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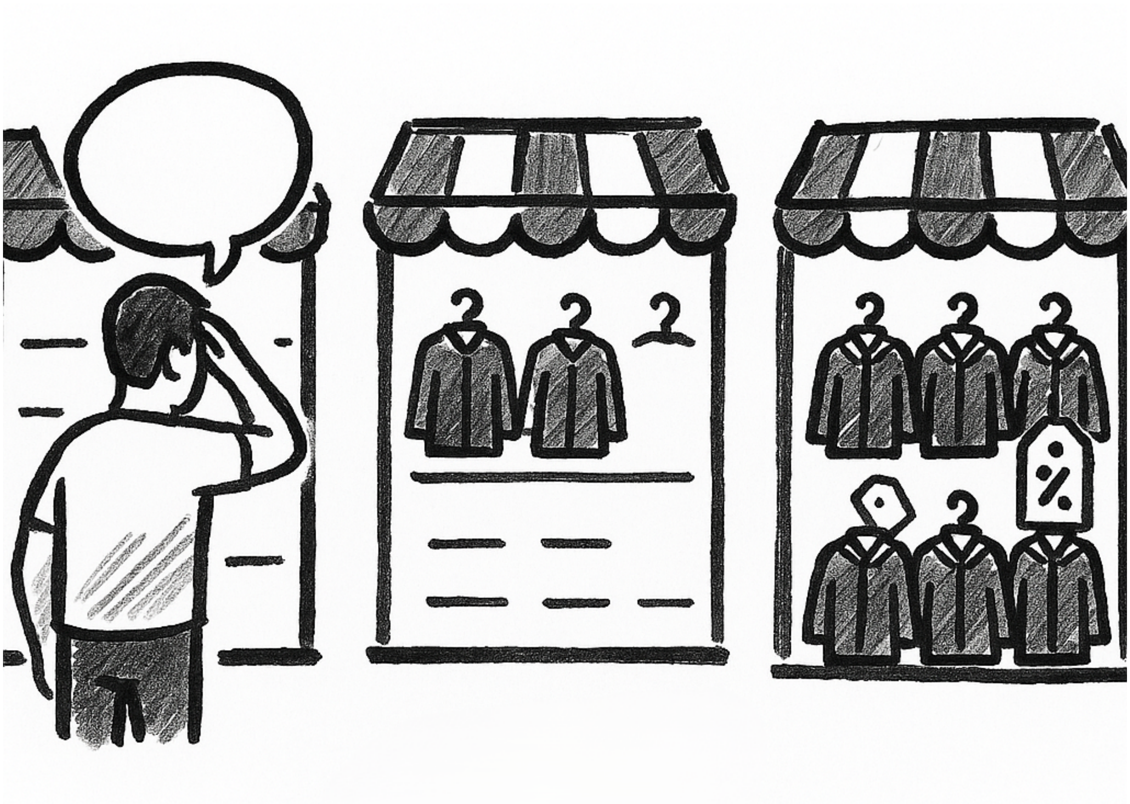

Minimising Balancing Issues in Seasonal Retail

Identifying and Addressing Causes of Stock Imbalances in Seasonal Retail

Master's thesis in Supply Chain Management

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Cover: Illustration generated with OpenAI's DALL · E, depicting stock imbalance across three stores from understocked to overstocked.

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Abstract

This thesis examines the causes of stock imbalances in seasonal retail, using Sports Inc. as a case company. Seasonal retail, and Sports Inc. particularly, pose unique inventory challenges. Circumstances such as long lead times, low and uncertain demand, as well as limited flexibility during the selling season, complicate inventory management. The study identifies which stages of the inventory process contribute to imbalance, in what way they do so, and how their negative effects can be minimised. A mixed methods approach was used. Interviews with key stakeholders were combined with analysis of sales and distribution data.

The thesis shows that the initial allocation and replenishment processes are the key contributors to stock imbalance. In the initial allocation, high minimum values lead to oversupply in small stores. The replenishment reinforces imbalances stemming from the initial allocation, due to its static reorder levels. Furthermore, the lack of adjustments for leftover stock and other changes worsens the problem.

To minimise these issues, the thesis proposes several changes. This includes dynamic reorder levels and further deepening the store grade differentiation. Complementary strategies like end-of-season consolidation and store-level fulfilment of online orders offer further means to mitigate the consequences when imbalance still occurs.

Keywords: Seasonal Retail, Inventory Management, Stock Imbalance, Allocation Strategy, Replenishment.

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Axel Davidsson & Daniel Johansson, Gothenburg, June 2025

Glossary

Below is the list of concepts, whose meaning was deemed to be less obvious to the reader, that have been used throughout this thesis listed alphabetically:

Term	**Definition**
Aggregated Season Model	A forecasting method that uses sales data at the product group level rather than individual items.
Balancing Issue	A systematic mismatch in inventory distribution across stores, where some receive more stock than they can sell, while others receive too little. Balance in this context means each store has an appropriate amount relative to its sales rate, not an equal quantity.
Broken Assortment Effect	The reduction in demand that occurs when inventory is too low, leading to incomplete product assortments (e.g., missing sizes or colors), which discourages customers from making a purchase.
Censored Demand	Censored demand refers to a situation where the true customer demand is not fully observed because a product becomes unavailable (out of stock) before all potential buyers can purchase it.
Demand Forecasting	The process of estimating future customer demand based on historical sales data.
Dynamic Inventory Allocation	An inventory strategy that continuously updates stock distribution based on real-time sales data.
Exponential Smoothing	A statistical method used for forecasting demand by giving more weight to recent observations.
Hurdle Shifted Poisson Model	A variation of the Poisson model that adjusts for periods with zero demand by including a probability adjustment before applying a Poisson distribution.
Initial Allocation	The distribution of seasonal inventory to stores at the beginning of the selling period.

Inventory Turnover	The rate at which inventory is sold and replaced within a given period.
Lead Time	The time between placing an order with a supplier and receiving the inventory.
Long-living products	Products that have a lifespan of multiple seasons.
Mean Absolute Scaled Error (MASE)	A forecasting accuracy metric that scales the absolute error of predictions relative to a benchmark, enabling comparisons across different models and datasets.
Markdown Percentage	The amount by which the price of a product is reduced to clear inventory.
Model Colour	Represents a product at the color level, where each color variant has a unique model colour number, but all sizes are grouped under the same Model Colour.
Moving Average Forecasting	A technique that predicts future demand based on the average sales over a specific period.
Naddor's Heuristic	Naddor's Heuristic is a simplified approach for determining the parameters of an (s,S) inventory policy, where s is the reorder level and S is the order-up-to inventory level. Naddor's approach uses only the mean and the variance of demand to estimate s and S.
Negative Binomial Model	A forecasting model that extends the Poisson model by allowing for greater variability in demand, meaning the variance does not have to equal the mean.
Pearson's Correlation Coefficient	A correlation coefficient that measures the strength and direction of a linear relationship between two variables. It assumes normally distributed data and is suitable when evaluating strict linear patterns.
Poisson Model	A statistical model that assumes demand occurs at a constant average rate and that the variance is equal to the mean, making it less suitable for fluctuating demand patterns.
Prediction Likelihood Score (PLS)	A metric that evaluates forecasting accuracy by considering the probability of observed demand given the predicted distribution, assessing how well a model captures demand variability.
Presentation Effect	The phenomenon where higher inventory levels in a store increase customer demand due to better product visibility, perceived popularity, and a more attractive shopping experience.

Reorder Level	The inventory level at which a replenishment order is triggered. It is typically calculated based on the sum of the expected demand during lead time and the safety stock.
Sell-through Rate	The percentage of inventory sold compared to the initial allocation.
Size Substitution	Estimating lost sales by checking how customers buy other available sizes when one is unavailable.
Spearman's Correlation Coefficient	A rank-based correlation coefficient that evaluates the strength and direction of a monotonic relationship between two variables. It does not require normally distributed data and is particularly useful when the relationship is non-linear or when data contains outliers.
Static Allocation	A method where inventory is allocated at the beginning of a season based on pre-season demand estimates, with no adjustments during the season.
Stock Imbalance	A situation where some stores have excess inventory while others face stockouts.
Stockout	When an item is unavailable for sale due to depletion of inventory.
Store Grade	A classification system used by Sports Inc. to determine the product assortment a store should receive, based on projected sales for sub-departments.

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1
Introduction

1.1 Background

Sports Inc. is a sports retailer with sales in both physical stores and online. The company operates in two primary seasons, spring/summer, and autumn/winter, and is currently facing challenges in its inventory management process. The lead times are long, the allocation process is rigid, and the demand is uncertain, especially on an individual product level.

Inventory management for seasonal goods is extra challenging, as these products typically have short selling seasons, high demand uncertainty, and limited value at the end of the season. Seasonal goods also generally have long lead times, and must be ordered from suppliers long before the season begins. Consequently, a product cannot be replenished from the suppliers during the selling season. As a result of this, Sports Inc. needs to buy large quantities arriving at the start of the season. They allocate around 60 percent to the stores initially, and the rest is stored at the central warehouse.

To account for the long lead times, Sports Inc. plans their purchases up to a year in advance. Today, inventory management is mainly driven by historical data and forecasting, which allows for coordinated operations, but it also limits flexibility. The predefined initial allocations are not adjusted at season start, and there is no process of redistributing products between stores. This means that there can be excess stock at some locations, while others experience stockouts at the same time.

1.2 Problem Formulation

Sports Inc.'s inventory management process creates challenges in balancing stock between stores. Although the system provides consistency, it lacks adaptability, which leads to imbalances in stock distribution. A balance issue occurs when some stores receive more inventory than needed, while others receive an insufficient amount. In this context, a balance does not mean that every store has an equal amount of the product, but rather that stores have an appropriate amount relative to their sales rate. The consequences of this imbalance are particularly apparent at the end of a season, when the central warehouse is out of stock. At that point, the central warehouse can no longer send replenishment to stores to cover shortages, resulting in some stores ending up with more volume than they can sell at full price, while others have nothing. This causes excess stock and markdowns in some stores, as well as stockouts and lost sales in others.

Once the initial allocation is established, the process offers limited flexibility to adjust inventory distribution throughout the season. As a result, stock imbalances caused by the initial allocation persist, negatively affecting both profitability and product availability. Moreover, there is no mechanism to reallocate inventory between stores. This worsens the impact of the balancing issue when demand deviates from initial expectations.

To address the balancing issue, it is necessary to identify the stages of the inventory management process that are key contributors. It is also important to understand how the process stages contribute in order to identify adjustments that minimise the balancing issue.

1.3 Purpose

The thesis aims to identify potential changes within the inventory management process in order to minimise the balancing issue between stores.

1.3.1 Research Questions

To aid in the fulfilment of the purpose, the thesis focuses on examining the inventory management process of seasonal products at Sports Inc., determining what stages of the process lead to the balancing issue. Furthermore, it ascertains how the process stages contribute to, and subsequently how they can be adapted to minimise, the balancing issue. The following research questions were composed to guide the investigation:

RQ1: *What stages of the inventory management process of seasonal products at Sports Inc. are the key contributors to their balancing issue?*

RQ2: *How do the identified process stages contribute to the balancing issue?*

RQ3: *What changes can be made within the identified process stages to minimise the balancing issue?*

1.4 Scope and Delimitations

This report will cover centrally owned stores and not franchise-owned stores, as their supply process differs. Furthermore, the thesis will only explore the inventory management of seasonal products and not long-living products, which have a lifespan of multiple seasons. The seasonal inventory accounts for about 70 percent of total inventory.

2
Literature review

This chapter provides a brief introduction to inventory management as a whole, and its core concepts. Additionally, the chapter reviews existing literature related to inventory management challenges in seasonal retail. It explores forecasting techniques, allocation strategies, the role of early sales data, management of low-demand items, markdown pricing, and the handling of lost sales. All providing a theoretical foundation for understanding and addressing stock imbalances. Lastly, important statistical measurements utilised in the report are explained.

2.1 Inventory Management

Inventory management concerns the processes used to ensure that the right amount of stock is available to meet customer demand while avoiding excessive holding costs (Slack & Brandon-Jones, 2019, pp. 445-484). It plays a central role in the operation of supply chains, especially in retail, where uncertainty in demand and lead times can cause significant challenges. Effective inventory control enables firms to buffer against fluctuations, decouple different stages of the supply chain, and maintain high service levels. According to Slack and Brandon-Jones (2019, pp. 445-484), three fundamental questions support inventory management: how much to order, when to place an order, and how inventory should be controlled. The answers to these questions determine the design and performance of an organization's replenishment systems and stock-holding policies.

2.1.1 Reorder Level

An inventory control method which provides a rule for determining when replenishment should occur is the reorder point system (Slack & Brandon-Jones, 2019, p. 468). In this system, an order is triggered when the available inventory drops to a pre-specified threshold known as the reorder level. This level is typically calculated as the expected demand during the lead time and may also include a safety stock to protect against demand variability or supply delays. An illustration of the system can be seen in Figure 2.1.

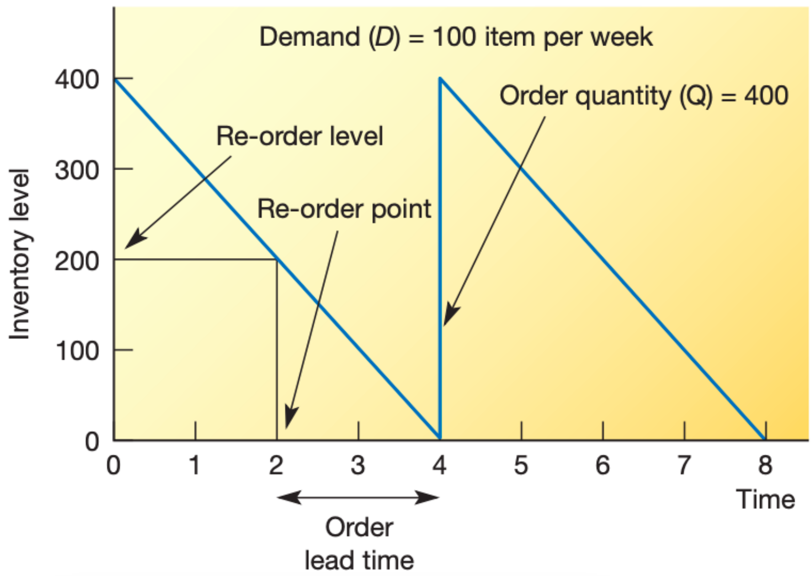

Figure 2.1: Illustration of the reorder point system. When inventory falls to the reorder level, a fixed quantity (Q) is ordered to replenish stock before it reaches zero. The lead time is the delay between order placement and delivery. Source: Slack and Brandon-Jones (2019, p. 468)

2.1.2 Exponential Smoothing

To support replenishment decisions, forecasting techniques that estimate future demand based on historical data are often used. One common approach is exponential smoothing. Unlike simple moving averages that assign equal weight to past data points, exponential smoothing allows for greater emphasis to more recent observations, enabling the forecast to adjust more rapidly to changes in demand (Slack & Brandon-Jones, 2019, pp. 362-364). The forecast is updated using the formula below.

$$F_t = \alpha A_{t-1} + (1 - \alpha) F_{t-1}$$

F_t represents the forecast for the current period, A_{t-1} is the actual demand in the preceding period, and α is the smoothing constant between 0 and 1. A larger α places more weight on the most recent demand, resulting in a more responsive forecast, while a smaller α produces a more stable and conservative forecast. Its simplicity, adaptability, and low data requirements have made exponential smoothing a preferred method in many operational forecasting systems.

