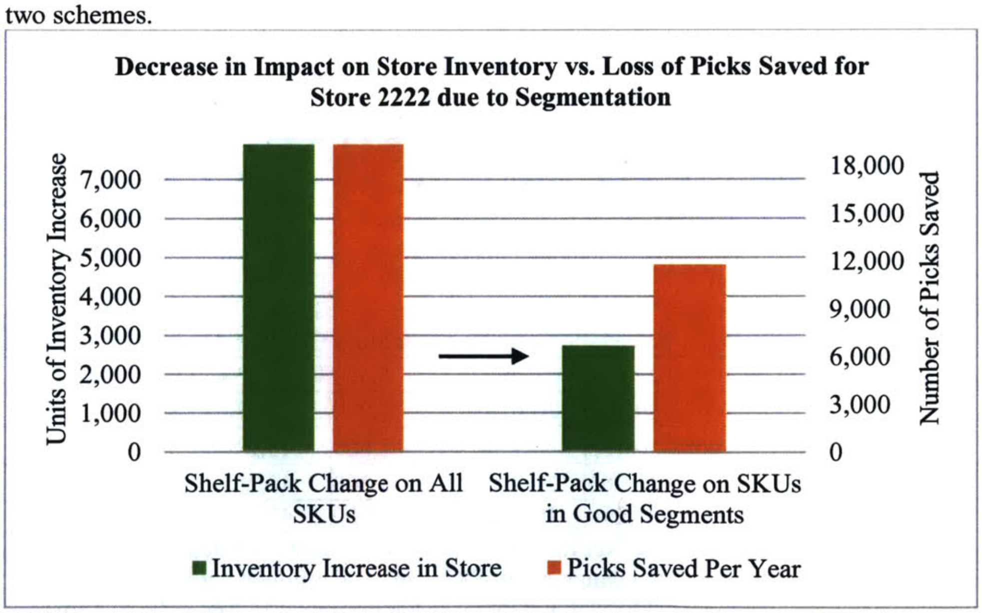

Figure 4.7b. Decrease in impact on store inventory vs. loss of picks saved for store 2222 due to segmentation. Adopted from data in Table 4.5 to compare the **proportion** of decrease in inventory change and picks saved between the two schemes.

Finally, picking efficiency still increases under shelf-pack change on only SKUs in good segments. In Table 4.6, each store's efficiency has increased by 0.36~0.38 units/line, with an average of 0.37 units/line across all the stores. This is smaller than the improvement under universal shelf-pack change, but it is a considerable improvement since it is attributed only to the approximately 44% store SKUs that undergo shelf-pack change. In fact, the improvement for only the SKUs changed in each store ranges from 0.60~0.63 units/line, with an average of 0.61 units/line across all 5 stores (Appendix C Table C-7).

Table 4.6. *Picking Efficiency with Shelf-Pack Change on All SKUs in Good Segments, 74 Weeks*

Store	1111		2222		3333		4444		5555	
Shelf-Pack Change	Before	After	Before	After	Before	After	Before	After	Before	After
Total Units Shipped	349,747	352,579	329,273	331,975	339,906	342,627	336,785	339,588	410,755	413,490
Total Picks	152,038	132,223	133,844	117,034	142,941	125,308	146,256	127,083	156,147	138,308
Average Units/Line	2.30	2.67	2.46	2.84	2.38	2.73	2.30	2.67	2.63	2.99
Change (Δ)		0.37		0.38		0.36		0.37		0.36

4.4 Shelf-Pack Change on Good-Segment SKUs Specific to Each Store

This section will present the results of applying shelf-pack change by store. The scheme is applied only to SKUs in the good segments specific to each store instead of a DC-wide implementation. Previously, we constructed the segments using SKU-store data rows. As a result, there are SKUs that belong to a suitable segment for one store but the unsuitable segment for another store. For instance, a SKU-store item 1234-1111 can be in the suitable segment 3 while 1234-4444 can be in the unsuitable segment 14. Though both stores contain SKU 1234, the SKU is suitable for the scheme only for store 1111. A store-specific scheme will apply shelf-pack change only to SKU 1234 for store 1111 but not for store 4444. Ultimately, this store-specific implementation further eliminates SKUs from the scheme for each store, so the scheme will be applied to even fewer SKUs than in Section 4.3's DC-wide shelf-pack change on good segments.

4.4.1 Impact on Inventory

Since fewer SKUs undergo shelf-pack change now, the scheme's impact on inventory is even smaller than that of the DC-wide implementation on all SKUs in good segments. Figure 4.8

presents three stores shedding light on the benefits of store-specific shelf-pack change. The net increase in each store's inventory is smaller, plateauing at a lower level than in Section 4.3.

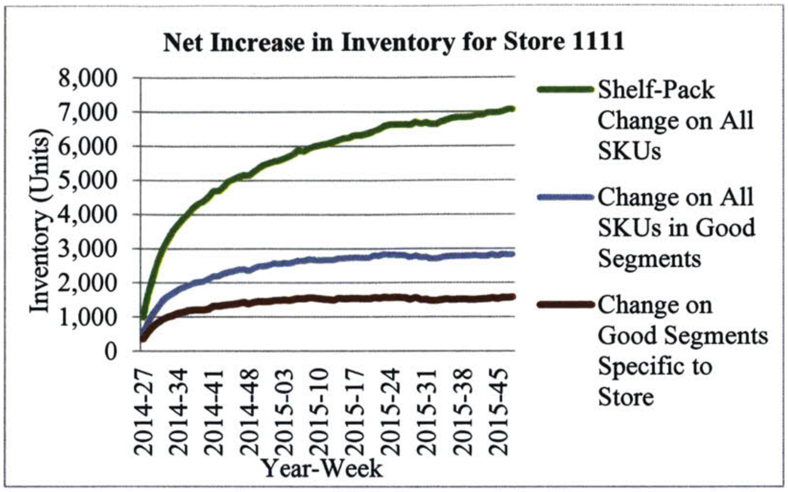

Figure 4.8a. Net increase in inventory for store 1111. Data used for Figure 4.8 can be found in Appendix C Tables C-1, C-3, and C-4.

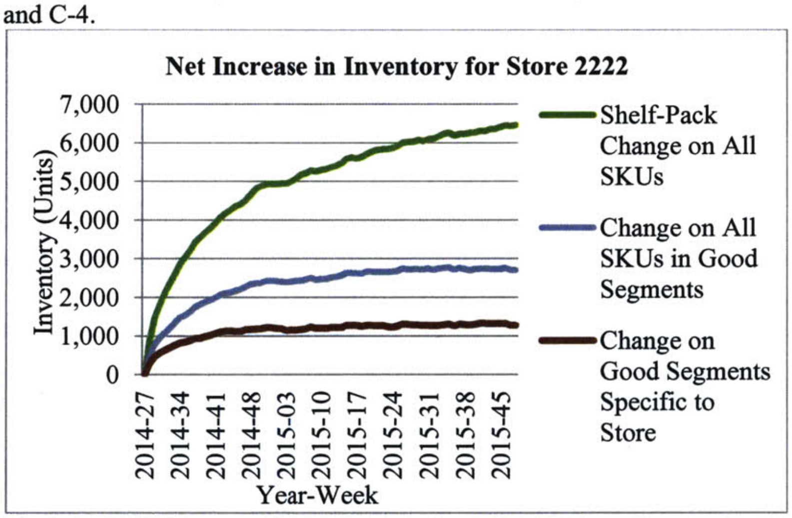

Figure 4.8b. Net increase in inventory for store 2222.

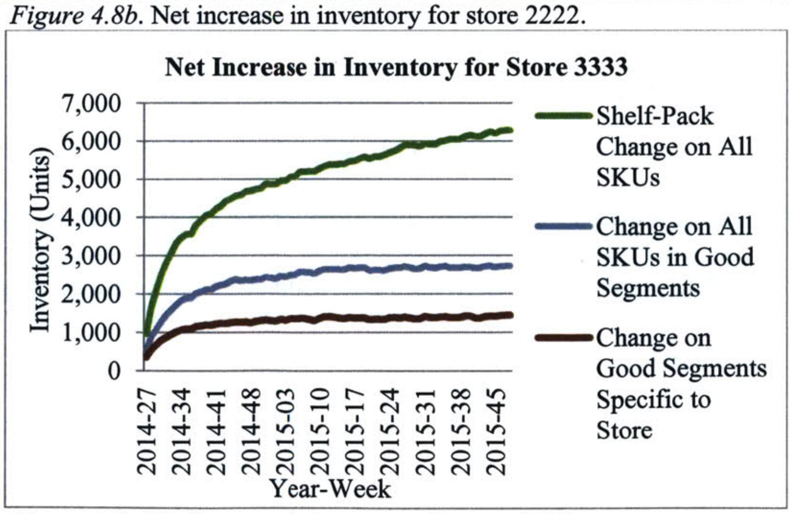

Figure 4.8c. Net increase in inventory for store 3333.

Under store-specific shelf-pack change, instead of continuously rising, the net increase again plateaus before the 74th week, reflecting clearly a one-time, permanent increase in store inventory. For each store, the increase in average inventory is 1,298 to 1,539 units (Table 4.7), calculated by averaging each week's net increase in the plateaued weeks (Appendix C Table C-4). Such increase is minimal, less than 0.25~0.3 standard deviations of each store's total inventory, as shown by the standard deviations in Table 4.5. Given 18 units/case and 60 cases/pallet, these units amount to a 1.2- to 1.4-pallet increase, about half of the increase from the DC-wide good-segment shelf-pack change. The increase in each store's end-of-week inventory becomes so negligible, at approximately only 1%, that the levels before and after shelf-pack change appear to overlap in Figure 4.9 given the same scales as Figure 4.6. Of course, such increase requires less space and handling than the increase in the DC-wide shelf-pack change on good segments. Given the much smaller increase, the units increased can very likely all fit onto the store shelves. Data used to construct Figure 4.9 are in Appendix C Table C-6.

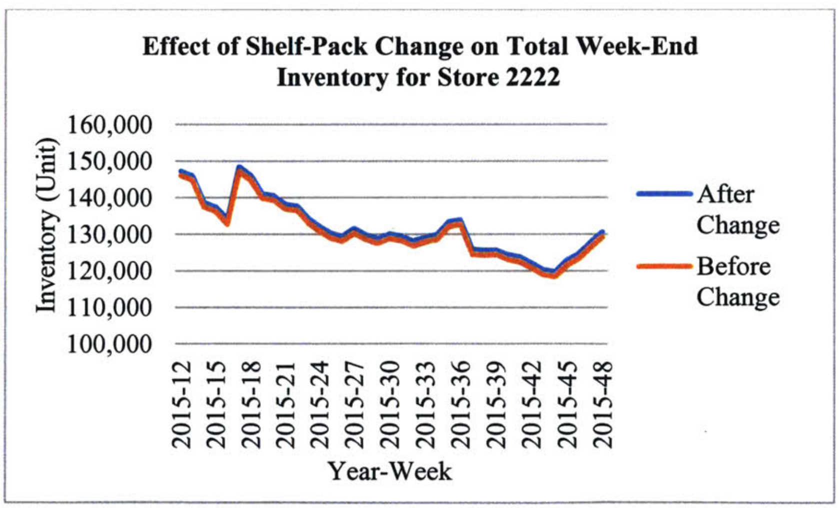

Figure 4.9a. Effect of shelf-pack change on total week-end inventory for store 2222.

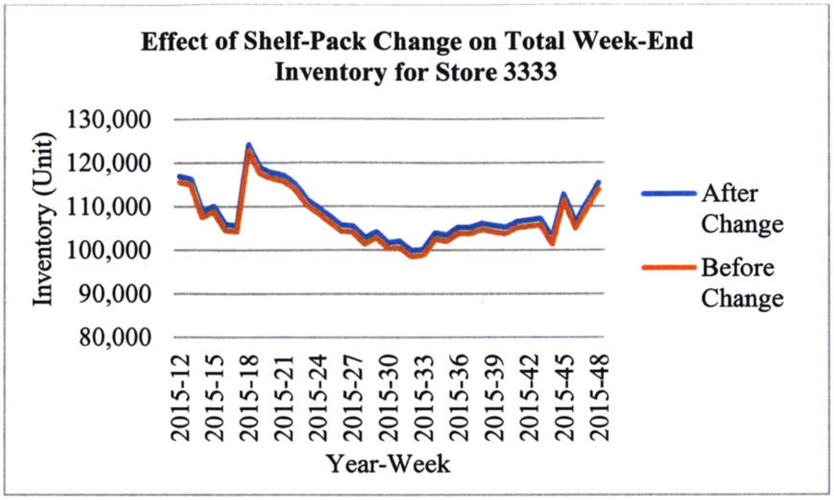

Figure 4.9b. Effect of shelf-pack change on total week-end inventory for store 3333.

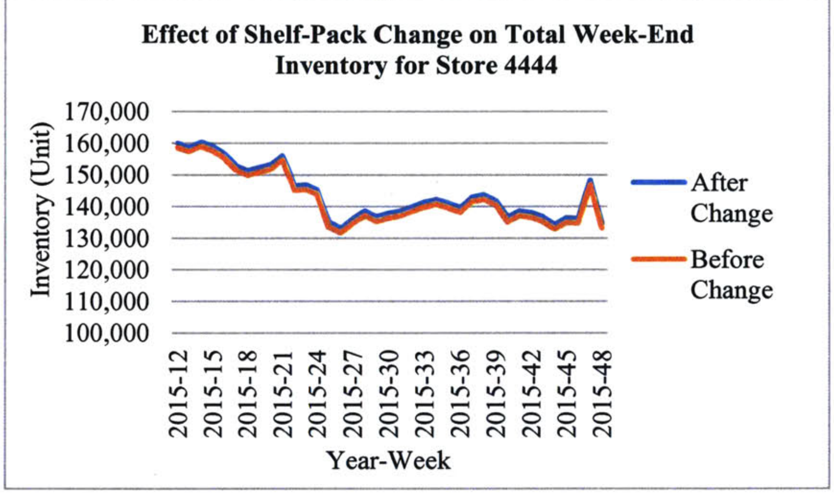

Figure 4.9c. Effect of shelf-pack change on total week-end inventory for store 4444.

Finally, in the case of the DC, the inventory will again encounter a decrease parallel to the increase in store inventory, a one-off inventory shift to the stores. Because the scheme is now applied only to about 22% of SKUs (Table 4.7), occasions when the scheme's prepositioning triggers DC replenishment is even fewer than in a DC-wide good-segment shelf-pack change. Consequently, company inventory will witness a negligible amount of change.

4.4.2 Savings from Shelf-Pack Change

Although store-specific shelf-pack change applies only to half of the SKUs that undergo the DC-wide good-segment shelf-pack change in Section 4.3, it generates about 75% to 80% of the savings yielded by the DC-wide change (e.g. store 1111: 10.5%÷13.0%=80.8% in Table 4.7).

Table 4.7. *Pick Reduction & Savings in Shelf-Pack Change on Suitable SKUs Specific to Store, Annual*

	Before Change	Shelf-Pack Change on All SKUs in Good Segments				Shelf-Pack Change on SKUs in Good Segments by Store			
Store	Number of Picks	Pct. of SKUs Changed	Picks Saved	Pct. of Savings	Net Increase in Average Inventory Units	Pct. of SKUs Changed	Picks Saved	Pct. of Savings	Net Increase in Average Inventory Units
1111	106,838	42.2%	13,924	13.0%	2,788	22.9%	11,214	10.5%	1,539
2222	94,053	44.0%	11,812	12.6%	2,735	20.4%	8,851	9.4%	1,298
3333	100,445	45.2%	12,391	12.3%	2,685	23.4%	9,647	9.6%	1,412
4444	102,774	45.2%	13,473	13.1%	2,819	24.0%	10,741	10.5%	1,496
5555	109,725	42.8%	12,536	11.4%	2,742	21.9%	9,761	8.9%	1,426

* Net Increase in Average Inventory Units is calculated from averaging the net increase each week for the weeks when net increase has plateaued. See Tables C-3 and C-4 in Appendix C.

This is illustrated in Figure 4.10. From a DC-wide scheme on all SKUs in good segments to a store-specific scheme, the number of SKUs changed and the increase in store inventory actually decrease by an amount proportionally larger than the savings lost from limiting the scope of the scheme. As such, the store-specific scheme yields higher savings given the same number of SKUs changed and inventory units increased in store. It generates savings with much lower impact on store inventory, creating an increase in store inventory that is only 47%~55% of the DC-wide good-segment scheme (e.g. store 1111: 1539÷2788 =55.2% in Table 4.7).