2.1.3 Naive Seasonality Model

Rodrigues de Camargo and Aparecido de Oliveira (2023) describe the naive model as one of the simplest forecasting methods. The naive model uses the most recent observation as the forecast for the next period. There is a common variant of the naive model, called the naive *seasonality* model. Instead of simply using the most recent observation, this variant sets the forecast equal to the observed value from the same period in the previous season. For example, using the value from the same month or week in the previous year. The advantage of this method is its simplicity. However, the method does not account for trends, cycles, or fluctuations, meaning that it often performs poorly in more complex environments. Nonetheless, the method is often employed as a benchmark for evaluating more sophisticated forecasting models. It acts as a base for assessing whether the other models provide meaningful improvements.

2.1.4 Aggregated Season model

Another approach, used by Sports Inc., is an aggregated season model. The model relies on historical sales data at product group level, rather than forecasting demand for each individual item (Chief Supply Chain Officer, Sports Inc., personal communication, February 11, 2025). By consolidating demand across similar products, aggregated season models reduce the variability associated with low-volume or erratic item-level sales, which is particularly relevant in seasonal retail contexts where many products have limited sales histories. This approach enables a more stable and reliable forecast for the overall seasonal volume. Forecasts can then be disaggregated to the item level using historical distributions. Although this method trades off some granularity, it enhances robustness in the early stages of the season, when sufficient live sales data is not yet available.

2.2 Utilising Early Sales Data to Improve Forecasts

Li et al. (2021) write about Dillard's, a large U.S. department store chain. They face significant challenges in allocating seasonal merchandise due to high demand uncertainty, long supplier lead times, and limited restocking opportunities. A key challenge in managing Dillard's seasonal inventory was the variation in demand across stores and products according to Li et al. The demand for some items could be as low as one unit per store over the entire selling period, while other items could sell more than 30 units of the same size in a single store in just a few weeks. Most sales occurred within a short window of two to three weeks, making predicting demand accurately before the season began nearly impossible. Initially, inventory was allocated based on pre-season demand estimates, with a portion kept at the distribution center to allow for later redistribution. While this offered some flexibility compared to a purely static approach, it still relied on pre-determined forecasts which could be highly inaccurate. The approach meant no ability to adjust as actual sales unfolded, an approach that often led to stockouts at some stores and overstocking at others. To address this, Li et al. developed a dynamic inventory allocation model that continuously updated inventory decisions throughout the season based on real-time sales data. Instead of making a single fixed allocation at the start of the season, the model re-evaluated inventory needs every week based on newly observed sales data.

The model used point-of-sales data and Poisson regression to refine demand forecasts (Li et al.). Each week, newly collected sales data was incorporated into the model, updating the expected demand distribution for each product and store. By incorporating this continuous learning process, Dillard's significantly reduced both stockouts and overstocking. This in turn led to higher sell-through rates and increased revenue. The study demonstrated that adaptive inventory allocation was superior to static allocation in this setting. Rather than relying solely on forecasts made months in advance, leveraging real-time sales data allowed Dillard's to respond to actual demand trends. In turn ensuring a better match between inventory and customer needs.

In a similar study, Gallien et al. (2015) examined the challenge of inventory allocation in fast fashion retail. A setting where demand uncertainty is high and products have short life cycles. The report focuses on Zara, a retailer that must balance sending large shipments upfront, to prevent stockouts and maximize early sales, against holding inventory centrally, to allow for flexible restocking as demand patterns become clearer. To handle Zara's high product turnover and frequent replenishment cycles, a decision support system that integrates forecast updating and dynamic optimization is used.

The forecast update model presented by Gallien et al. is designed for fast-moving products, refining initial demand estimates based on early sales observations from the first few days after product launch. Stores are classified into three demand categories—low, medium, or high—based on how their actual sales compare to initial forecasts. Each category is then assigned a revised demand distribution, which updates expectations for the remaining selling period. Fisher and Raman (1996) draws the same conclusion, that early sales data improves forecasting, in their paper "Reducing the cost of demand uncertainty through accurate response to early sales".

To complement Zara's forecasting, a dynamic optimization model built as a Mixed-Integer Program (MIP) helps balance early inventory allocation, lost sales risks, and warehouse constraints (Gallien et al.). The model incorporates frequent replenishment opportunities, ensuring that inventory is redistributed efficiently across Zara's store network. It also accounts for minimum stock levels required for visual merchandising. A field experiment across 34 products showed that this approach increased total sales by two percent and reduced unsold inventory by four percent, demonstrating the effectiveness of high-frequency demand learning in a fast-paced retail environment.

2.3 Forecasting low demand items

Forecasting low-demand items is challenging due to high variability and low sales volumes per product. (Sani & Kingsman, 1997). Standard methods like exponential smoothing and moving averages often struggle in such environments, leading to inaccurate demand predictions and stock imbalances. Sani and Kingsman conclude that for low and intermittent demand items, inventory control must be adaptive to minimise both stockouts and excess inventory. They find that (s, S) heuristics, particularly Naddor's heuristic, is best in very low demand environments (<20 units per year).

Naddor's heuristic is a simplified inventory control method (s, S), where s is the reorder level and S is the order up to level (Sani and Kingsman). The method determines these levels using only the mean and variance of the demand, making it easier to implement than models that require a complete demand distribution. The model is especially effective for very low-demand items, where other forecasting methods struggle due to infrequent sales.

Snyder et al. (2012) state that Poisson and Negative Binomial models have better forecasting accuracy for low-demand items compared to standard models. The Poisson model comes with the assumptions that demand is a constant average rate and that the variance in demand is equal to the mean. The latter being a major limitation of the model, that makes it a less accurate reflection of reality in cases with significant demand fluctuations. To overcome this issue and improve upon the Poisson model, the authors introduce the Hurdle Shifted Poisson model. The hurdle model adjusts for cases where demand is often zero by including a probability adjustment to separate periods with and without sales, before applying a Poisson distribution. The Negative Binomial model improves upon the Poisson model further, by allowing for greater variability in demand. It does not necessitate that the variance is equal to the mean like the Poisson model does. This makes it more flexible for forecasting low-demand products, situations where standard Poisson models tend to underestimate variability.

To evaluate forecasting performance, Snyder et al. recommend using mean absolute scaled error (MASE) and prediction likelihood score (PLS). MASE allows for comparison across different models and datasets by scaling the absolute error of the predictions relative to a benchmark. PLS determines how well a model captures demand by considering the probability of observed demand given the predicted distribution.

In supply chains characterized by limited data, forecast aggregation has gained increased attention to improve forecasting accuracy. Babai et al. (2022), present how aggregating demand data across products, time periods, or organizational levels can reduce uncertainty through risk pooling. They describe both temporal and cross-sectional aggregation approaches, as well as bottom-up and top-down methods, which allow forecasts to be generated at one level, and adjusted across others. This is especially relevant in retail environments with seasonal products, where historical data at the individual product level, may be too limited to support reliable forecasting. Aggregation offers a practical alternative that leverages group-level patterns to enhance both forecast accuracy and inventory performance.

2.4 Accounting for Lost Sales

According to Li et al. (2021), one critical improvement to Dillard's previously mentioned forecasting model was that it now accounted for lost sales. When a store ran out of stock for a product, previous models would assume that demand had stopped. However, Dillard's approach recognized that stockouts often hid true demand. The model corrected for this by using demand censoring techniques, to estimate how many additional units would have been sold if there had been inventory available. By utilising sales data from similar products as well as regional demand trends, the system could approximate unfulfilled demand. Additionally, the model compared sales trends across stores. Consider for example multiple stores, with sufficient inventory, continues selling a product at a steady rate while one store is out of stock. The model then assumed that demand at the stocked-out store was still present but unmet. This prevented the system from mistakenly interpreting stockouts as a drop in demand. Ensuring that high-performing products received additional stock in the next allocation cycle.

Similarly to Li et al.'s model for Dillard's, the model introduced by Gallien et al. (2015) also accounts for censored demand. To include the lost sales data, they use patterns within days. They look at the sales when products are in stock during one part of the day to estimate how much could have sold for the rest of the day. They also consider size substitution, estimating lost sales by checking how customers buy other available sizes when one is sold out. Furthermore, Sani and Kingsman (1997) also highlight the importance of including lost sales data in forecasting. According to the authors, accounting for lost sales can help avoid a systematic cycle of underestimating demand.

2.5 Optimal Markdown Pricing and Inventory Allocation for Retail Chains with Inventory Dependent Demand

In seasonal retail, where products have short selling periods and uncertain demand, it is important to have effective markdown pricing and inventory allocation (Smith & Agrawal, 2017). Traditionally, markdowns rely on fixed discount schedules, but today there are dynamic pricing models that adjust prices and inventory, based on real-time demand and stock levels. To maximise revenue and reduce stock imbalances, Smith and Agrawal have developed an optimisation model, that considers markdown pricing, inventory allocation, and store consolidation. Their study focuses on the inventory-dependent demand effect, meaning that the sales volumes are influenced by the quantity of inventory available in a store. The authors mention two effects relating to this concept, the presentation effect, and the broken assortment effect. The presentation effect means that a higher inventory level enhances product visibility, attracting more customers, leading to increased sales. On the other hand, the broken assortment effect means that a low inventory level instead reduces demand, due to an incomplete assortment, for example, sizes and colors being out of stock.

The mathematical model developed by Smith and Agrawal, shows the optimal price trajectory for a product. It denotes how markdown prices should decrease over time as inventory decreases. Their model is not fixed, but instead suggests that prices should be set dynamically, based on the proportion of inventory sold at each store location. The report also shows that larger stores should receive a larger share of inventory, since they benefit more from the presentation effect, meanwhile smaller stores should receive a proportionally lower allocation to prevent overstocking.

The study by Smith and Agrawal also discusses how consolidating markdown inventory in a set of stores can increase profitability. By reducing the number of stores stocked, the inventory in the stocked stores will increase. This results in a reinforced presentation effect, and a reduced risk of the broken assortment effect. Now, with a more complete assortment in both size and color in the consolidated stores, initial demand may be higher, allowing prices to remain stable longer. However, as inventory builds up in fewer locations, greater markdowns may be needed later in the season to clear excess stock. Moreover, the authors emphasize additional trade-offs in store consolidation. While stocking too many stores disperses inventory and reduces demand via the broken assortment effect, over-consolidating inventory into just a few locations risks forfeiting potential demand at unstocked stores, leading to lost revenue and diminished customer reach.

According to the study, optimal consolidation increases profitability, but it results in a slightly lower fraction of inventory sold. This means that a larger portion of the inventory must be salvaged. The final markdown prices will tend to be lower in the consolidation case, compared to when the inventory is spread across all stores. While consolidation initially allows for higher prices, due to stronger presentation effects, it can result in more significant markdowns later in the season.

Smith and Agrawal suggest that an optimal balance exists, where markdown inventory should be strategically concentrated in high-demand stores, and at the same time ensure sufficient market coverage to prevent excessive lost sales. Their example in the report show how retailers can improve profit margins by shifting from a static pricing and allocation strategy, to an integrated markdown pricing and redistribution model.

2.6 Statistical Measurements

This section presents correlation coefficients and coefficient of variation.

2.6.1 Correlation Coefficients

Spearman's rank correlation coefficient (ρ) measures the strength and direction of a relationship between two variables (Hauke & Kossowski, 2011). It assumes a linear relationship and require normally distributed data, which is a difference compared to Pearson's correlation that is great for evaluating linear relationships. The Spearman correlation evaluates how well the relationship between two variables can be described using a monotonic function (i.e., it constantly increases or decreases). This means evaluating how well one variable tends to increase or decrease consistently with the other, but not necessarily at a constant rate. Spearman's is used on ranked data rather than raw values, which makes it suitable for non-linear relationships.

Hauke and Kossowski (2011), also show that Spearman's correlation is particularly beneficial when dealing with data that is not normally distributed or have unequal variance. In the authors' comparison of Pearson's and Spearman's coefficients, they show that Spearman's more often remains statistically significant, compared to Pearson's. This demonstrates Spearman's strength in identifying associations where the data structure does not support a strict linear pattern. By ranking values before the analysis, Spearman's correlation focuses on relative positioning between observations rather than absolute differences. This makes it more reliable in studies where the interest lies in trend or patterns, rather than precise numerical relationships. Table 2.1 presents a rule of thumb for interpreting the strength of correlation coefficients, as outlined by (Mukaka, 2012).

Table 2.1: Rule of Thumb for Interpreting the Size of a Correlation Coefficient (Mukaka, 2012)

Size of Correlation		Interpretation
.90 to 1.00	(-.90 to -1.00)	Very high positive (negative) correlation
.70 to .90	(-.70 to - .90)	High positive (negative) correlation
.50 to .70	(-.50 to - .70)	Moderate positive (negative) correlation
.30 to .50	(-.30 to - .50)	Low positive (negative) correlation
.00 to .30	(.00 to - .30)	Negligible correlation

2.6.2 Coefficient of Variation

The coefficient of variation is a tool for comparing relative variability, calculated by dividing the standard deviation by the mean (Slack & Brandon-Jones, 2019, pp. 403-404). It normalises variation when the mean differs between data points, enabling relative comparison across data series. According to Syntetos et al. (2005), a squared coefficient of variation CV^2 greater than 0.49 can be used as a threshold to identify more erratic or lumpy demand patterns. This corresponds to a CV above approximately 0.7 and indicates a high degree of variability.

3
Methodology

This chapter presents the research methodology that was used in the thesis. It also explains why the different parts and their sum is relevant to answering the research questions. Firstly, an intrinsic case study methodology was employed. Meaning that the case itself was the main point of interest, rather than a broader generalisation (Bryman & Bell, 2015, p.68).

Within the case study a mixed method approach, where both qualitative and quantitative data was collected and analysed to answer our research questions, was used. The qualitative part consists of a literature study and interviews, while the quantitative part consists of a sales data analysis. By integrating theoretical insights from literature, expert perspectives from interviews, and empirical sales data, the mixed-methods approach ensures a more comprehensive understanding of the inventory management process.

Mixed methods contribute to research in several ways, with triangulation, complementarity, and development being the most relevant for this thesis. In triangulation, multiple sources are used to cross-verify findings, strengthening validity (Hesse-Biber, 2010, pp. 3-5). Both Sales data and interviews highlight the effect of distribution decisions on the balancing issue. Further, Hesse-Biber, state that complementarity provides a fuller understanding of the research problem from multiple perspectives. Sales data shows where the inefficiencies occur, while the interviews explain why they are happening, adding depth to the analysis. Development ensures that one method informs the other (Hesse-Biber). In this study, insights from literature and interviews guided the selection data points for analysis, while the findings from the data analysis in turn generated further interview questions.

Integrating these methods in a mixed methods approach, ensures reliable and applicable conclusions. The literature review and interviews provide qualitative insights into best practices and challenges, while data analysis offers empirical evidence to support findings. Specifically, the interviews coupled with the sales data analysis helps identify what process stages are key contributors to the balancing issue, directly addressing RQ1. The same methods also help uncover how the identified process stages contribute, addressing RQ2. Meanwhile, the interviews and literature review provide insights into what changes can be made to minimise the balancing issue, answering RQ3. The following figure (3.1), visualises the connections just mentioned.

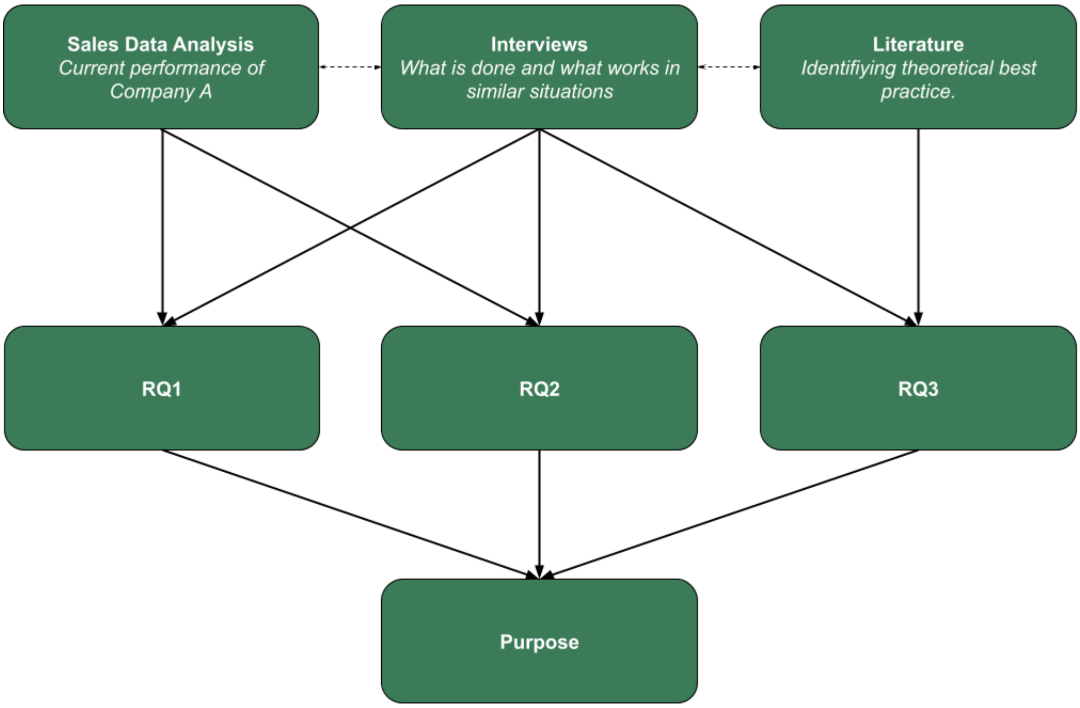

Figure 3.1: Contribution of methodology to purpose.

3.1 Literature Review

The literature review provides a theoretical foundation for analysing Sports Inc.'s process. It identifies existing frameworks, models and best practices within the retail industry. The academic sources were gathered from Google Scholar, Scopus and Chalmers Library. Keywords like *seasonal retail inventory management*, *forecasting low demand items*, *inventory replenishment*, and *markdown pricing and inventory allocation* were used to find appropriate literature on the subject. The literature review commenced early in the timeline for the project. The findings then acted as a base for and guided the interviews and data analysis, shaping questions and highlighting specific data points to analyse.

To explore literature, citation chaining was used. Citation chaining is a structured method for exploring academic literature, by both tracing backward citations and forward citations (Cribbin, 2013). Backwards citations was mostly used, where references used in papers are evaluated to get a deeper and wider view of the relevant literature. Forward citations were also used, where later works citing the papers are reviewed. The utilisation of citation chaining expands the search space and improves access to citation networks. However, all literature was not found by using this method, since the network can be limited to the specific area (Cribbin, 2013). This report uses literature from multiple areas and citation chaining was used for each different area.

3.2 Interviews

Relevant professionals from Sports Inc. were interviewed since they are privy to information regarding the process and its flaws. Specifically, the Chief Supply Chain Officer, Business Controllers and Supply Chain Planners from Sports Inc. were interviewed. Experts from a similar company were also interviewed to provide insights and practical examples of how circumstances similar to Sports Inc.'s can be handled. The interviews, in both cases, help contextualise findings from the literature to apply them in relevant settings. Semi-structured interviews were used in both instances. A semi-structured approach allows the interviewer to guide the interview in the desired direction while leaving flexibility to explore interviewee's perspectives (Bryman & Bell, 2015, p. 481). This is important since the interviewees are more knowledgable on the subject. The approach also leaves room for follow up questions to be asked as they arise. Permission to record was asked, in accordance with GDPR (Regulation 2016/679 of the European parliament and of the council). This in turn enabled transcription of relevant parts of the interviews for more convenient analysis. Initial transcription was performed using AI, before manual revision was made where needed.

The external company interviewed was selected based on a set of criteria. Firstly, the company has a seasonal inventory. Secondly, it has multiple physical stores, as well as online sales. Lastly, the selected company belongs to occasional purchase retail, meaning that purchases are infrequent and typically driven by a specific need rather than daily necessity.

For the purposes of confidentiality, the focal company is referred to as Sports Inc. in this thesis. The external company is referred to as Home Inc. due to them being a home goods retailer. Similarly, interviewees are referred to by their role to minimise the risk of the company being identifiable through them.

3.3 Data analysis

To assess the performance of the current allocation process, a quantitative sales data analysis was done. Raw transaction data was provided from Sports Inc.. Descriptive statistics was used to analyse performance trends across a broader set of products rather than focusing on individual items. Descriptive statistics is effective in discerning patterns within the data (Nick, 2007). This is also the reason that descriptive statistics were employed, its ability to reveal patterns in sales performance across multiple seasons. The data analysis was performed using Microsoft Excel.

Two subsets of data were analysed on the model colour level, meaning that each model has a unique article number for each colour, while sizes are grouped and not individually distinguished. The selection of subsets was made in collaboration with professionals at Sports Inc., ensuring an accurate representation of the entire dataset. The groups chosen to be analysed were shoes and winter clothing. Within these groups, all products across all stores were analysed, to provide a full picture of the current state. Sales and replenishment data were extracted respectively, and then merged. The raw data was cleaned as to include only products where complete data was available. Products with partial data were removed. The cleaned data contains roughly 400 products representing approximately 21 percent of Sports Inc.'s assortment of seasonal items. Initially, data for only one season was analysed. But in order to minimise interference from random weather variation, the originally analysed winter was very mild, another season was added for winter products. This further increased the sample size.

In the data analysis, coefficient of variation was used to measure inventory imbalance across stores. In accordance with the definition from Slack and Brandon-Jones (2019), it was calculated by dividing the standard deviation of the end stock (across stores) with the mean end stock.

Furthermore, Spearman's rank correlation was used to examine the relationship between variables as a supplement to Pearson's correlation. A rank-based approach was more suitable than a linear correlation in some cases. This was due to the fact that the objective was to determine whether higher values in one variable generally corresponded to higher values in the other variable, regardless of the exact numerical difference. This is in line with the article by Hauke and Kossowski (2011), who states that Spearman's correlation is particularly useful when the relationship follows an upward or downward trend, and not necessarily linear. The ranking of the data before calculating the correlation therefore ensured an appropriate measure. To interpret the strength of correlation, the ranges defined by Mukaka (2012), were used. The interpretation of correlation strengths can slightly vary across different articles, but still provides a useful reference for evaluating the results in this study.

4
Empirical data

The following chapter presents the empirical data.

4.1 Sports Inc.´s Supply Chain Structure

This section presents the supply chain structure of seasonal products at Sports Inc.. The information has been attained through interviews with the Chief Supply Chain Officer, a Business Controller, Supply Planners and Store Managers at Sports Inc..

4.1.1 Overview of Sports Inc.'s Supply Chain

Within the retail industry, effective supply chain management is crucial for ensuring product availability and minimising excess inventory. Seasonal retail face especially large challenges due to fluctuating demand. Tackling these complexities requires a structured approach to purchasing and inventory management. Sports Inc. operates in this seasonal retail industry within Sweden. They have two main seasons, spring/summer and autumn/winter. The company is a sports retail company with online sales and physical stores. The supply chain planning of Sports Inc. is complex, with planning being done a year in advance. While this allows for coordinated planning, it also limits flexibility. This chapter provides an overview of Sports Inc.'s purchasing and inventory management, which is summarised in Figure 4.1 below.

Timeline	Stage	Description
12 to 8 months before season	Budgeting & Planning	• **Season planning:** Divided into spring/summer & autumn/winter • **Sales budget:** Created centrally by the purchasing/assortment department and locally by stores. Based on historical data and experience. • **Decision meetings:** Sales managers and central teams align sales budgets • **Purchasing budget:** Sales budget is converted into a purchasing budget (e.g., 100 000 sek in sales -> 50 000 sek purchases) • **Assortment and volumes:** Procurement team compose product mix and volumes • **Store Grade:** Each store have sub departments that has a Store Grade from 1 - 6. Sub departments with Store Grade 1 gets basic range of products, and Store Grade 6 (e-commerce) has the widest assortment. • **Distribution key:** A min- and max volume is set for each product based on experience. In the initial distribution, each store will receive volume in relative to their proportion of the sales budget, compared to the total sales budget. However only within the previously set min- and max range.
8 to 6 months before season	Ordering	• **Order placement:** Orders are placed with suppliers. • **Lead times:** Long lead times of 6–8 months depending on supplier and production capacity.
Season start	Initial Allocation, Delivery and Distribution	• **Allocation:** Around 60% of goods are distributed to stores initially. based on sales budgets and store categories (Store Grades). • **Direct deliveries:** Some goods go directly from supplier to stores to save costs, while most are repackaged in the central warehouse.
During the season	Replenishment and optimization	• **Replenishment models:** Forecast-based tools (e.g., MRP) are used, though forecast accuracy is low. • **Adjustments:** Central teams analyze sales and stock data weekly and adjust replenishment volumes. • **Transport:** Central warehouse handles deliveries to stores according to a schedule (usually 5 days/week). • **Delivery cycle:** Orders are generated overnight, reviewed centrally on day 2, picked on day 3, and delivered on day 4. • **Flexibility:** Limited ability to increase/reduce volumes mid-season.

Figure 4.1: Purchasing and inventory management process of Sports Inc..

4.1.2 Purchasing and Budgeting Process

The purchasing process starts around 12 months before the start of the season, with budgeting and planning. Each store makes a sales budget and sends it to the central purchasing department. The central purchasing department also makes a separate aggregated sales budget for the total sales in Sweden. When this is done, sales managers and the central team meet to compare, discuss and together produce the final aggregated sales budget. Then, the sales budget will be converted into a purchasing budget. For example, if the sales budget states 100 000 sek in sales, this would generate a need of 50 000 sek in purchasing budget, if they have a margin of 50 percent. After the purchasing budget is done, a procurement team will compose suitable product mixes and volumes. In relation to the product mix, it is important to note that stores have store grades on a sub-departmental level. How sub-departments relate to the product structure is explained in Figure 4.2.

4.1.3 Store Grades and Assortment

Each store has several departments, that in turn consist of sub-departments. Sub-departments are then made up of product groups, which contain specific products. An example would be *a specific pair of running tights for men*. This is a product included in the product group *running tights men*, which is a part of the sub-department *performance apparel men*, in the department *performance textiles*. The potential store grade ranges from one to six. Sub-departments with store grade 1 receive a basic range of products, while higher store grades add a successively wider assortment. Store grades are based on the projected sales for a specific store´s sub-department. The store grades for the sub-departments in a specific store are generally similar, with some exceptions. For example, a store with store grade 2 for most of their sub-departments might be located in a city where people have a disproportionately large interest in football. Then, the store in this city, would likely have higher sales in the sub-department *football accessories*, leading to a higher store grade and wider assortment for this sub-department. This means that a store can have store grade 2 for some of their sub-departments, and store grade 3 for others. Note that a store grade can be manually changed, if there for example is a physical constraint on how large of an assortment a store can stock.

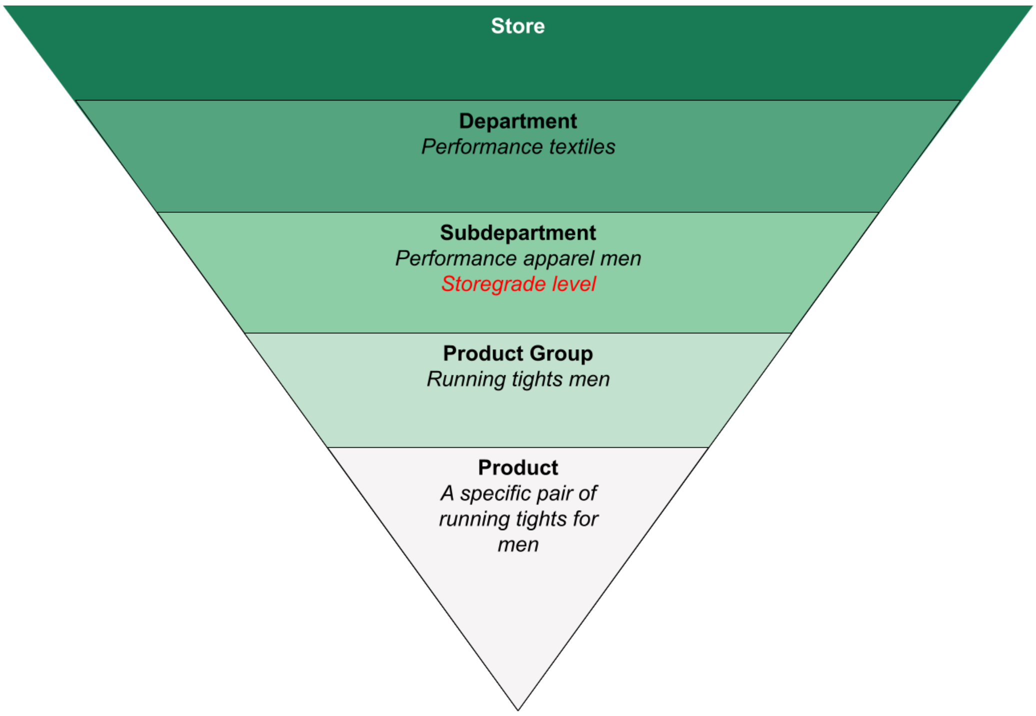

Figure 4.2: Product structure in relation to store structure.