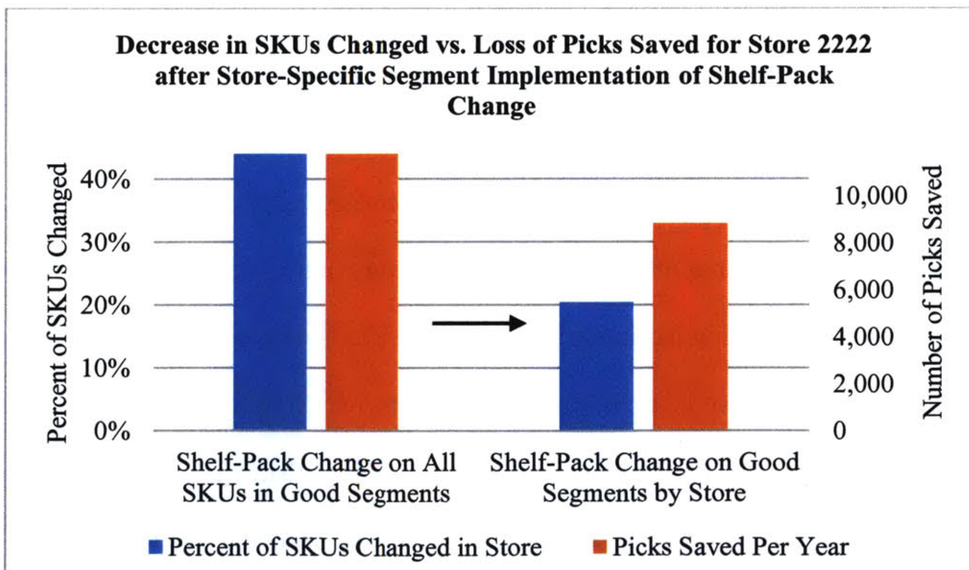

Figure 4.10a. Decrease in SKUs changed vs. loss in picks saved for store 2222 after store-specific segment implementation of shelf-pack change. Adopted from data in Table 4.7 to compare the **proportion** of decrease in SKUs changed and picks saved between two schemes.

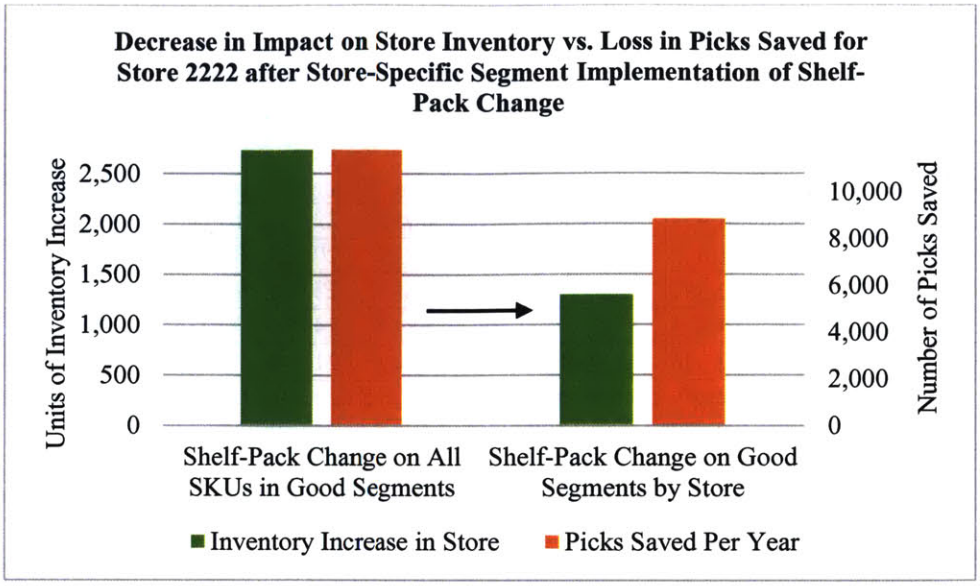

Figure 4.10b. Decrease in impact on store inventory vs. loss in picks saved for store 2222 after store-specific segment implementation of shelf-pack change. Adopted from data in Table 4.7 to compare the **proportion** of decrease in inventory change and picks saved between the two schemes.

In fact, the juxtaposition of Figures 4.7 and 4.10 reveals that, from universal to store-specific shelf-pack change, the store inventory increase has been proportionally diminishing against the savings obtained. Figure 4.11 illustrates this from a reversed perspective, where the picks reduced against inventory increase—the slope of the line for each store—is turning less negative. Figure 4.11b makes it clear that from no shelf-pack change to store-specific change, to change on all SKUs in good segments, and to change on all SKUs, the picks saved are proportionally diminishing against the store inventory increase. In this order, the shelf-pack policy is reducing fewer number of picks for every inventory unit increased due to the policy. In other words, SKU segmentation has indeed sifted out the SKUs whose shelf-pack, if changed, can generate larger savings relative to the inventory impact created. Moreover, raising the specificity of the scheme to the store level can generate even larger savings than a DC-wide good-segment implementation, forming a discovery that will be discussed in Chapter 5 Section 2.

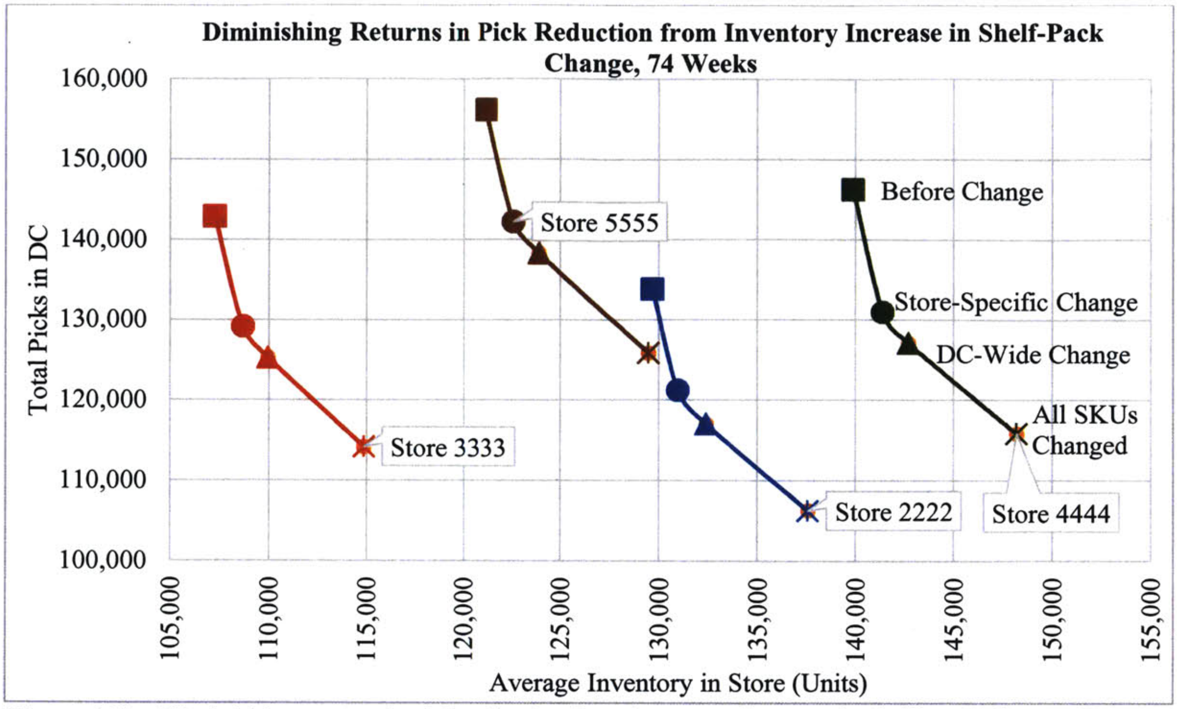

Figure 4.11a. Diminishing returns in pick reduction from inventory increase in shelf-pack change, 74 weeks. From no shelf-pack change to change on all SKUs, the picks saved are proportionally diminishing against the increase in store inventory. There is a diminishing returns occurring.