4.1.4 Initial Allocation and Order Placement

When the budgeting and planning is done, the ordering stage will begin, which occurs around 6-8 months before the start of the season. Here the orders are placed to the suppliers. The reason this stage is 6-8 months before the start of the season, is mainly because the lead time from ordering a product to receiving the order is around this time, 6-8 months.

When the season starts, there will be an initial allocation of products, where around 60 percent of the goods are distributed to the stores initially. The rest of the products will be used to replenish the stores when needed, and are normally stored in the central warehouse. Around 85 percent of products go through the central warehouse, but from some suppliers it is more suitable to have direct delivery to the store. When deciding the initial volume each store should receive, a minimum and maximum value for each product is used. These values were previously set, after building the product mix. The minimum value is set to ensure that the store has every size available, but also that the store looks visually pleasing. A maximum value is set to ensure that a store does not receive too many products initially. In the initial allocation, each store will receive volume relative to their proportion of the sales budget, compared to the total sales budget. However, only within the range between the previously set minimum and maximum values. Note that any changes that occur from the time the sales budget is made until the season starts are not taken into account when allocating. For example, if a store has large quantities left over from previous seasons or if a nearby construction has affected the flow of customers. The allocation set months earlier is adhered to irregardless of changed conditions.

4.1.5 Replenishment and Forecasting

When in season, Sports Inc. has a limited ability to increase or decrease volumes of orders placed 6-8 months earlier. This means that the focus is on replenishment and optimising the balance between stores and the central warehouse. Today, the replenishment volumes are mainly based on three forecasting methods, exponential smoothing, moving average, and aggregated season, but the accuracy is low. The reason for this is that turnover for a specific product in a specific store, color and size is low. This means that with current forecasting models, the average weekly sales are close to zero. In practice, the restocking process is based on a reorder level that tries to maintain the inventory level of the initial allocation. There is a central team analysing sales and stock data to adjust replenishment volumes, but this is mainly done to find abnormalities. During the start of a season there is no forecasting at all. The forecasting for a specific product in a specific store starts either when the store has sold three pieces or 28 days into the season. Before any of these criteria has been met, it is considered to be too little data to perform an accurate forecast, which may increase the risk of overstocking.

If they randomly sell two pieces on the first day, the forecast would likely be too high. For this period, they instead utilise a basic logic. For example, if they sell one they restock one, or if they sell two, they replenish one, depending on the risk of overstocking.

When there is enough data, Sports Inc. uses forecasting models. A multi-step process is used to determine the best forecasting method for each product-location (specific product at specific store). The selection of forecasting models is based on historic sales data. Patterns of seasonality and trends, or their absence, are used to limit the possible forecasting methods.. Statistical tests are done to classify product-locations into different categories. The product-locations are tested for constant demand, trend-based demand, seasonal demand, intermittent demand, and random demand. Constant demand has minimal fluctuations. Trend-based demand shows a consistent increase or decrease in sales. Seasonal demand shows recurring peak and low sales periods. Intermittent demand displays irregular sales patterns, where zero sales are frequent. Random demand has no clear pattern at all. All these are tested to be either true or false, and each classification narrows down to the most suitable forecasting models.

When the statistical tests are done, and the product-location is determined by a demand class, only the most suitable forecasting models will be tested. Since the thesis' focus lies on seasonal products, the classes when seasonal demand is present will be further explained. In this case, there can be two alternative classes, with or without a trend. If seasonal demand is present, but trend is not, there are two forecasting methods that will be tested, exponential smoothing with seasonal indices, and the naive seasonality model. If instead both seasonal demand and trend is true, exponential smoothing with both seasonal indices and trend will be tested. The trend can be both additive or multiplicative, and with or without a dampening of the trend. The base value for dampening the trend is 0.6 but can be changed manually if thought necessary. However, multiplicative trend is never used for single products, since it has difficulties in handling 0 values, so this method is only used when manually set, which almost never occurs. When the most suitable forecasting models have been tested, the MAE (Mean Absolute Error), is calculated for each, and the model with lowest MAE will be used. However, there is one more criterion for this to work, that has not been mentioned so far, which is that sufficient historical data will be needed for all those methods.

For seasonal products with insufficient historical sales data, the aggregated season model is instead used. The aggregated season model starts with an analysis of demand at the product group or product group-location level, instead of individual product-locations. Then, seasonal patterns are identified, by analysing multiple prior years. At least one full season of data should be available. Based on this, seasonal indices are calculated, which represent the expected fluctuations in demand for the period. The individual product-location sales are then adjusted by normalising them based on the seasonal indices just calculated. After this, a baseline demand is established, by taking the average of the normalised sales at product-location level. Lastly, the final forecast is produced by applying the seasonal indices from the aggregate level to the baseline demand. This ensures that individual store forecasts align with broader market trends.

4.1.6 Transportation and Distribution

For managing the transportation and distribution, Sports Inc. buys the transportation service from PostNord. They have a parcel-based logistics model, where products are packed by Sports Inc. at the central warehouse, before being handed over to PostNord, who are responsible for the sorting and distribution. From the central warehouse to the stores, they have a fixed price per package, maximum 120 cm and 20 kg, for a standard package. For shipments between the stores, the fixed price per package is around 75 percent higher, and additional administrative and handling costs in the stores will be added on top. Currently, Sports Inc. does not redistribute stock between stores. Due to the additional incurred costs, it is an deemed economically unfeasible venture. Postnord collects shipments from the central warehouse three times a day, which are delivered to the stores in Sweden. The deliveries follow a schedule, and deliveries to most of the stores occur Monday to Friday, and are made in one day. Some stores located far in the North of Sweden will have a delivery time of two days. In terms of replenishing lead time, stores are replenished from the central warehouse each business day. If a product gets out of stock on day 1, orders are generated overnight, reviewed centrally on day 2, picked on day 3, and delivered on day 4.

4.1.7 Store-Level Inventory Management

The following subsection presents insights from store managers: Store Manager 1 and Store Manager 2, who manage large stores, and Store Manager 3, who manages a small store.

Initial Allocation

All three store managers view the initial allocation as an important part of obtaining a good stock balance. A poor initial allocation has negative consequences for the stock at the end of the season. According to Store Manager 1, the logic behind the initial allocation is reasonable, but the outcome of it is not always as desired. Sometimes they receive unreasonably high volumes initially, which cannot be sold out during a season. The individual store has no influence over incoming volumes, which is controlled centrally, and is thereby forced to adapt to the situation.

Store Manager 2 had similar experiences, but also talked about the opposite situation. The initial allocation for new products sometimes consist of only one item per size, where the popular sizes would sell out immediately, with limited possibilities of getting replenishment. Store Manager 2 also mentioned how they are working in industry influenced by external circumstances. For example, weather can greatly impact the sales across stores, potentially causing balancing issues.

Store Manager 3 concludes that the initial allocation in general has improved in recent years. For long-living products, the initial allocation now takes left over stock from previous seasons into account. However, this is not the case for seasonal products. The stock level of the similar item from last season, that the product now being allocated is replacing, is not considered. Store Manager 3 states that they, due to their small store size, generally only receive one of each size. Given how highly they value having every size in stock, the store manager finds the initial allocation fitting. This despite that peripheral sizes might not sell until the end of the season, at a high markdown.

Reorder Level

Replenishment is managed entirely through a central system. It does, however, allow store managers to suggest adjustments to desired inventory levels. Store Manager 1 explained that stock levels can be adjusted, but any changes must be approved centrally. Store Manager 2 also noted that while adjustments are possible, there are limitations in practice. In particular, it is not possible to fully stop replenishment, as the system does not allow stock levels to be set to zero. Instead, decimal values must be entered, which are then rounded up to the nearest whole number. This restricts the ability to completely prevent further shipments of a product. Store Manager 3 added that adjustments of the reorder level for seasonal products are very rare. The function is mostly used for long-living products.

Inventory Checks

All stores perform eight partial inventory counts per month, meaning they do an inventory count for specific products or brands. These are often focused on high-value items or theft-prone brands. A full inventory check is performed annually. All three store managers emphasised the importance of the inventory checks to ensure system accuracy. Frequent discrepancies are accredited to misplaced items, theft, or scanning errors. Discrepancies occur more often in the larger stores than in smaller ones, likely due to the difference in inventory size according to Store Manager 3. Inaccurate stock levels can result in products appearing available online when they in reality are not, which the store managers stated, leads to customer frustration and lost sales. Regular inventory checks are therefore seen as critical, both for operational planning and maintaining customer satisfaction.

Broken Assortment

Maintaining all sizes in stock throughout the season was described as essential by all store managers. Not having all sizes in stock is, according to the store managers, likely to negatively affect sales. Common sizes were deemed especially important to keep in stock, as their absence often results in immediate lost sales. On the other end, store managers 1 and 2 noted that fringe sizes tend to remain unsold and cycle through multiple clearance rounds. However, it was still emphasised that these less common sizes should be available at all times. Customers expect a complete range and may go elsewhere if their size is missing. Store Manager 3 reiterated the conclusions of the other store managers. Having all sizes in stock is crucial to maintaining customer service, even if peripheral sizes often do not sell until the end of the season.

Markdowns

Markdowns are an important strategic tool for Sports Inc., to manage seasonal overstocking. Store Manager 3 described markdowns as necessary to free up space and capital for the next season's goods. All three store managers stated that markdown decisions are centralized, with limited possibility of local adjustments, mostly for products left over from previous seasons. Store Manager 1 described that the markdown is increased successively each year. For products older than three years, an aggressive markdown is applied, in order to sell before the product completely loses its value.

Store Manager 2 explained how the centralized markdown strategy can sometimes have disadvantages. For example, during a warm winter, shops in the south of Sweden may sell poorly, resulting in them having large stocks left. At the same time, stores in northern Sweden may have sold well and have normal levels of winter products left. The total stock for Sports Inc. will be higher than usual, and thus the winter products will be sold with large price reductions. The centrally initiated sale helps the stores in the south to sell out excess inventory, but the stores in the north are dissatisfied because they are now selling products for a lower price, even if there was sufficient demand at full price.

4.1.8 Outlet Store

Currently, Sports Inc. does not operate any outlet stores, but there are talks about establishing one in connection with its central warehouse. The exact role and operation model have not yet been decided. As a result, the outlet concept has not been included in the current process descriptions or data analysis. However, its future implementation may influence and open up new possibilities for how end-of-season inventory is handled.

4.2 Sales and Distribution Data from Sports Inc.

This section presents the findings from the analysis of sales and distribution data from Sports Inc..

4.2.1 The Balancing Issue

When observing the inventory levels across stores at the end of a product's intended season, the balancing issue is clear. The issue, observed across a wide range of products, is exemplified by Figure 4.3. There are stockouts in several stores, while others hold superfluous stock. The extent of the imbalance is further illustrated by the coefficient of variation (CV), which was calculated for each product to measure how unevenly inventory was distributed across stores at the end of the season. For winter products, the average CV was 0.83 and the median 0.45. 31 percent of products exceeded a CV of 0.7, a level that Syntetos et al. (2005) call a strong imbalance. For shoes, the average CV was 0.42 with a median at 0.38. Nine percent of products still exceeded the 0.7 threshold. The lower CV for shoes is due to the end stock being larger. These findings confirm that the imbalance is not limited to a few isolated cases, but rather a systematic pattern of uneven distribution.

Since Sports Inc.'s business model includes selling the final inventory at a discount, there will be overall inventory left over at the end of the intended season. However, it is important for this inventory to be distributed as optimally as possible to minimise the necessary discount. A stock imbalance not only negatively impacts availability in the stores with low stock, but also forces lower prices in those with excess inventory. The latter consequence is portrayed by figures 4.4 and 4.5, displaying that the price reduction for a product is significantly higher after the intended season compared to during it. For shoes, the average price reduction increased by 17 percentage points to 47 percent. The jump was even larger for winter clothing, rising by 19 percentage points to an average of 50 percent after the season ended.

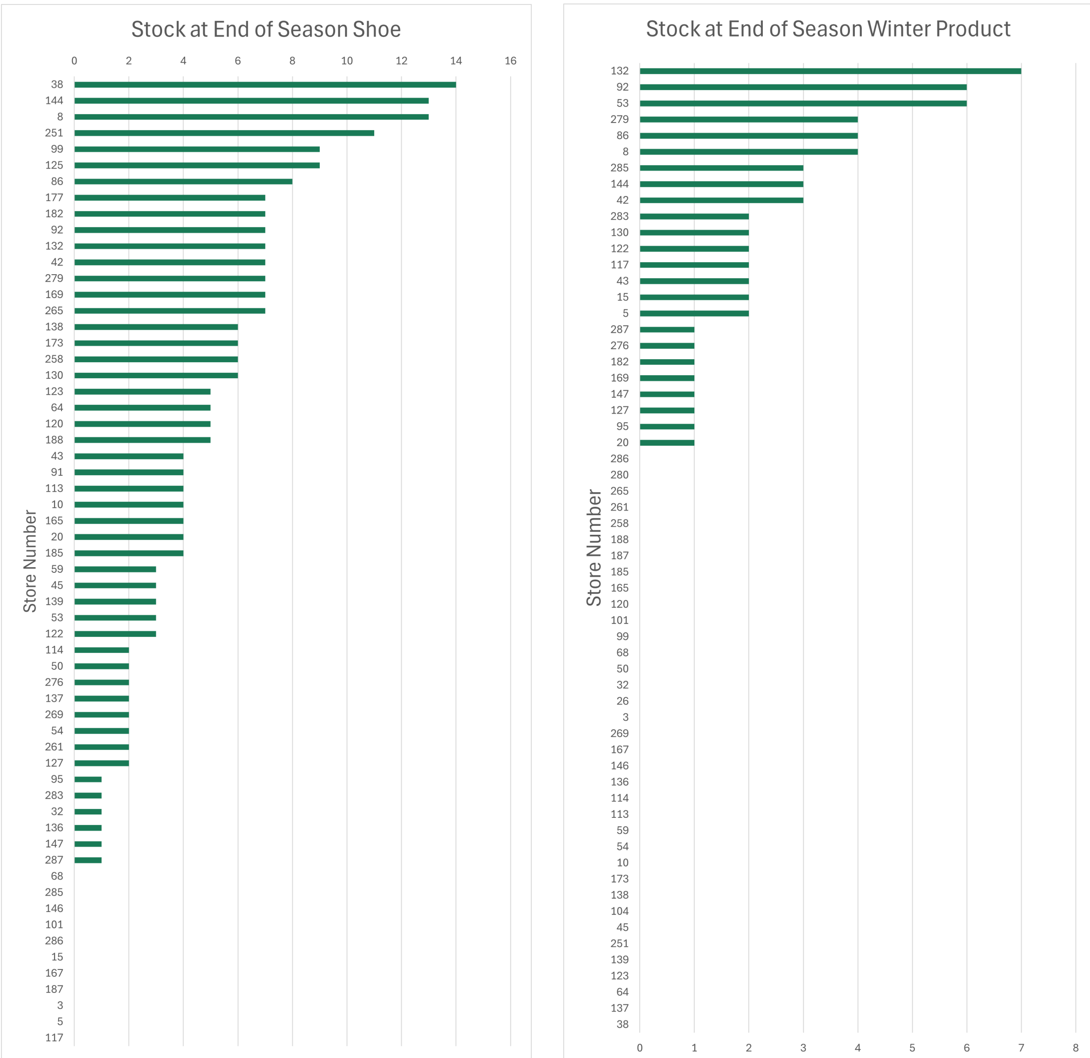

Figure 4.3: Stock across stores at the end of intended season for a specific shoe (left) and winter product (right).

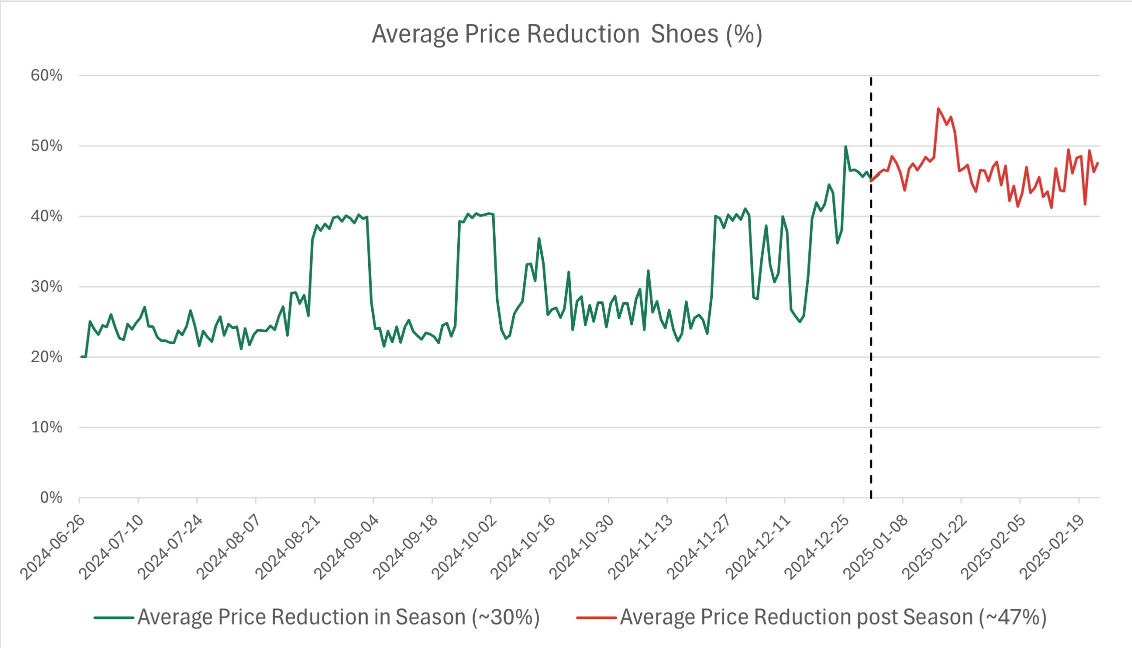

Figure 4.4: Comparison of price reduction during and after season for all shoes. The dashed vertical line denotes the end of the intended season. The average price reduction during the intended season is 30%, while the average price reduction after the season is 47%.

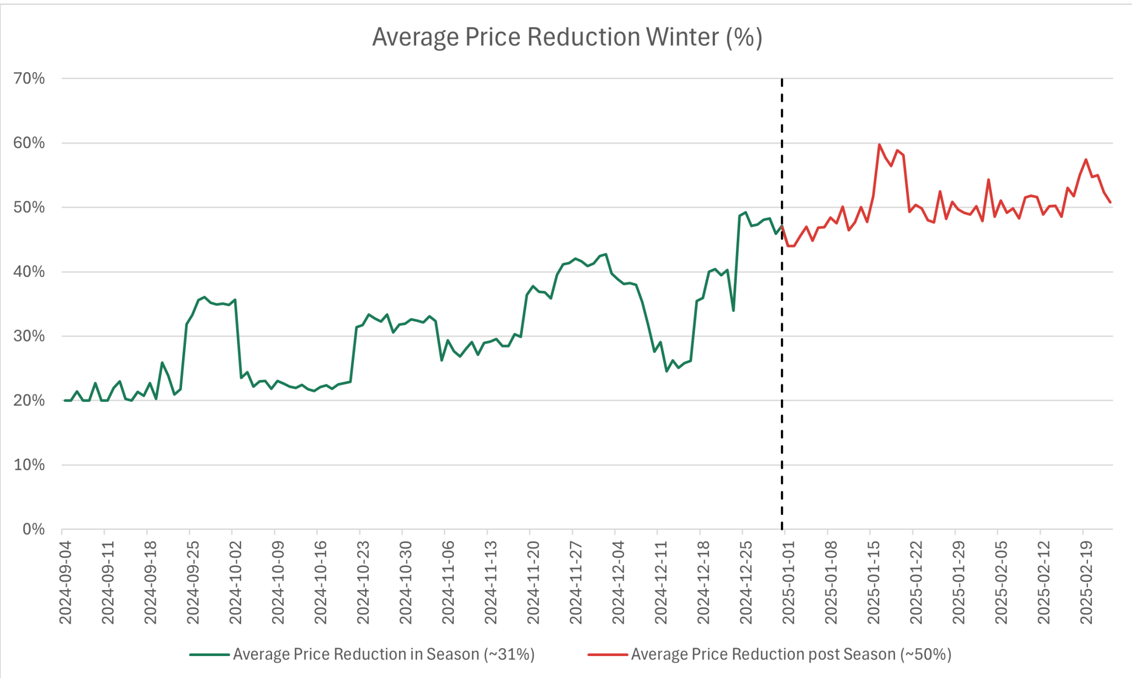

Figure 4.5: Comparison of price reduction during and after season for all winter clothing. The dashed vertical line denotes the end of the intended season. The average price reduction during the intended season is 31%, while the average price reduction after the season is 50%.

4.2.2 Initial Allocation and End Stock

Comparing initial allocations to sales shows that 80 percent of store-product combinations for shoes, and 50 percent for winter products, sell less than their initial allocation within intended season. Moreover, when aggregating to store level, all stores sell less shoes than their initial allocation. There is also a negligible relationship between store grade and percentage level, since Pearson's correlation coefficient is <0.3. For winter products most stores sell more than their initial allocation, although some sell less. The relationship between store grade and sales percentage is also strong, with a correlations coefficient of 0.77 . These correlations are represented by the trendlines in Figure 4.6. As can also be seen in the graph below, lower store grades generally have lower sales in comparison to initial allocation.

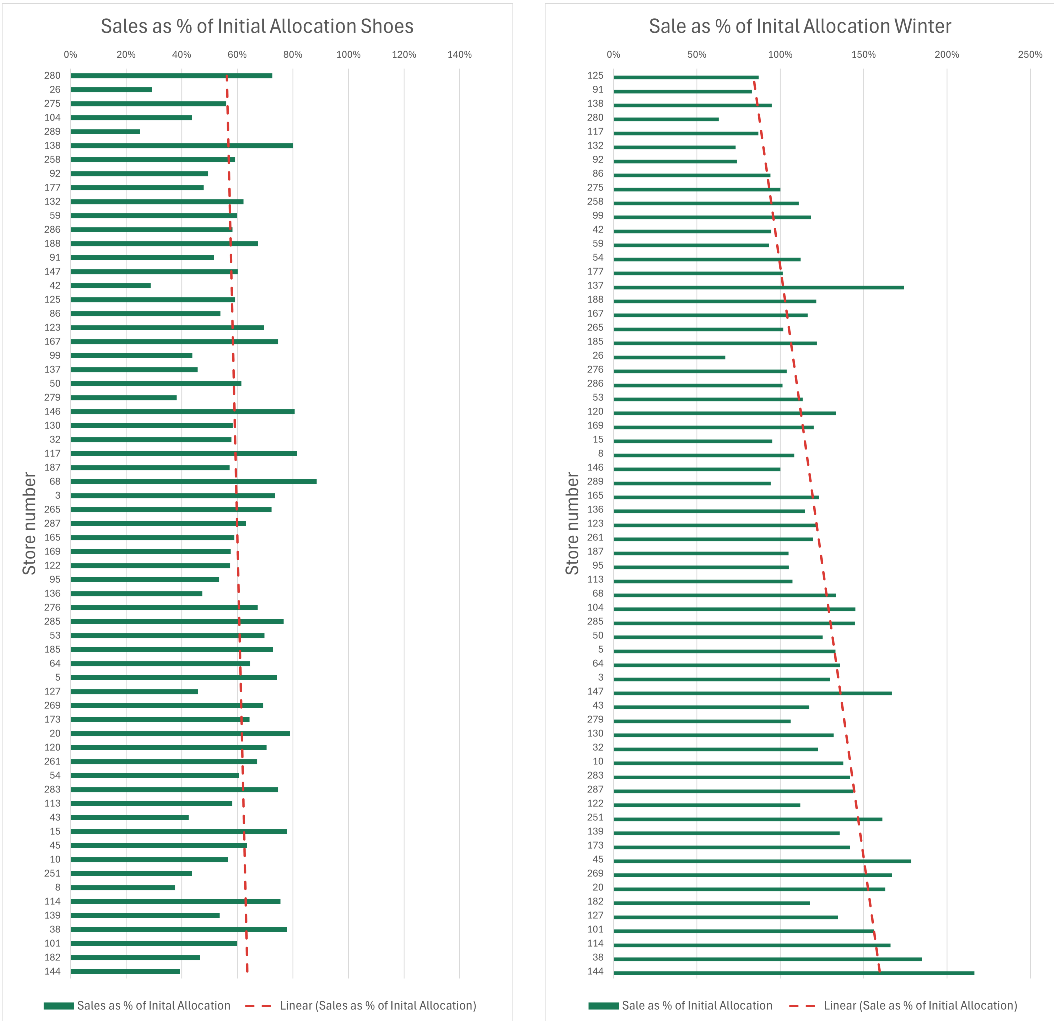

Figure 4.6: Sales within intended season as a percentage of the initial allocation by store for shoes (left) and winter products (right), with stores ranked in ascending order of their average store grade. The left graph has a correlation below 0.3 between store grade and sales percentage, while the right graph has a correlation of 0.77. This is represented by the dashed line.

Figure 4.7 displays the impact of geographical conditions, as the stores are grouped by climate region. The red bars in the graph show the average for each respective climate region, all between 110 and 150 percent.

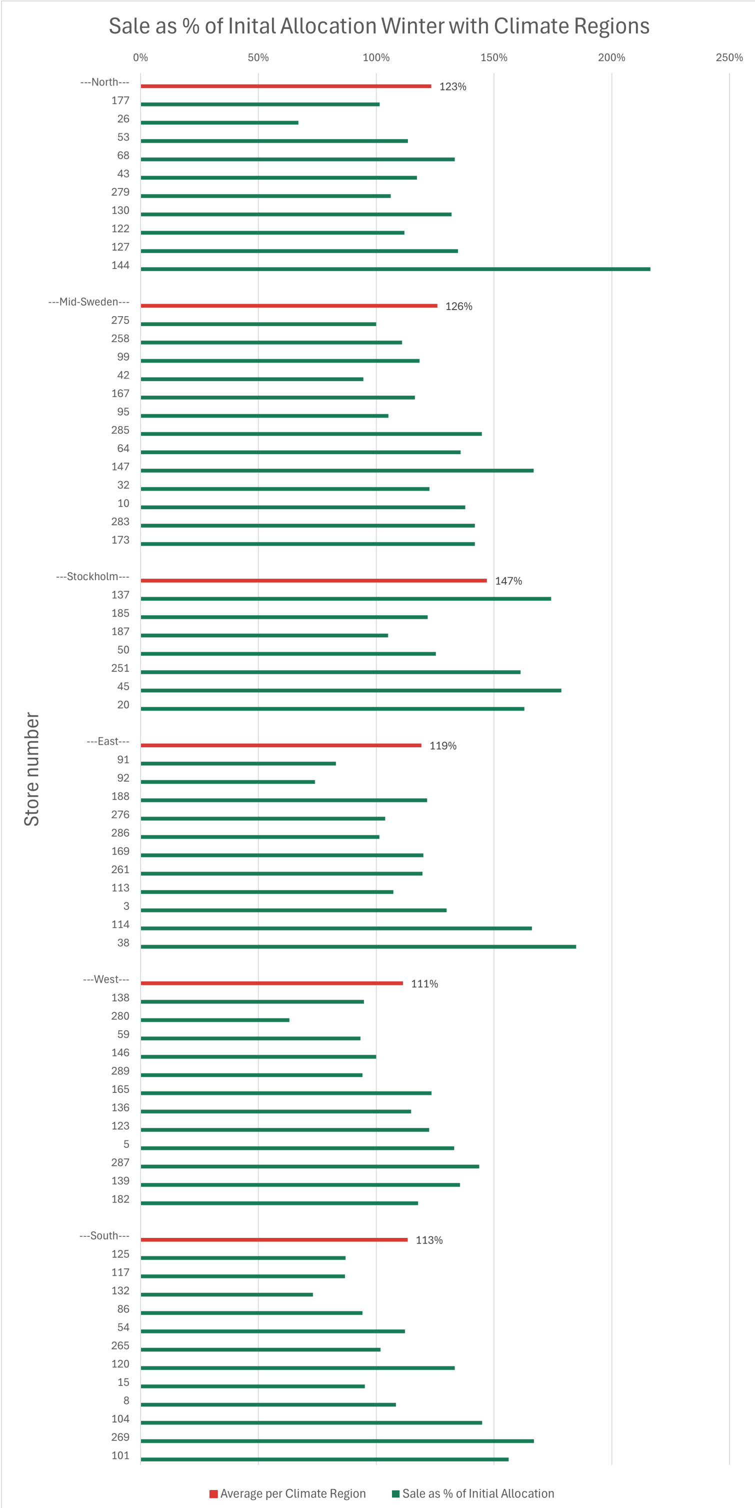

Figure 4.7: Sales of winter products within intended season as a percentage of the initial allocation divided by store and grouped by climate region. The red bars show the average of the climate region.