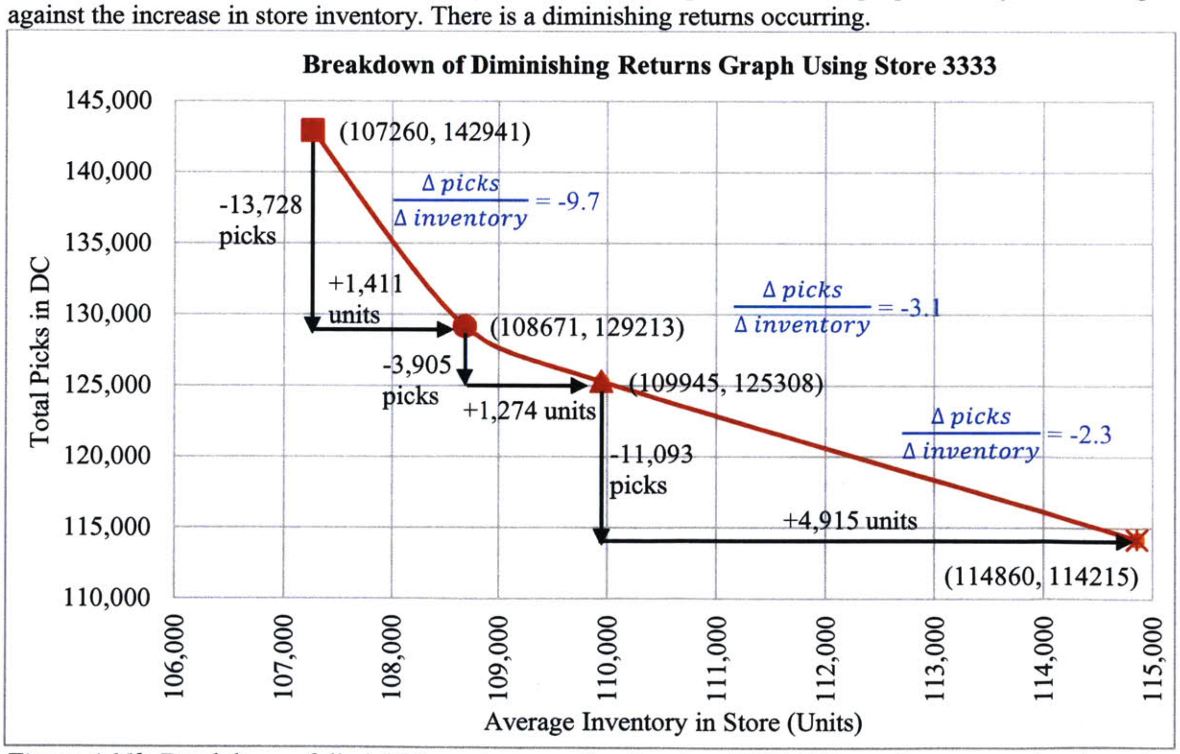

Figure 4.11b. Breakdown of diminishing returns graph using store 3333. This graph uses one store to make it clear that the slope, the picks reduced over the inventory increase in the store, is becoming less negative. In the order of no shelf-pack change, store-specific change, change on all SKUs in good segments throughout DC, and change on all SKUs, for every unit of inventory increased due to the shelf-pack policy, the number of picks saved is decreasing. Note that if any number in this graph does not match the numbers mentioned in the tables of this thesis, it is because all the numbers are rounded.

Finally, picking efficiency has also increased in store-specific shelf-pack change as the scheme eliminates picks and increases the units picked per line. Compared with no shelf-pack change, the efficiency has improved between 0.24 and 0.28 units/line for each store. The average increase across all 5 stores is 0.266 units/line. Again, although this seems to be a smaller improvement than in universal shelf-pack change, the improvement is actually attributed to only 20%~24% of the SKUs in each store. In fact, the efficiency has increased by 0.71 units/line on average across the 5 stores if we only look at the SKUs that undergo shelf-pack change (Appendix C Table C-8). Such increase points to the efficacy of the SKU segmentation process in sifting out SKUs suitable for shelf-pack change at the store-specific level as well.

Table 4.8. *Picking Efficiency with Shelf-Pack Change on Good-Segment SKUs Specific to Store, 74 Weeks*

Store	1111		2222		3333		4444		5555	
Shelf-Pack Change	Before	After	Before	After	Before	After	Before	After	Before	After
Total Units Shipped	349,747	351,328	329,273	330,551	339,906	341,356	336,785	338,274	410,755	412,092
Total Picks	152,038	136,080	133,844	121,249	142,941	129,213	146,256	130,971	156,147	142,256
Average Units/Line	2.30	2.58	2.46	2.73	2.38	2.64	2.30	2.58	2.63	2.90
Change (Δ)		0.28		0.27		0.26		0.28		0.24

4.5 Summary of Results

This chapter has shown that changing the shelf-pack from 1 to 2 is an effective means to improve picking efficiency and reduce the costs incurred in piece-picking and store shelving trips. While it shifts an inventory unit from DC to store each time a future order or a SKU unit is prepositioned to a current week in a store, a SKU selection process such as SKU segmentation can resolve this conundrum without compromising much of the savings. The results of SKU segmentation can be implemented in a DC-wide or store-specific fashion to eliminate SKUs whose inventories are being shifted to store at a high volume relative to the savings on picks and store shelf visits. The savings-per-inventory-impact efficacy from shelf-pack change can be increased. In sum, the proposal in this thesis can yield savings with minimal inventory impact for XYZ. In fact, if XYZ can alter their system to apply shelf-pack change specific to store, the efficacy of shelf-pack change can be even higher.

5. Discussion

First, this chapter will explore the applicability of shelf-pack change for companies beyond XYZ. Second, the chapter also discusses the trend where more specific shelf-packs can generate more efficiencies with lower inventory impact. However, a balance must be struck between over-specification and avoidance of operational complexity. Next, the limitations of this thesis and alternative methodologies are explored in Section 5.3, with a final section on possible future research design and directions.

5.1 Applicability of Shelf-Pack Change beyond XYZ

While the thesis has evaluated shelf-pack change implementation specific to XYZ, the scheme is not necessarily constrained to the operating context of XYZ. In fact, it can be applied to any company that operates with some kind of a shelf-pack system, wherein SKUs must be retrieved in a quantity that is a multiple of a number. For instance, regardless of whether a company employs a picker-to-parts or parts-to-picker system, an increase in shelf-pack always raises the quantity per pick, decreasing the number of picks needed per SKU. Under an automated system, shelf-pack increase can reduce the number of machine-based SKU retrievals and prolong machine life, maximizing the potential of a company's capital investment. Changing the shelf-pack is a simple yet effective method to improve the efficiency and reduce the cost of material retrieval.

Nevertheless, the repercussions of inventory impact needs to be taken into account. As demonstrated by Tables 3.8 and 4.4, SKU unit cost is negatively associated with the savings gained from shelf-pack change given a set amount of inventory increase in the store. A higher SKU cost leads to a higher value of inventory being shifted from one location to the next, affecting the financials and inventory budgets of the subsequent location. Moreover, while less pertinent to XYZ, which carries mostly small-sized items, if a company handles mainly large-sized items, it may not be ideal to preposition those items. Large-sized items are difficult to maneuver: prepositioning them and picking them in two's can be arduous and time-consuming.

The extra inventory prepositioned may also consume too much retail or storage space to justify the savings in picking cost, unless the picking cost outweighs the retail-space or storage cost due to the considerable effort needed to pick such large items. Finally, perishable goods with short shelf-life are not ideal for the scheme: they can perish on shelf if prepositioned earlier than planned. Although shelf-pack increase is applicable across different company platforms, it is not viable for certain industries and operations.

Furthermore, the scheme is also unconducive to case-picking and companies without an integrated forecast and replenishment system like XYZ's. First, by applying the scheme and increasing the number of cases per pick, a company will be prepositioning numerous piece-units across many weeks. This will significantly amplify the scheme's impact on the inventory of the cases' destination location. Meanwhile, companies without an integrated system of forecast and warehouse (WH) replenishment may encounter an even more severe repercussion. Without an integrated system, once a unit or a case of a SKU is prepositioned to the next location, the loss of this unit or case may trigger the WH management system to replenish from supplier although the company, as an integrated whole, still owns enough units and cases. With one unit or case prepositioned to another location within the company and replenishment arriving at the WH, the company's total inventory increases, raising its inventory carrying cost. In this regard, instead of an inventory shift from one place to the next, the shelf-pack change triggers a replenishment that increases company inventory. The scheme is not as viable for case-picking or companies without integrated systems.

5.2 <u>Specificity of the Scheme</u>

Chapter 4 has illustrated that more specific shelf-pack change can generate more savings, but its implementation entails certain constraints. For a SKU in a retail company, different shelf-packs can be established specific to different stores rather than a DC-wide unified shelf-pack. In fact, with further research, an ideal shelf-pack may be set for each SKU by store. However, this requires a non-manual management system to optimally assign different shelf-packs to each SKU for different stores and generate pick lists accordingly so that the pickers can just follow the pick lists instead of having to learn the shelf-pack for each store. Without such a system, the pickers can become perplexed over different shelf-packs for different stores, leading to picking errors. Meanwhile, to support the system, the company will need an analytics team to calculate the optimal shelf-pack for each SKU by store. Therefore, while more specific shelf-packs and changes can generate more savings, company infrastructure needs to be ready for such specificity. A balance needs to be reached between savings and the level of operational complexity a company can embrace.

5.3 Limitations of the Thesis and Alternative Methodology

This thesis' scope was limited due to constraints in time and information. Further analyses could have been conducted on the size, perishability, piece-unit picking time, retail shelf space occupied, store shelving cost, and DC picking cost specific to each SKU. Doing so, we could have calculated a more exact impact in prepositioning a SKU to its retail space, the cost of its perishability, and the cost and time of picking it at the DC and shelving it in the store. From this, we could have measured if the time and cost saved from picks and shelf visits eliminated by the scheme for each SKU were worth prepositioning the SKU to occupy more shelf space. The SKU segmentation system could have then included factors such as the DC picking cost, store shelving cost, size, and perishability specific to each SKU in finding the SKUs suitable for shelf-pack change. These can certainly improve the exactness and accuracy of the study.

In the meantime, an alternative methodology—linear regression—was considered for determining SKU suitability. We could have made Shipment Frequency, SKU Cost, and other SKU characteristics variables independent variables regressing on each of the two savings-to-inventory-impact ratios, Cost Saved/$ Inventory Shifted and Picks Decreased/Unit Shifted. However, our initial findings from ordinary least-squares linear regression showed that we needed to transform several variables using the natural logarithmic and inverse functions, making the final equation obtained unconducive to a DC or WH's daily operations. The DC or WH personnel would have had to calculate the values of SKU characteristics variables, transform them using logarithmic and inverse functions, input the results into the regression equation, then determine each SKU's scheme suitability based on the savings-to-inventory-impact ratios calculated from the equation. A lot more operational resources would have been required than SKU segmentation, which merely allots SKUs by the magnitude of their SKU characteristics and applies shelf-pack change according to the segments. Hence, we excluded regression from the thesis.

5.4 Future Research

This thesis has provided a framework for constructing, simulating, and evaluating a method of improvement for piece-picking. However, only 5 stores from one DC are used in the analyses. They can by no means account for the impact on all of XYZ's SKUs in the DC and the stores served by the DC when the improvement scheme of shelf-pack change is implemented. Given enough time and simulation power, future studies can scrutinize and simulate shelf-pack change at the individual SKU level across all the stores in the DC. In addition, the studies can incorporate the logic and data behind XYZ's forecast and inventory management systems for a full analysis on the exact movement of every unit for each SKU from XYZ's suppliers through the DC to the stores under shelf-pack change. This will provide a more accurate picture of the savings and repercussions from shelf-pack change in the DC. Similar studies can then be replicated across different DCs in XYZ's network to examine the effect of implementing shelf-pack change across the entire network.

Next, it is important to note that the simulations and calculations in this thesis are acting within the boundary of theoretical logic that cannot account for complete reality. Actual data on the efficiency improvement, number of picks and store shelf visits eliminated, and cost reduction are needed to verify the efficacy of the scheme proposed. Moreover, operational factors that cannot be examined due to the limited capacity of simulation should be evaluated. While the thesis speculates on the scheme's impact on the DC and the stores, reactions from the staff and the operational changes needed at each location cannot be immediately predicted. Thus, future research may focus on actual field experiment, implementing shelf-pack change to a certain limited set of SKUs in a DC and recording the changes this leads to in picking efficiency, picks and store shelf visits, DC and store inventory, DC and store operating expenses, and responses from the pickers, store managers and staff. Such research can more closely examine the effect of the scheme and evaluate its applicability for larger-scale or company-wide implementation.

Finally, although this thesis has treated inventory prepositioning as a negative outcome of shelf-pack change, future research can actually focus on its merits. Retailers often suffer from lost sales due to unpredictable demand variability and seasonality. Their forecast systems usually rely heavily on past sales records, which cannot capture the extent of lost sales suffered from stock-outs. The prepositioning of inventory from DC to store ahead of forecasted demand may capture the unpredicted part of the demand and reduce lost sales. Future research can look at the change in sales of the SKUs prepositioned after shelf-pack change to evaluate the amount of lost sales that can be captured through inventory prepositioning. This will most likely add to the evidence supporting the implementation of shelf-pack change, especially for XYZ. In turn, these data can become the basis for another research that aims at improving forecast accuracy. The data collected on how much lost sales is captured can be analyzed and funneled into forecast systems, allowing the systems to incorporate the captured sales as additional demand. In this way, companies can begin to capture more glimpses of true demand instead of past sales record.

6. Conclusion

The proposal of changing the shelf-pack from 1 to 2 for piece-picking is a novel approach in research. Recent order-picking studies have been exploring more precision-based systems, such as the dynamic storage and dynamic picking that rely on SKUs being stored and brought out to the right place at the right time with pickers traversing the right routes to perform the right picks, and the orders fed to the pickers in a precisely timed manner. The need for precision is high, decreasing the range of tolerance and increasing the probability for human error.

In contrast, shelf-pack change provides simple yet effective picking improvement. Even with store-specific shelf-pack change, operational complexity is avoided. The company simply needs to store shelf-packs specific to each store for each SKU in a data system and refer to them in generating pick lists for the pickers. This does not require tightly timed actions. Moreover, SKU suitability for shelf-pack change can be easily determined by segmenting SKUs according to whether they have high, medium, or low values for a few SKU characteristics. Shelf-pack change offers non-complicated process optimization.

Not only is the scheme novel in research, it is also novel in its use of inventory prepositioning. The prepositioning of inventory is usually used by military and humanitarian logistics in forward placing inventory in locations closer to end users to accelerate response and increase supply preparedness (Davis, Samanlioglu, Qu, & Root, 2013; Kunz, Reiner, & Gold, 2014; Skipper, Bell, Cunningham, & Mattioda, 2010; Ukkusuri & Yushimito, 2008; Verma & Gaukler, 2015). While prepositioning creates an impact on store inventories, under selective implementation, the impact is outweighed by savings from the reduction in picks, store shelf visits, and the costs they incur. The scheme may even create extra benefits through the capture of lost sales. Moreover, it can be rolled out SKU by SKU or DC by DC, each implementation contingent on the outcome of the previous one without instant company-wide change. Store-specific shelf-packs can also be introduced to reduce the effect of inventory prepositioning with negligible decrease in savings. In sum, shelf-pack change is a viable, simple, and flexible way of picking optimization. Finally, though shelf-pack change may not have been studied in current literatures, it may have been implemented in reality. Hence, this thesis serves as a conduit into further research on the different applications and implications of shelf-pack change and inventory prepositioning.

Appendix A. Equivalence among Shipment, Order Line, Bin Trip, and Pick

This appendix aims to illustrate the equivalence among a single week's shipment quantity, an order line on a pick list, a bin trip, and a pick for a SKU in a store. As seen below, for every SKU in store 4444, each week's shipment quantity can be treated as the proxy for the SKU's quantity in a line item of one order or pick list. A picker who receives the pick list will travel to the pick bin containing the SKU and pick the quantity required for that order line. Therefore, for each SKU in every store, each week's shipment quantity not only becomes one line item on the store's order and pick list, but also a bin visit or a pick. If a week's shipment quantity is zero, it means that there is no bin visit or pick conducted for the SKU.

Partial Samples of Three Orders (Pick Lists) for Store 4444

Order for 2014 Week 29		Order for 2014 Week 30		Order for 2014 Week 31	
SKU #	Qty	SKU #	Qty	SKU #	Qty
0001	2	0001	1	0002	2
0002	3			0003	1
0003	1				

Partial Weekly Shipment Quantities from the Above Orders

		Week Numbers		
SKU	Description	201429	201430	201431
0001	Product A	2 units	1 units	0 units
0002	Product B	3 units	0 units	2 units
0003	Product C	1 units	0 units	1 units

Figure A-1. Illustration of equivalence between orders (pick lists) and shipment quantities.

Appendix B. Illustration of Pre- and Post-Simulation Shipment Data

BEFORE SIMULATIOM Year and week of shipment

Store	SKU	SKU Descrip	Shelf Pack	SKU Cost	201427	201428	201429	201546	201547	201548
xxxx	xxx1	xxxx	1	x.xx4		1	1			
xxxx	xxx5	xxxx	1	x.xx2					1	
xxxx	xxx3	xxxx	1	x.xx5						
xxxx	xxx8	xxxx	1	x.x4		1				1

This table is given for each store, so all store numbers in each row are the same.

Number in each cell above is the quantity picked and shipped for that week for the SKU listed on the left.

Figure B-1. Illustration of data table from XYZ before simulation. Irrelevant fields excluded.

AFTER SIMULATION

Variable values generated by simulation or Excel calculations. Some variables are excluded for convenience of presentation.