Figure 4.8 displays the sales within the intended season as a percentage of the initial allocation, broken down by product group for winter products. The data reveals substantial variation between product groups. Some product groups, namely the Winter Jacket categories, sold a notably larger proportion of their initial allocation compared to others.

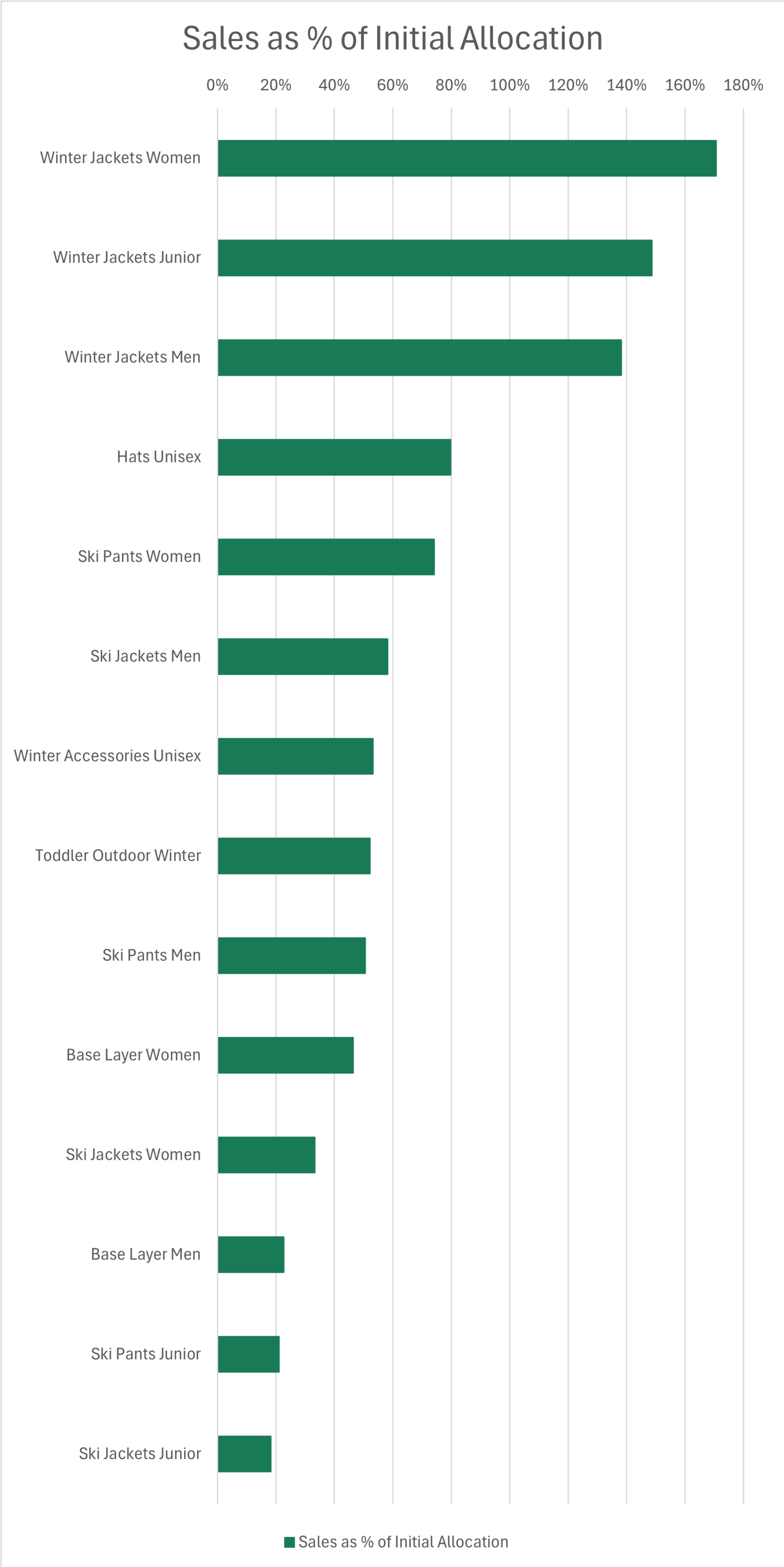

Figure 4.8: Sales within intended season as a percentage of the initial allocation by product group for winter products.

To further examine how initial allocation relates to sales and how this differs between product groups, Figure 4.9 displays sales as a percentage of initial allocation by store grade for selected product groups. The stores are sorted by ascending store grade, meaning that stores with lower grades appear at the top and those with higher grades at the bottom of each graph. The red trendline indicates the relationship between store grade and the share of initially allocated stock sold.

In most cases, a positive slope is observed, indicating that stores with higher store grades tend to sell a larger share of their allocated inventory. Conversely, lower store grades sell a lower proportion of their initial allocation. This trend is particularly evident in product groups such as Winter Jackets Junior, Winter Jackets Men, and Ski Pants Women. In contrast, flatter or slightly negative slopes are seen in groups like Ski Pants Junior and Winter Jackets Women. This suggests a weaker or inverse relationship between store grade and sales performance in those cases.

Figure 4.9: Sales as percentage of initial allocation by store grade for selected product groups. Stores are sorted by ascending store grade (top to bottom). The red trendline indicates the overall linear trend across stores, quantified by the correlations in Table 4.1. The lower number of stores for Ski Pants Junior is due to the fact that they are only sold in stores with store grade 4 and 5.

To quantify the trends seen in Figure 4.9, Table 4.1 presents the Pearson correlation coefficients between store grade and sales as a percentage of initial allocation for the same product groups. The correlations confirm the visual trends seen in the figure. Winter Jackets Junior shows a high positive correlation (0.72), while Winter Jackets Men (0.55) show moderate positive correlation. Ski Pants Women (0.47) and Ski Pants Men (0.34) both display low positive correlations. The remaining depicted product groups, Winter Jackets Women and Ski Pants Junior, have negligible correlations.

Table 4.1: Pearson's correlation between storegrade and sales as a percentage of initial allocation for the product groups displayed in Figure 4.9.

Product Group	**Correlation**
Winter Jackets Women	−0.21
Winter Jackets Men	0.55
Winter Jackets Junior	0.72
Ski Pants Women	0.47
Ski Pants Men	0.34
Ski Pants Junior	0.28

4.2.3 Relationship Between Early Overstocking and Final Inventory

To understand the consequences of inaccurate initial allocations, figures 4.10 and 4.11 examine the relationship between unsold initial inventory and end-of-season stock for shoes and winter products. The plots show that a poor initial stock level tends to remain to the end of the season. The unsold initial inventory is calculated by subtracting the sales in the intended season, from the initial allocation of the products. Each point in the scatterplot represents a store-product combination, which is ranked based on two variables. The x-axis represents the ranking of unsold initial inventory for each combination. A low rank denotes a relatively low number (negative) of unsold items, and a high rank implies a large amount of unsold stock, compared to its initial allocation. The y-axis represents the ranking of end stock for each store-product combination. A low rank indicates that there is little stock left at the end of the season, and a high rank means that the store retained a significant amount of stock by the end of the season. The points in the top-right corner had both high unsold initial inventory and high end stock. While those in the bottom-left corner had low unsold inventory and ended up with low end stock. The red trendline indicates a positive correlation, indicating that stores that are ranked high in unsold initial inventory also are ranked high in end stock. For the shoes, Spearman's correlation coefficient is 0.74, indicating a high positive relationship between the two variables. For the winter products, Spearman's correlation coefficient is 0.56, indicating a moderate positive relationship. These correlations are represented by the red line in figures 4.10 and 4.11.

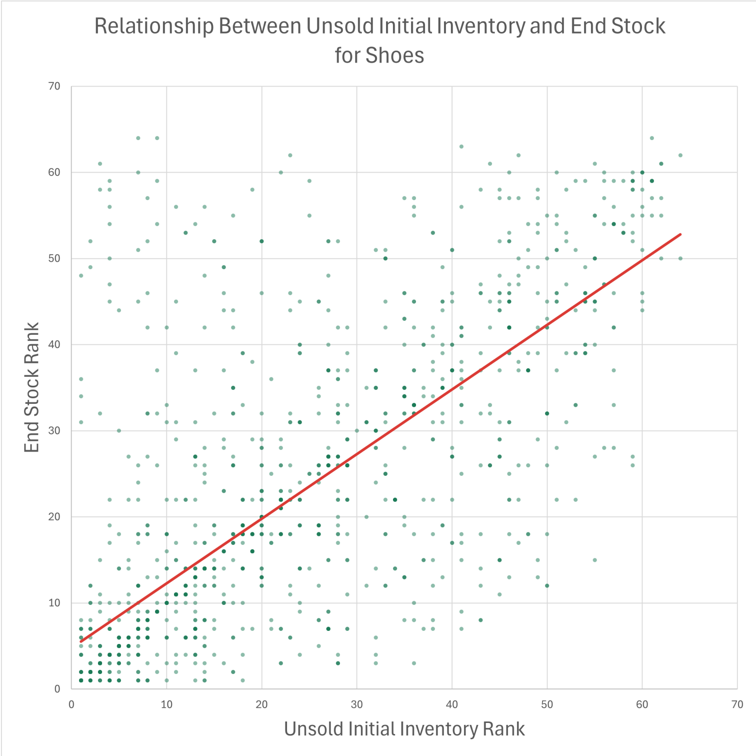

Figure 4.10: Correlation between Unsold Initial Inventory and End Stock for Shoes, indicating that stores with higher unsold initial inventory tend to retain more stock at season end. Marker transparency (50%) was applied to reveal overlapping data points, with darker areas indicating higher concentration. The red line represents the correlation, in this case 0.74, which indicates a high positive relationship between the variables.

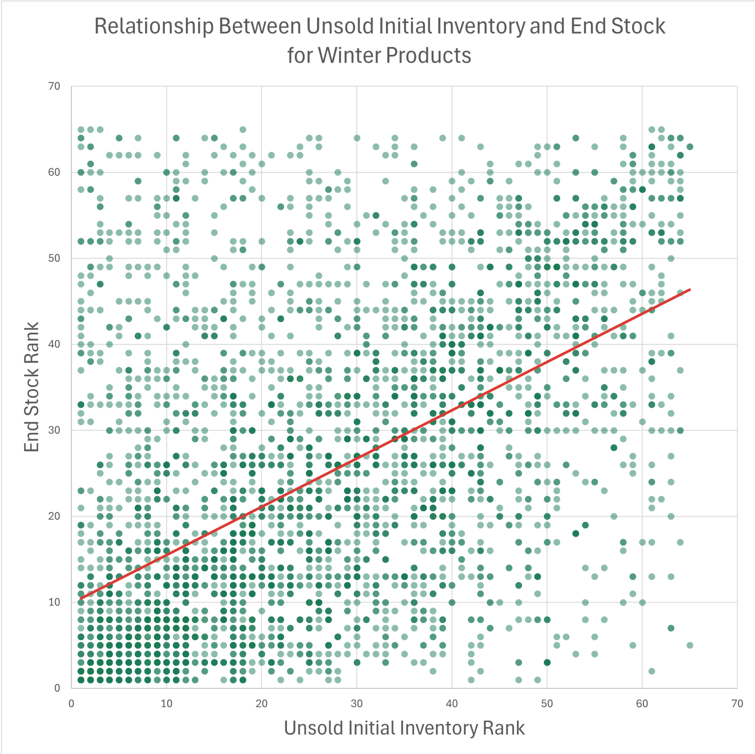

Figure 4.11: Correlation between Unsold Initial Inventory and End Stock for Winter Products, showing that stores with higher unsold initial inventory tend to retain more stock at season end. Marker transparency (50%) was applied to reveal overlapping data points, with darker areas indicating higher concentration. The red line represents the correlation, in this case 0.56, which indicates a moderate positive relationship between the variables.

4.2.4 Patterns Across Winter Seasons

During the data analysis, concerns arose that the winter product results might be impacted by the mild winter in that particular season (2024/2025) (SMHI, 2025). To investigate whether that is the case, another season of winter products was added (2023/2024). The added season being colder (SMHI, 2024), creating more favourable conditions for the sale of winter clothing. The data shows that 52 percent of store-product combinations have sales lower than initial allocation, similar to that of 50 percent for the original season. Additionally, the trend of lower store grades selling a lower portion of their initial allocation compared to higher store grades was observable in this season as well. The correlation was however weaker (0.36). Figure A.1, showing this correlation, can be found in Appendix A. Furthermore, the added season also displays variance among product groups, albeit with a greater portion of product groups surpassing the 100 percent mark. The dispersion of sales relative to initial allocation by product group for the added season can be found in Figure A.2, Appendix A.

The main difference between the years, possibly related to the colder winter, was that a greater portion of inventory was sold earlier in the season in 2023. The inventory was also sold at a higher price reduction, a six-percentage point difference between the years. First three months of the season in 2023, 32 percent of inventory was sold at an average price reduction of 26 percent. In 2024, during the corresponding period, 20 percent of inventory was sold at an average price reduction of 31 percent. The figures mentioned in this subsection are summarised in Table 4.2 below.

Table 4.2: This table compares 2023 and 2024 across four key data points.

Data point	**2023**	**2024**
Sales < initial allocation (%)	52%	50%
Correlation (store grade vs. sales)	0.36	0.77
Inventory sold in first 3 months (%)	32%	20%
Average price reduction (first 3 months) (%)	26%	31%

4.3 External Company

To complement the internal analysis of Sports Inc., professionals from a company operating under similar conditions were interviewed. The company, referred to in this report as *Home Inc.*, is a large home goods retailer with a seasonal assortment and sales through both physical stores and online channels.

At Home Inc., a centralised distribution system is used. Most stores are supplied via central warehouses, although some items are shipped directly from suppliers. The company has a cautious approach to initial allocation. They often start with small quantities, only one to two units for display purposes. The stock is then replenished based on sales performance. Their short lead time of 24-48 hours allows them to maintain a low stock level in stores. Moreover, the semi-automatic order planning system used updates desired stock levels by combining historical data and expected campaign performance. Like Sports Inc., Home Inc. avoids redistributing goods between stores during the season. Instead, targeted campaigns are utilised to handle overstock. The home goods retailer also stated the importance of maintaining a complete assortment to support sales. Since a large portion of their sales is campaign-driven, maintaining a full offering of items currently on campaign is most important. Due to sizes not being a factor, Home Inc. also has a significantly lower number of product variants compared to Sports Inc. Additionally, Home Inc. have higher sales volume per product, partly induced by the lower number of variants. This provides them with sufficient sales signals quicker, enabling responsive replenishment.