Store	SKU	SKU Descrip	Shelf Pack	SKU Cost	201427	201428	201429	201546	201547	201548	Before / After Change	Total Pcs Shped	Wks Shped	1-Unit Shpmts /Yr	Shpmt Freq	Decrease in Wks Shped	Picking Cost /Line	Change in Picking Cost	Unit* Week's Prepositioned
xxxx	xxx1	xxxx	1	x.xx4	0	1	1	0	0	0	before	20	15	7.027	0.203	5	0.0546	0.273	18
xxxx	xxx1	xxxx	1	x.xx4	0	2	0	0	0	0	after	20	10	0.000	0.135		0.0546		18
xxxx	xxx5	xxxx	1	x.xx2	0	0	0	0	1	0	before	9	6	2.811	0.081	2	0.0546	0.109	9
xxxx	xxx5	xxxx	1	x.xx2	0	0	0	0	2	0	after	10	4	0.000	0.054		0.0546		9
xxxx	xxx3	xxxx	1	x.xx5	0	0	0	0	0	0	before	7	6	3.514	0.081	2	0.0546	0.109	58
xxxx	xxx3	xxxx	1	x.xx5	0	0	0	0	0	0	after	8	4	0.000	0.054		0.0546		58
xxxx	xxx8	xxxx	1	x.x4	0	1	0	0	0	1	before	16	13	7.027	0.176	5	0.0546	0.273	61
xxxx	xxx8	xxxx	1	x.x4	0	2	0	0	0	0	after	16	8	0.000	0.108		0.0546		61

Figure B-2. Illustration of data table after simulation.

Appendix C. Data Used in Thesis Graphs and Average Calculations

Table C-1. *Net Increase in Store Inventory by Units with Shelf-Pack Change on All SKUs*

Year-Week	2014-27	2014-28	2014-29	2014-30	2014-31	2014-32	2014-33	2014-34	2014-35	2014-36	2014-37	2014-38	2014-39	2014-40	2014-41	2014-42	2014-43	2014-44	2014-45	2014-46	2014-47	2014-48	2014-49	2014-50	2014-51
Store 1111	994	1642	2164	2640	3013	3269	3526	3708	3883	4021	4195	4311	4383	4514	4691	4691	4814	4976	5037	5114	5154	5151	5264	5363	5461
Store 2222	0	874	1461	1811	2108	2368	2591	2858	3034	3208	3426	3554	3674	3785	3927	4072	4172	4253	4353	4417	4515	4663	4819	4871	4926
Store 3333	968	1662	2087	2487	2808	3058	3316	3465	3559	3559	3802	3925	4043	4092	4224	4298	4428	4483	4558	4583	4681	4692	4734	4756	4882
Store 4444	968	1598	2023	2394	2701	2976	3177	3360	3542	3738	3891	3958	4090	4176	4302	4302	4339	4435	4532	4532	4518	4603	4719	4755	4757
Store 5555	0	1015	1672	2140	2465	2792	3037	3272	3470	3653	3836	4018	4183	4289	4363	4438	4586	4606	4784	4797	4957	5016	5134	5240	5281

Year-Week	2014-52	2015-01	2015-02	2015-03	2015-04	2015-05	2015-06	2015-07	2015-08	2015-09	2015-10	2015-11	2015-12	2015-13	2015-14	2015-15	2015-16	2015-17	2015-18	2015-19	2015-20	2015-21	2015-22	2015-23	2015-24
Store 1111	5515	5560	5590	5655	5700	5765	5885	5851	5933	5991	6021	6059	6081	6135	6191	6230	6247	6317	6314	6350	6392	6449	6511	6595	6633
Store 2222	4926	4926	4942	4944	5000	5061	5167	5208	5286	5263	5296	5319	5363	5399	5470	5582	5614	5591	5636	5710	5771	5812	5834	5838	5861
Store 3333	4862	4865	4951	4960	5058	5058	5186	5186	5211	5198	5272	5336	5384	5371	5395	5404	5460	5476	5536	5578	5532	5585	5585	5624	5694
Store 4444	4778	4856	4872	4910	4975	5048	5177	5144	5176	5210	5334	5406	5420	5443	5492	5538	5559	5590	5700	5679	5728	5763	5796	5884	5899
Store 5555	5281	5315	5356	5381	5344	5366	5363	5337	5428	5455	5547	5556	5621	5687	5751	5767	5802	5876	5930	5978	5997	6054	6119	6079	6098

Year-Week	2015-25	2015-26	2015-27	2015-28	2015-29	2015-30	2015-31	2015-32	2015-33	2015-34	2015-35	2015-36	2015-37	2015-38	2015-39	2015-40	2015-41	2015-42	2015-43	2015-44	2015-45	2015-46	2015-47	2015-48
Store 1111	6639	6632	6649	6624	6714	6649	6693	6641	6641	6724	6769	6815	6844	6845	6847	6860	6915	6907	6969	6986	6972	7010	7067	7069
Store 2222	5917	6007	6026	6028	6068	6045	6093	6112	6172	6234	6266	6186	6230	6232	6262	6271	6307	6307	6351	6365	6404	6456	6439	6463
Store 3333	5739	5801	5899	5908	5885	5865	5935	5915	5916	5988	6015	6052	6048	6054	6121	6159	6132	6122	6188	6250	6202	6265	6286	6286
Store 4444	5974	5922	5951	5965	5986	6007	6004	5982	5982	6018	6052	6120	6126	6132	6215	6255	6326	6330	6376	6373	6516	6506	6525	6545
Store 5555	6151	6148	6140	6201	6235	6244	6317	6312	6354	6415	6479	6476	6472	6463	6492	6548	6558	6558	6548	6621	6574	6659	6657	6619

*Data for Figures 4.4, 4.5, and 4.8. Commas are omitted from the numbers to ensure the table's page integrity.

Table C-2. *Comprehensive Version of Table 4.4, Segments Formed from Different Combination of SKU Categories by Variable Value*

Segment	Combinations of SKUs by Categories of Variable Values			No. of SKU-Store Rows	Pct. of All Data	Ratio: Picks Decrease/ Avg Inventory Units Shifted						Ratio: Pick Cost Saved/$ Avg Inventory Shifted					
	Shipment Frequency	1-Unit Shipments /Year	SKU Cost			Ratio Average	Good or Not	Ratio STDEV	Ratio CV	95% Confidence Interval		Ratio Average	Good or Not	Ratio STDEV	Ratio CV	95% Confidence Interval	
1	H	H	H	130	0.21%	17.52	G	5.76	0.33	16.53	18.50	0.06	N	0.03	0.45	0.05	0.06
2	H	H	M	373	0.59%	17.20	G	5.63	0.33	16.63	17.77	0.13	N	0.05	0.36	0.12	0.13
3	H	H	L	2,000	3.19%	17.12	G	5.90	0.34	16.86	17.37	0.55	G	0.53	0.95	0.53	0.58
4	H	L	H	90	0.14%	2.95	N	3.57	1.21	2.22	3.69	0.01	N	0.01	1.33	0.01	0.01
5	H	L	L	1,682	2.68%	2.96	N	3.70	1.25	2.78	3.14	0.13	N	0.20	1.55	0.12	0.14
6	H	L	M	156	0.25%	3.26	N	3.28	1.01	2.75	3.78	0.02	N	0.03	1.06	0.02	0.03
7	H	M	H	77	0.12%	8.80	G	3.34	0.38	8.06	9.55	0.03	N	0.01	0.45	0.02	0.03
8	H	M	L	1,358	2.16%	10.26	G	4.25	0.41	10.03	10.49	0.39	G	0.38	0.99	0.37	0.41
9	H	M	M	198	0.32%	11.46	G	4.94	0.43	10.77	12.15	0.08	N	0.04	0.48	0.08	0.09
10	L	H	H	32	0.05%	14.29	G	4.81	0.34	12.63	15.96	0.05	N	0.02	0.44	0.04	0.05
11	L	H	L	120	0.19%	15.71	G	6.32	0.40	14.58	16.84	0.42	G	0.46	1.08	0.34	0.50
12	L	H	M	45	0.07%	15.21	G	7.80	0.51	12.94	17.49	0.11	N	0.05	0.44	0.09	0.12
13	L	L	H	4,552	7.25%	6.27	N	11.44	1.83	5.93	6.60	0.02	N	0.04	1.90	0.02	0.02
14	L	L	L	23,721	37.80%	6.30	N	11.66	1.85	6.15	6.45	0.17	N	0.41	2.43	0.16	0.17
15	L	L	M	8,120	12.94%	6.92	N	12.41	1.79	6.65	7.19	0.05	N	0.09	1.84	0.05	0.05
16	L	M	H	727	1.16%	10.47	G	5.81	0.55	10.05	10.90	0.03	N	0.02	0.67	0.03	0.04
17	L	M	L	4,385	6.99%	11.01	G	7.11	0.65	10.80	11.22	0.29	G	0.33	1.12	0.28	0.30
18	L	M	M	1,509	2.40%	10.39	G	6.34	0.61	10.07	10.71	0.07	N	0.05	0.63	0.07	0.08
19	M	H	H	243	0.39%	15.81	G	5.41	0.34	15.13	16.49	0.06	N	0.02	0.45	0.05	0.06
20	M	H	L	2,342	3.73%	15.97	G	6.16	0.39	15.72	16.22	0.45	G	0.46	1.02	0.43	0.47
21	M	H	M	675	1.08%	15.63	G	5.68	0.36	15.20	16.06	0.11	N	0.04	0.40	0.11	0.11
22	M	L	H	177	0.28%	3.93	N	5.76	1.47	3.08	4.78	0.01	N	0.02	1.67	0.01	0.02
23	M	L	L	4,390	7.00%	3.56	N	4.69	1.32	3.43	3.70	0.12	N	0.21	1.81	0.11	0.12
24	M	L	M	592	0.94%	4.19	N	4.60	1.10	3.82	4.56	0.03	N	0.04	1.16	0.03	0.03
25	M	M	H	246	0.39%	11.25	G	5.82	0.52	10.52	11.97	0.04	N	0.02	0.61	0.04	0.04
26	M	M	L	3,926	6.26%	11.42	G	6.30	0.55	11.22	11.61	0.35	G	0.38	1.09	0.34	0.36
27	M	M	M	889	1.42%	11.40	G	5.71	0.50	11.02	11.77	0.08	N	0.04	0.54	0.08	0.09

Table C-3. *Net Increase in Store Inventory by Units with Shelf-Pack Change only on SKUs in Good Segments*

Year-Week	2014-27	2014-28	2014-29	2014-30	2014-31	2014-32	2014-33	2014-34	2014-35	2014-36	2014-37	2014-38	2014-39	2014-40	2014-41	2014-42	2014-43	2014-44	2014-45	2014-46	2014-47	2014-48	2014-49	2014-50	2014-51
Store 1111	524	836	1087	1292	1491	1607	1696	1785	1863	1925	1989	2023	2042	2106	2189	2189	2268	2312	2338	2384	2399	2362	2424	2483	2490
Store 2222	0	490	784	955	1078	1205	1337	1474	1535	1629	1750	1817	1874	1927	1995	2067	2107	2125	2166	2216	2271	2340	2368	2377	2422
Store 3333	534	883	1076	1280	1446	1578	1713	1822	1888	1888	2016	2057	2122	2118	2198	2235	2264	2338	2377	2348	2369	2358	2380	2381	2441
Store 4444	546	895	1114	1294	1466	1616	1726	1793	1909	2010	2059	2099	2158	2228	2302	2302	2267	2319	2364	2364	2337	2384	2433	2443	2415
Store 5555	0	562	824	1065	1228	1379	1515	1621	1718	1817	1872	2000	2082	2113	2135	2149	2228	2245	2357	2314	2373	2384	2417	2499	2485

Year-Week	2014-52	2015-01	2015-02	2015-03	2015-04	2015-05	2015-06	2015-07	2015-08	2015-09	2015-10	2015-11	2015-12	2015-13	2015-14	2015-15	2015-16	2015-17	2015-18	2015-19	2015-20	2015-21	2015-22	2015-23	2015-24
Store 1111	2522	2572	2558	2583	2569	2606	2654	2637	2688	2680	2659	2672	2676	2672	2716	2724	2734	2743	2748	2738	2745	2807	2791	2836	2820
Store 2222	2422	2427	2407	2389	2407	2426	2433	2454	2503	2449	2471	2473	2514	2535	2566	2633	2629	2625	2618	2660	2660	2652	2663	2658	2668
Store 3333	2421	2394	2461	2447	2499	2499	2571	2571	2561	2523	2595	2643	2640	2643	2645	2631	2688	2666	2680	2691	2611	2620	2620	2610	2656
Store 4444	2418	2464	2480	2482	2479	2522	2562	2531	2534	2546	2636	2654	2666	2646	2653	2667	2643	2658	2730	2699	2732	2685	2693	2729	2725
Store 5555	2485	2493	2485	2514	2468	2456	2453	2410	2476	2493	2528	2517	2531	2522	2549	2559	2585	2608	2618	2647	2646	2667	2683	2670	2667

Year-Week	2015-25	2015-26	2015-27	2015-28	2015-29	2015-30	2015-31	2015-32	2015-33	2015-34	2015-35	2015-36	2015-37	2015-38	2015-39	2015-40	2015-41	2015-42	2015-43	2015-44	2015-45	2015-46	2015-47	2015-48
Store 1111	2820	2811	2811	2742	2798	2747	2762	2702	2702	2745	2771	2778	2792	2779	2789	2801	2797	2785	2779	2828	2791	2835	2822	2832
Store 2222	2683	2744	2725	2727	2726	2723	2746	2715	2745	2766	2781	2715	2763	2726	2697	2726	2742	2742	2741	2728	2734	2766	2715	2702
Store 3333	2685	2685	2714	2693	2652	2659	2735	2703	2677	2711	2722	2685	2680	2679	2711	2702	2677	2678	2719	2732	2700	2715	2721	2721
Store 4444	2778	2715	2725	2732	2775	2762	2773	2734	2734	2747	2800	2843	2791	2803	2825	2832	2834	2827	2841	2806	2832	2824	2803	2803
Store 5555	2677	2659	2646	2657	2670	2650	2671	2664	2666	2706	2714	2726	2721	2695	2687	2724	2743	2743	2730	2757	2709	2751	2765	2735

*Data for Figures 4.5 and 4.8. Highlighted cells consist of weeks during which the net increase has plateaued. Commas are omitted from the numbers to ensure the table's page integrity.

Table C-4. *Net Increase in Store Inventory with Shelf-Pack Change on Good-Segment SKUs Specific to Each Store*

Year-Week	2014-27	2014-28	2014-29	2014-30	2014-31	2014-32	2014-33	2014-34	2014-35	2014-36	2014-37	2014-38	2014-39	2014-40	2014-41	2014-42	2014-43	2014-44	2014-45	2014-46	2014-47	2014-48	2014-49	2014-50	2014-51
Store 1111	354	551	730	842	942	1003	1046	1117	1147	1186	1213	1210	1214	1238	1319	1319	1350	1370	1382	1409	1432	1385	1438	1464	1448
Store 2222	0	293	475	565	633	702	767	819	849	887	940	950	985	1021	1068	1112	1126	1134	1124	1122	1174	1177	1191	1200	1219
Store 3333	353	556	683	795	875	952	1021	1070	1097	1097	1162	1180	1204	1198	1230	1247	1238	1264	1278	1267	1278	1256	1298	1311	1329
Store 4444	341	560	663	774	876	969	1026	1062	1126	1177	1189	1213	1230	1276	1328	1328	1285	1312	1346	1346	1324	1353	1398	1393	1376
Store 5555	0	350	505	639	714	790	859	904	969	1040	1079	1139	1179	1194	1184	1200	1252	1249	1320	1281	1302	1293	1301	1342	1348

Year-Week	2014-52	2015-01	2015-02	2015-03	2015-04	2015-05	2015-06	2015-07	2015-08	2015-09	2015-10	2015-11	2015-12	2015-13	2015-14	2015-15	2015-16	2015-17	2015-18	2015-19	2015-20	2015-21	2015-22	2015-23	2015-24
Store 1111	1458	1488	1486	1509	1488	1521	1550	1533	1566	1561	1547	1528	1521	1504	1556	1537	1543	1546	1546	1534	1533	1572	1555	1582	1565
Store 2222	1219	1203	1197	1147	1159	1157	1169	1186	1238	1201	1215	1206	1219	1228	1223	1282	1282	1277	1258	1277	1275	1272	1279	1245	1233
Store 3333	1314	1296	1349	1321	1360	1360	1371	1371	1349	1314	1374	1414	1420	1405	1378	1363	1399	1383	1380	1383	1337	1347	1347	1338	1385
Store 4444	1356	1372	1361	1372	1353	1389	1418	1392	1398	1405	1466	1462	1470	1448	1469	1474	1449	1477	1535	1497	1516	1493	1469	1503	1476
Store 5555	1348	1346	1319	1357	1336	1311	1308	1278	1311	1307	1324	1307	1306	1289	1304	1298	1337	1348	1339	1384	1380	1382	1377	1350	1346

Year-Week	2015-25	2015-26	2015-27	2015-28	2015-29	2015-30	2015-31	2015-32	2015-33	2015-34	2015-35	2015-36	2015-37	2015-38	2015-39	2015-40	2015-41	2015-42	2015-43	2015-44	2015-45	2015-46	2015-47	2015-48
Store 1111	1579	1570	1563	1514	1570	1513	1522	1483	1483	1510	1529	1511	1521	1514	1515	1511	1514	1526	1535	1566	1537	1571	1565	1581
Store 2222	1261	1312	1305	1286	1290	1277	1277	1273	1275	1298	1308	1266	1310	1294	1285	1307	1325	1325	1318	1322	1318	1330	1279	1278
Store 3333	1393	1377	1404	1379	1352	1350	1422	1398	1384	1400	1412	1389	1391	1399	1426	1432	1380	1373	1409	1432	1423	1437	1450	1450
Store 4444	1515	1479	1475	1489	1505	1500	1504	1450	1450	1464	1492	1522	1507	1485	1505	1513	1520	1516	1532	1498	1514	1496	1491	1489
Store 5555	1367	1368	1357	1367	1378	1367	1373	1368	1358	1370	1383	1402	1379	1361	1354	1394	1406	1406	1403	1434	1404	1457	1464	1437

*Data for Figure 4.8. Highlighted cells consist of weeks during which the net increase has plateaued. Commas are omitted from the numbers to ensure the table's page integrity.