5

Analysis and Discussion

The following chapter will provide analysis regarding, and discuss the answers to, the research questions presented in 1.3.1. Prior to that we can establish with the help of the data analysis that there in fact is a systematic balancing issue, particularly for the winter products. 31 percent of winter products showed a strong imbalance according to the coefficient of variation. The lower number, of nine percent, for shoes is due to the much larger end-of-season stock within that segment, making the variation less in comparison. From the data analysis, it can also be confirmed that the price reduction increased significantly after the end of the season. 17 percentage points for shoes and 19 percentage points for winter products. This highlights the negative economic aspects of an unbalanced inventory at the end of the season. More stock left over in some stores means lower prices, which means less profit. Stores that instead have little or no stock suffer from lost sales, also negatively impacting the bottom line.

5.1 RQ1

This section analyses which stages of Sports Inc.'s inventory management process are key contributors to the balancing issue.

5.1.1 The Key Process Stages

From reviewing Sports Inc.'s supply chain structure, it is apparent that there are two processes influencing balancing: Initial allocation and replenishment. The data analysis shows that the initial allocation often causes an imbalance. For example, 80 percent of store-product combinations for shoes and 50 percent for winter products sold less than their initial allocation within the intended season. Furthermore, the imbalance persists until the end of the season in most cases, showing that the initial allocation has great impact on the end-of-season balance. This is demonstrated in Figure 5.1, which shows a Spearman correlation of 0.74 for shoes and 0.56 for winter products, between unsold initial inventory and end-of-season stock. The same figure also demonstrates the replenishment process' inability to correct the imbalance.

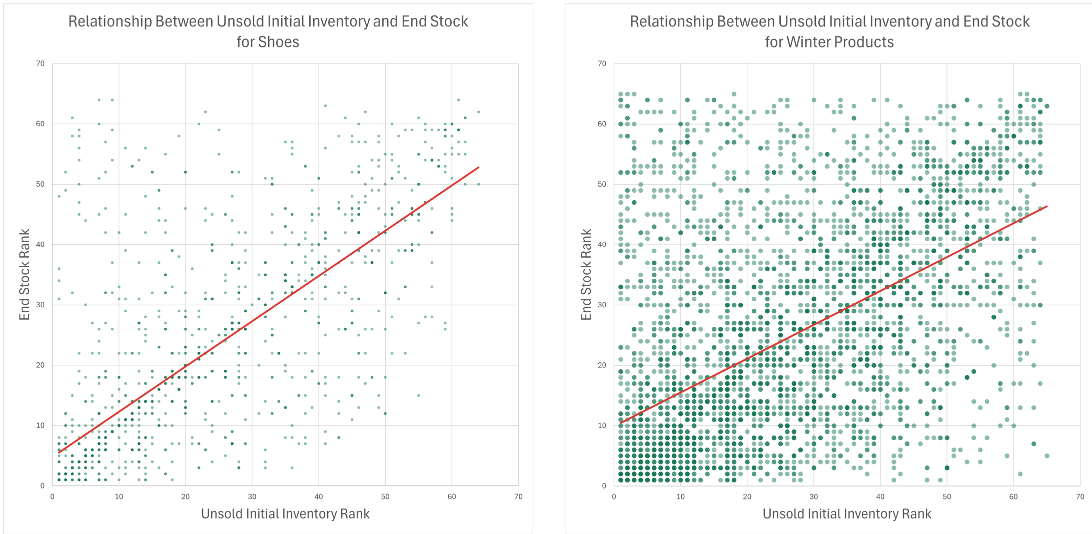

Figure 5.1: This figure is a reproduction of Figures 4.10 and 4.11, showing the correlation between Unsold Initial Inventory and End Stock for Shoes (Left) and Winter Products (Right). It indicates that stores with higher unsold initial inventory tend to retain more stock at season end. Marker transparency (50%) was applied to reveal overlapping data points, with darker areas indicating higher concentration. The red line illustrates the correlation, with values of 0.74 for Shoes and 0.56 for Winter Products, indicating a strong and moderate positive relationship between the variables, respectively.

An overview of the balancing issue and its contributing factors is illustrated in Figure 5.2. To summarise, both initial allocation and replenishment play a part in the imbalance seen at the end of the season. Specific features within these processes, such as the minimum-maximum range in initial allocation and the static nature of the reorder level in replenishment, emerge as major issues. How these, and other, components contribute to the balancing issue will be analysed further in the following section.

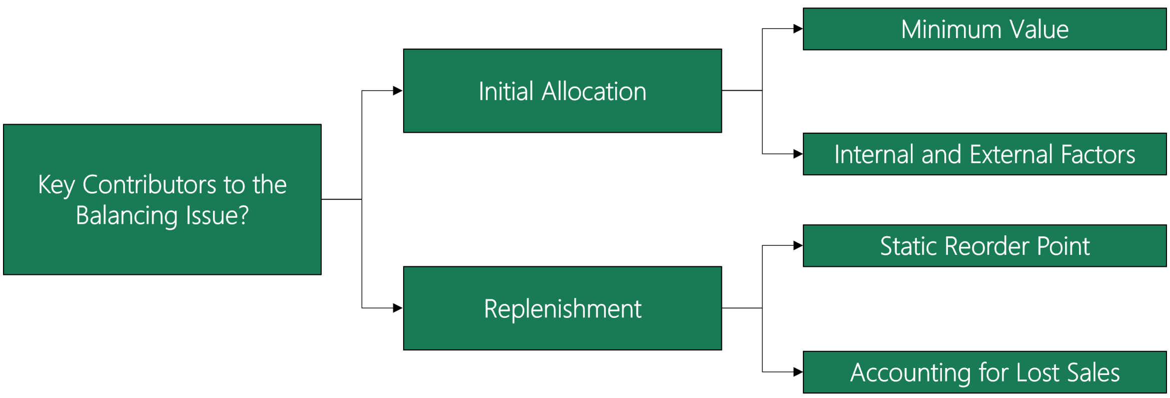

Figure 5.2: The balancing Issue divided into initial allocation and replenishment, each with specific factors contributing to the problem.

5.2 RQ2

This section analyses how the stages identified in Section 5.1, namely the initial allocation and replenishment, contribute to the balancing issue.

5.2.1 Initial Allocation

In this subsection, the contribution of design choices in the initial allocation process, such as minimum values and static assumptions, to the stock imbalance is analysed and discussed.

Minimum Value

The logic behind the initial allocation, allocating based on projected sales, is sound. However, it is hindered by the minimum value. The minimum value is problematic in multiple ways. Stores with low store grades to receive more units than they can realistically sell. However, the main reason for this is rather simple. The minimum values are often set to ensure that stores have a range of all sizes, to improve the customer experience. This is particularly problematic for products with many sizes or variants, such as outerwear or shoes, where a full range of sizes can represent a large proportion of a low store grade's expected sales. The effects of this is not only inflated stock levels in underperforming stores, but it also ties up inventory that could have been used in higher-grade stores with larger sales volume. This results in excess inventory for some stores, generally low store grades, while other stores, generally higher store grades, experience stockouts.

This imbalance becomes clear when looking at specific examples. A small store with low store grades can have a forecasted volume of 5 pairs for a shoe, but if the minimum value is set to 10, it receives more than it is expected to sell. At the same time, a larger store may be able to sell 35 pairs but only receives 15. Since there is no redistribution between stores during the season, the initial allocation becomes even more important, and setting the minimum and maximum values optimally is crucial to avoid this kind of imbalance.

A general conclusion can be drawn with the help of Figure 5.1, coupled with Figure 5.3. The former one show that stores with higher unsold inventory tend to retain more stock at the end of the season. The latter indicates that stores with low store grades generally sell a smaller share of its initial inventory. These together lead to the conclusion that lower store grade stores are likely to have excess stock at the end of the season. This is because they are excessively allocated at the start of the season, often due to a high minimum value.

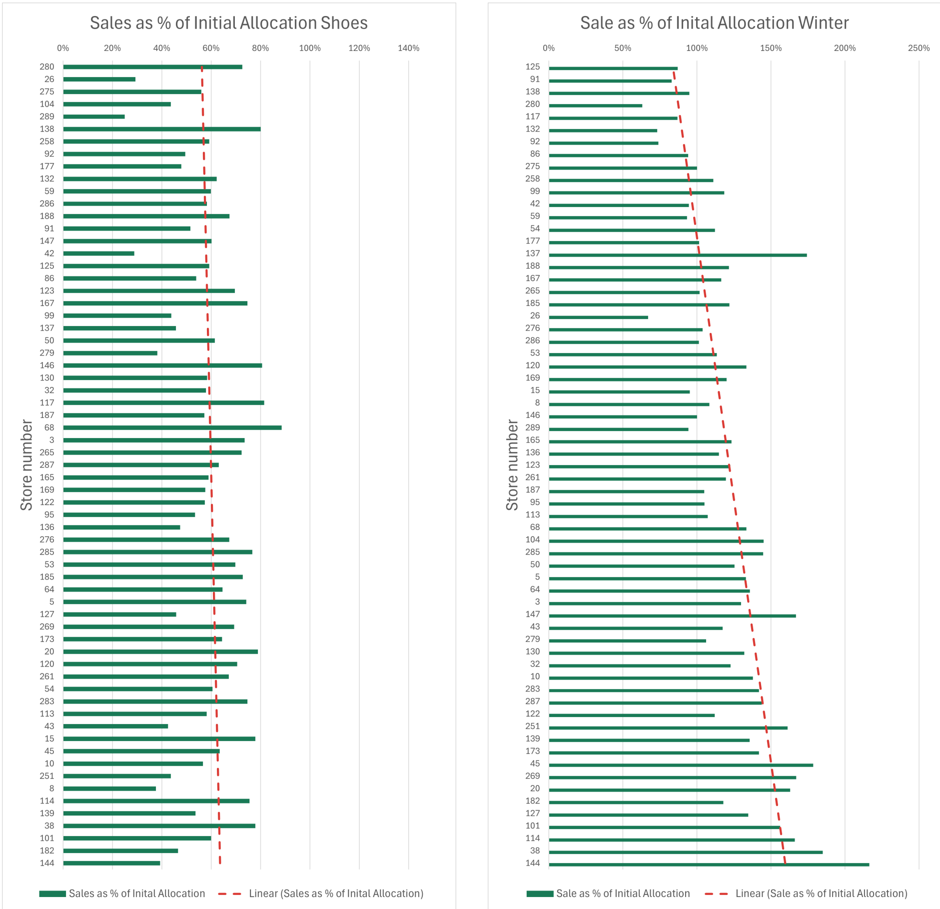

Figure 5.3: Identical to Figure 4.6. Sales within intended season as a percentage of the initial allocation by store for shoes (left) and winter products (right), with stores ranked in ascending order of their average store grade. The left graph has a correlation below 0.3 between store grade and sales percentage, while the right graph has a correlation of 0.77. This is represented by the dashed line.

Internal and External Factors

Another factor within the initial allocation that contributes to the balancing issue is that the initial allocation does not take left over stock of similar products, from previous seasons, into account. A store that has a large stock of similar products left over will not receive fewer products of the substitute for this season. When the assortment for this season arrives, they will have to sell both the new product and similar ones from previous seasons. This means that these stores will start the new season with an imbalance that is invisible to the system, as the new products have different product numbers in the system.

Similarly, external factors that occur after the ordering but before the initial allocation are not taken into account. Allocations are planned 6–8 months in advance and remain unchanged despite updated information, such as leftover stock or construction disruptions. The initial allocation reflects store conditions eight months prior, and not current conditions, which can lead to a less than optimised initial allocation.

The analysis at product group level shows that there is variation in sales relative to initial allocation. However, the variations are not consistent between seasons. For instance, during the colder winter of 2023, a larger share of product groups sold above 100 percent of their initial allocation. In contrast, during the milder winter of 2024, different product groups instead showed stronger sales performance. This suggests that the success of individual product groups is influenced by external factors such as weather, and cannot be assumed to be stable from year to year. Since weather is unpredictable, this further highlights the importance of enabling lower initial allocations in order to increase flexibility of the inventory.

Regional climate differences were expected to influence sales of winter products due to the unusually mild winter. Stores in the north of Sweden were hypothesised to sell at a normal rate while the other regions would sell less. However, the data analysis, and more specifically Figure 5.4 show that sales relative to the initial allocation were consistent across all climate regions. The findings thus suggest that climate alone is not a major driver of the balancing issue and that other factors play a more significant role.

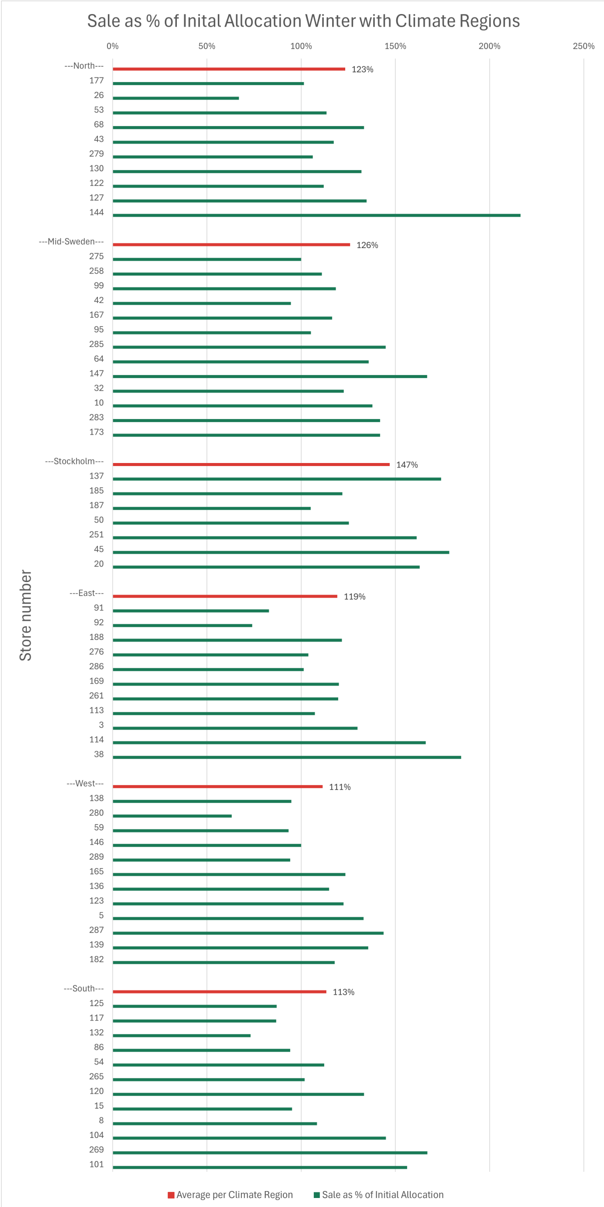

Figure 5.4: Replica of Figure 4.7. Sales of winter products within intended season as a percentage of the initial allocation divided by store and grouped by climate region. The red bars show the average of the climate region.