Table C-5. *Increase in Total Week-End Inventory by Units under Shelf-Pack Change on SKUs in Good Segments*

Store No.	Year-Week	2015-12	2015-13	2015-14	2015-15	2015-16	2015-17	2015-18	2015-19	2015-20	2015-21	2015-22	2015-23	2015-24
2222	Before	145,983	144,757	137,527	136,217	132,772	147,085	144,826	139,855	139,298	136,894	136,486	133,141	131,014
	After	148,497	147,292	140,093	138,850	135,401	149,710	147,444	142,515	141,958	139,546	139,149	135,799	133,682
3333	Before	115,553	115,017	107,458	108,760	104,560	104,292	122,794	117,493	116,425	115,853	113,870	110,286	108,578
	After	118,193	117,660	110,103	111,391	107,248	106,958	125,474	120,184	119,036	118,473	116,490	112,896	111,234
4444	Before	158,574	157,390	158,990	157,640	155,431	151,546	149,865	150,802	151,821	154,703	145,154	145,393	143,941
	After	161,240	160,036	161,643	160,307	158,074	154,204	152,595	153,501	154,553	157,388	147,847	148,122	146,666

Store No.	Year-Week	2015-25	2015-26	2015-27	2015-28	2015-29	2015-30	2015-31	2015-32	2015-33	2015-34	2015-35	2015-36
2222	Before	129,062	128,102	130,268	128,577	127,447	128,852	128,262	126,882	127,855	128,635	132,135	132,728
	After	131,745	130,846	132,993	131,304	130,173	131,575	131,008	129,597	130,600	131,401	134,916	135,443
3333	Before	106,489	104,367	104,132	101,420	102,832	100,396	100,638	98,571	98,828	102,616	102,092	103,897
	After	109,174	107,052	106,846	104,113	105,484	103,055	103,373	101,274	101,505	105,327	104,814	106,582
4444	Before	133,555	131,693	134,752	137,079	135,385	136,402	137,113	138,507	139,861	140,793	139,643	138,214
	After	136,333	134,408	137,477	139,811	138,160	139,164	139,886	141,241	142,595	143,540	142,443	141,057

Store No.	Year-Week	2015-37	2015-38	2015-39	2015-40	2015-41	2015-42	2015-43	2015-44	2015-45	2015-46	2015-47	2015-48
2222	Before	124,599	124,293	124,439	123,172	122,552	120,835	118,997	118,448	121,601	123,379	126,445	129,344
	After	127,362	127,019	127,136	125,898	125,294	123,577	121,738	121,176	124,335	126,145	129,160	132,046
3333	Before	103,839	104,810	104,244	103,883	105,186	105,570	105,861	101,453	111,420	104,939	109,545	113,972
	After	106,519	107,489	106,955	106,585	107,863	108,248	108,580	104,185	114,120	107,654	112,266	116,693
4444	Before	141,510	142,287	140,496	135,153	137,066	136,571	135,275	132,900	134,954	134,744	146,868	133,203
	After	144,301	145,090	143,321	137,985	139,900	139,398	138,116	135,706	137,786	137,568	149,671	136,006

*Data for Figure 4.6.

Table C-6. *Increase in Total Week-End Inventory in Units with Shelf-Pack Change on Good-Segment SKUs Specific to Each Store*

Store No.	Year-Week	2015-12	2015-13	2015-14	2015-15	2015-16	2015-17	2015-18	2015-19	2015-20	2015-21	2015-22	2015-23	2015-24
2222	Before	145,983	144,757	137,527	136,217	132,772	147,085	144,826	139,855	139,298	136,894	136,486	133,141	131,014
	After	147,202	145,985	138,750	137,499	134,054	148,362	146,084	141,132	140,573	138,166	137,765	134,386	132,247
3333	Before	115,553	115,017	107,458	108,760	104,560	104,292	122,794	117,493	116,425	115,853	113,870	110,286	108,578
	After	116,973	116,422	108,836	110,123	105,959	105,675	124,174	118,876	117,762	117,200	115,217	111,624	109,963
4444	Before	158,574	157,390	158,990	157,640	155,431	151,546	149,865	150,802	151,821	154,703	145,154	145,393	143,941
	After	160,044	158,838	160,459	159,114	156,880	153,023	151,400	152,299	153,337	156,196	146,623	146,896	145,417

Store No.	Year-Week	2015-25	2015-26	2015-27	2015-28	2015-29	2015-30	2015-31	2015-32	2015-33	2015-34	2015-35	2015-36
2222	Before	129,062	128,102	130,268	128,577	127,447	128,852	128,262	126,882	127,855	128,635	132,135	132,728
	After	130,323	129,414	131,573	129,863	128,737	130,129	129,539	128,155	129,130	129,933	133,443	133,994
3333	Before	106,489	104,367	104,132	101,420	102,832	100,396	100,638	98,571	98,828	102,616	102,092	103,897
	After	107,882	105,744	105,536	102,799	104,184	101,746	102,060	99,969	100,212	104,016	103,504	105,286
4444	Before	133,555	131,693	134,752	137,079	135,385	136,402	137,113	138,507	139,861	140,793	139,643	138,214
	After	135,070	133,172	136,227	138,568	136,890	137,902	138,617	139,957	141,311	142,257	141,135	139,736

Store No.	Year-Week	2015-37	2015-38	2015-39	2015-40	2015-41	2015-42	2015-43	2015-44	2015-45	2015-46	2015-47	2015-48
2222	Before	124,599	124,293	124,439	123,172	122,552	120,835	118,997	118,448	121,601	123,379	126,445	129,344
	After	125,909	125,587	125,724	124,479	123,877	122,160	120,315	119,770	122,919	124,709	127,724	130,622
3333	Before	103,839	104,810	104,244	103,883	105,186	105,570	105,861	101,453	111,420	104,939	109,545	113,972
	After	105,230	106,209	105,670	105,315	106,566	106,943	107,270	102,885	112,843	106,376	110,995	115,422
4444	Before	141,510	142,287	140,496	135,153	137,066	136,571	135,275	132,900	134,954	134,744	146,868	133,203
	After	143,017	143,772	142,001	136,666	138,586	138,087	136,807	134,398	136,468	136,240	148,359	134,692

*Data for Figure 4.9.

Table C-7. *Picking Efficiency with Shelf-Pack Change on All SKUs in Good Segments, Effect on Those SKUs Only (74 Weeks)*

Store	1111		2222		3333		4444		5555	
Shelf-Pack Change	Before	After	Before	After	Before	After	Before	After	Before	After
Total Units Shipped	153,892	156,724	141,278	143,980	148,301	151,022	161,717	164,520	161,229	163,964
Total Picks on Good-Segment SKUs	83,129	63,314	72,606	55,796	77,293	59,660	83,896	64,723	81,292	63,453
Average Units / Line	1.85	2.48	1.95	2.58	1.92	2.53	1.93	2.54	1.98	2.58
Change (Δ)		0.62		0.63		0.61		0.61		0.60

Table C-8. *Picking Efficiency with Shelf-Pack Change on SKUs in Good Segments Specific to Store, Effect on Those SKUs Only (74 Weeks)*

Store	1111		2222		3333		4444		5555	
Shelf-Pack Change	Before	After	Before	After	Before	After	Before	After	Before	After
Total Units Shipped	91,905	93,486	72,594	73,872	81,270	87,720	91,303	92,792	86,189	87,626
Total Picks on SKUs in Good Segments Specific to Store	56,270	40,312	43,996	31,401	49,193	35,465	55,125	39,840	50,714	36,823
Average Units / Line	1.63	2.32	1.65	2.35	1.65	2.47	1.66	2.33	1.70	2.38
Change (Δ)		0.69		0.70		0.82		0.67		0.68

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