Additionally, despite a much colder winter, the data from 2023 points in the same direction as the 2024 data. The 2023 season sold larger volumes early in the season, limiting need for price reductions and increasing revenue. However, the same symptoms are observable at the end of the season, only partially alleviated by the increased volumes. This shows that the period investigated is more representative than anticipated.

5.2.2 Replenishment

This subsection analyses and discusses the contribution of design choices in the replenishment process, such as the static reorder level and the failure to account for lost sales, to the stock imbalance.

Static Reorder Level

The replenishment works largely as intended. Well founded forecast methods are used to project future sales to keep the stock at desired level. The forecast methods are based on early sales data, which is in line with what the literature review suggests for seasonal products. The forecast methods themselves are however not quite in accordance with the literature for low demand products, that suggest using heuristics and negative binomial models. That said, they do aggregate the forecasts which is consistent with the literatures advice for situations like Sports Inc.'s. The aggregation increases the demand per forecasted item and improves the chance of accuracy. However, while the replenishment succeeds in keeping stores at the desired stock level, the reorder level itself remains static and unadaptable, meaning that it is fixed and does not change in response to sales.

Currently, the reorder level is only updated manually, and no forecasting or other data driven solutions are employed towards this purpose. Stores are replenished to the initially decided point, no matter how they are performing. This reinforces the balancing issues caused by the initial allocation. A store with a high relative reorder level is restocked at that level no matter the rate at which they are selling. The same is true for a store with a low relative reorder level. This means that if a store received a lot in the initial allocation but sold little, the system still tops them back up, even though the rate of demand is low. Conversely, stores that had a low initial allocation but have had high sales, may not receive sufficient replenishment if their reorder level is set too low. This approach makes low performing stores, with high reorder level, stock too much, while high performing stores with low reorder level will be stocked to low. This is especially true when the central warehouse is out of stock, the low performing stores will be stuck with leftover stock while the high performing ones will have sold out.

Accounting for Lost Sales

Another limitation in the forecasting and replenishment process, is the failure to account for lost sales. This is according to the literature, as shown in Section 2.4, a very important aspect of obtaining an accurate forecast. Not accounting for censored demand leads to potentially misaligned forecasts and thus further missed sales opportunities. If this issue is not tackled, it risks reinforcing a feedback loop of suppressed demand. For Sports Inc., the usefulness lies in approximating demand during short term stockouts within season, but also for updating demand seasonal demand to better align planning for next season.

5.3 RQ3

This section presents suggested improvements to the identified process stages, with the aim of reducing the balancing issue.

5.3.1 Initial Allocation

This section suggests improvements to previously discussed process stages related to the initial allocation, to minimise the balancing issue.

Minimum Value

We have established that the minimum value exceeds predicted sales in many cases, causing small stores with lower store grades to have excessive initial allocation volumes. The reasoning behind the minimum value is often to provide each store with a full range of sizes, even if the allocated volume then exceeds the total sales of the product for the season. Store managers also argue that full size ranges need to be available in store at all times to satisfy potential customers. There are two main pathways to go down to reduce (or remove) the minimum value. Option one entails cutting fringe, or half, sizes from the assortment. Alternatively, if maintaining all sizes in stock is deemed too important for long term customers satisfaction and retention, the width of the assortment can instead be reduced in terms of number of products. Limiting the sales budget to fewer variants means each variant has a higher budget, allowing for all sizes while still staying above the minimum value. This is reflected in the practices of Home Inc. By working with fewer product variants, Home Inc. achieves higher sales volume per item. While Home Inc. and Sports Inc. may allocate a similar quantity per specific product initially, the proportion of initial allocation relative to total sales is significantly lower at Home Inc. This means Home Inc. is unlikely to sell less than its initial allocation over the course of a season, thereby reducing the risk of overstock at the end of the season. This is a situation shown to commonly occur at Sports Inc. The Home Inc. example demonstrates how a lower number of variants can enable a more restrictive, and thus more flexible, initial allocation strategy.

There are potential hazards with both assortment reduction options for Sports Inc. Removing end sizes will limit small stores' ability to service the entire customer base. This could drive customers seeking the removed sizes away from Sports Inc., towards the competition. On the other hand, these sizes sell so rarely in these stores that it might still be beneficial. By not stocking end sizes in small stores, that most often have to be sold at a discount after season end anyway, they can be sold at a higher prize in larger stores. In the case of half sizes, the ideal outcome is that customers simply buy half a size up or down. There is, however, the risk of customers choosing competition in this case as well. It is important to note that Sports Inc.'s smallest stores are located in smaller cities that do not offer much competition. If so, it is often online or in another city, where Sports Inc. can compete with their own online or larger store assortment. This makes the competition scenario unlikely. Especially if the small store utilises the online assortment by offering to order that for the customer.

Alternatively, reducing the number of product variants while retaining the size range presents similar problems. Firstly, store managers and assortment builders at Sports Inc. assert that a varied assortment is important for building an appealing store demonstration. This means that reducing the assortment could negatively impact the store's customer appeal and therefore sales. Customers not finding what they are looking for might go to competitors instead. However, the same reasoning previously used for missing sizes can be used here as well. If the online assortment is used effectively, this should be a small problem.

Sports Inc. already utilises store grades to differentiate the assortment width across stores. Stores with lower grades receive a more limited product selection. However, the data analysis demonstrates that the current state is not enough. The principle should therefore be extended further through one of the approaches outlined above. This could be done either by further reducing assortment width in low store grades, or by extending the store grade differentiation to include the number of sizes. Either of the discussed strategies, or a combination thereof, could effectively avoid an initial allocation exceeding total sales within the season. Ultimately, by rethinking the use of minimum values, Sports Inc. can better align initial allocation with demand. This would reduce excess stock, limit markdowns, and improve inventory balance across the store network.

Internal and External Factors

Although the data analysis shows that the balancing issue was not an effect of weather, other internal and external factors still influence the accuracy of the initial allocation. Firstly, left over stock from previous seasons needs to be taken into account. This can be done by simply linking products from previous seasons to their replacements the coming season in the system. By doing this the stock becomes visible and the initial allocation can be planned accordingly. Secondly, a process for including circumstantial changes within the 6-8 month planing period needs to be crafted. This could for example be done by incorporating a system function that allows store managers to report relevant changes that could impact the upcoming season's sales. For more overarching changes, such as the rise of the Danish currency relative to the Swedish driving cross-border shopping, a central function might be necessary. Implementing these functions will, of course, come with a cost. However, the time consumption is likely minimal and the system implementation small. This means that the costs incurred are likely to be outweighed by the benefits.

Implementing updated information into the initial allocation process could be useful in several scenarios. The idea is to include updated information about events that have occurred between the time of placing the order, typically six to eight months before the season, and the actual start of the season. Doing so would allow recalibration and adjustment of the initial allocation to better reflect updated local conditions, either by a reduction or an increase in a store's initial allocation. For example, planned construction work outside a store may lead to lower foot traffic and reduced sales potential compared to what was budgeted. If this is reported in time, it can lead to a lower initial allocation, which reduces the risk of overstocking and prevents excess inventory from being tied up in the store in question. The stock can then be used more efficiently in other stores. However, if the negative effect is overestimated, the adjustment can instead result in missed sales and customer dissatisfaction. To report new information can also be important in the opposite case. For example, updated currency policies could increase the shopping cross border. By reporting this in time, higher initial allocation can help to maximise sales, by avoiding early stockouts for these stores. But, if the newly predicted sales increase is not as high as anticipated, the store will likely be left with surplus inventory at the end of the season. This is backed up by the empirical data, showing that a high initial inventory correlates with a high stock at the end of the season.

These examples show the potential of combining local knowledge, with a structured system for collecting updated information. This would allow for more accurate and informed decisions for the allocation and replenishment strategy. By including and acting current information and hence being more flexible, Sports Inc. could reduce the risk of some stores being overstocked while others face shortages. This directly addresses the underlying balancing issue by improving the accuracy of the initial allocation. However, for this approach to work, new systems and routines need to be implemented and compatible with the current allocation system. It would also require the system to support flexibility within a relatively short time frame before the season begins. Another important aspect of this is how the store managers, carrying the local knowledge, are incentivised. If their performance is judged solely on their sales targets, they may be unwilling to report information that could lead to reduced allocation, even when it would improve the overall balance in the supply chain. An incentive system should, therefore, recognize good forecasting accuracy and contributions to inventory efficiency, not only the sales performance.

5.3.2 Replenishment

This section suggests improvements to previously discussed process stages related to the replenishment, to minimise the balancing issue.

Static Reorder Level

The static approach currently used for the reorder level reinforces the balancing issue originating from the initial allocation. To alleviate this issue, the reorder level should be dynamically adjusted based on recent sales patterns. The same methods currently utilised for forecasting, to identify need for replenishment relative to the reorder level, can also be applied to improve the reorder level itself. This dynamic approach aligns with the practices of retailers like Dillard's and Zara, as discussed in the literature review. Both companies significantly improved their sell-through rates and inventory efficiency by updating allocation decisions in real time. Similarly, Home Inc. employs a semi-automatic order planning system that dynamically adjusts desired stock levels based on both historical sales data and expected campaign performance. This enables a more responsive replenishment process. It should be noted that their higher per-product sales volume also allow them to accumulate reliable sales data earlier in the season, increasing the effectiveness of the approach.

Dynamically adjusting the reorder level would allow Sports Inc.'s replenishment process to gradually correct the imbalances created by the initial allocation. reorder levels could be lowered for underperforming stores and increased for higher-performing stores, helping to achieve a more balanced stock position by the end of the season. However, this approach comes with a risk, where if replenishment is reduced too much for underperforming stores, the forecast may suggest stopping replenishing some sizes entirely. This could result in a broken assortment, which could negatively impact the sales of other sizes or products still in stock, further lowering overall performance. At the same time, it reduces the risk of ending the season with large stocks that need to be sold to high price reductions. It is a trade-off between minimising excess inventory and maintaining a complete and appealing assortment throughout the season.

To successfully implement dynamic adjustment of the reorder level, Sports Inc. would need to ensure access to timely sales data as well as system support for the calculations. The data is already available as it is used for current forecasting. The system support for the calculations is also in place, again because it is already used. However, it remains unclear whether the system supports automated updates to the reorder level, as adjustments are currently performed manually. This is a potential limitation that would need to be addressed. The dynamic approach does introduce a risk of overreacting to short-term fluctuations, especially for low-demand items as is the case for Sports Inc.. To mitigate this, safeguards such as minimum adjustment thresholds or time-based smoothing could be applied. Such measures would reduce the likelihood of overfitting forecasts, and thus reorder level, to early sales data and help prevent unnecessary inventory movements. Clear ownership of the process, whether managed centrally or through automated logic, would also be essential to maintain consistency and avoid unfavourable inventory swings.

Accounting for Lost Sales

As previously discussed, accounting for lost sales data would improve Sports Inc.'s ability to produce accurate forecasts, both short and long term. The literature suggests methods such as using sales data from similar products, regional demand trends, cross-store sales comparisons, intra-day sales patterns, and size substitution. Among these, cross-store sales comparisons, utilising sales in similar stores to approximate lost sales, appear most suitable for Sports Inc.. Since sales and stock levels are tracked centrally, it would be feasible to estimate lost sales by comparing stores that remain stocked with those that sell out early. This approach requires minimal system changes and would provide valuable insights into true demand. Size substitution analysis also has potential, particularly for size-intensive product categories like shoes. This method could help estimate unmet demand when one size sells out. In contrast, a technique such as intra-day sales pattern analysis are less applicable. Sports Inc. does not currently utilize intra-day sales data, and the demand is also so low on a daily basis that it would likely not yield any insights. Regional demand trends sales may also be effective. However, due to the non-existent relationship between regional climate and demand observed in the data as well as the large size difference between stores within a region, regional demand trends are unlikely to provide better results than cross-store comparisons. Lastly, utilising similar products to approximate lost sales is also an option. There is however likely a reason why one product is sold out and another is not, meaning that their demand patterns are unlikely to match. To summarise, cross -store sales comparisons is likely Sports Inc.'s best bet if they were to choose a single demand censoring technique. Although they could probably achieve even better results, meaning more accurate forecasts and avoiding a systematic cycle of underestimating demand, by combining two or more of them.

An important note to make is that if you are to aggressive with your demand censoring technique, you risk double counting. Let's say that a customer instead of buying from a competitor or not at all when an item is out of stock, they buy from another Sports Inc. store nearby. This purchase is then included in the actual sales data, while also potentially being counted in lost sales data. The same scenario can manifest itself when a customer simply chooses to postpone their purchase until the item is back in stock. To avoid overestimating lost sales in these scenarios, it is important to have a firm grasp of what percentages of customers requesting an out of stock item actually lead to a customer buying from elsewhere. To obtain this knowledge, consumer pattern research is necessary.

5.3.3 Alternative strategies

There are other strategies that can be employed to limit the impact of the balancing issue on revenue, rather than solving the problem as such. Two of them, end-of-season consolidation and store-clearing order fulfilment, are outlined in this subsection.

End-of-Season Consolidation

One potential strategy, is end-of-season consolidation. This is a strategy where leftover inventory is gathered from multiple stores, and sent to a smaller set of stores with high sales volume. The strategy leans in to the imbalance rather than trying to move away from it, reaping the benefits of being able to offer a full assortment for longer. The approach is supported by Smith and Agrawal (2017), who mention that when demand is inventory dependent, for example shoes and other size sensitive products, the overall demand and profitability can be increased by concentrating stock into fewer stores. Their model shows benefits of avoiding the broken assortment effect, while at the same time enhancing the presentation effect. This aligns with the thoughts from Sports Inc.'s store managers, who also see this as an important factor for the sales performance of the stores. According to Smith and Agrawal, prices would be allowed to remain stable for a longer period when consolidating to fewer stores, potentially increasing the margin and revenue. However, they also mention that over consolidating can lead to missed sales in now unstocked stores, leading to lost customer reach and revenue, which also would be a risk for

Sports Inc.. The study shows that in many cases, it can be beneficial to consolidate to fewer stores to some degree. For this to be relevant to Sports Inc., they would need to compare the potential increase in margin, with the additional costs that would arise. The additional costs would not only be the potential missed sales, but also the operational costs that arise when consolidating. Costs for processes such as handling, packaging, and transport. A way to mitigate these additional costs could be to coordinate a store's shipments to a specific day, for example a couple of weeks before the end of the season. This could allow for larger packages to be sent more efficiently, reducing the administration and transportation cost per unit. Consolidating inventory to fewer stores may not be beneficial for all products, but for selected seasonal items with many sizes or fragmented assortment, this could lead to a more complete offering in key stores.

The outlet store that Sports Inc. is considering opening presents an additional opportunity. Instead of redistributing inventory across the regular stores, selected stock could be transferred directly to the outlet. This could both simplify the logistics process, and also allow for markdowns without impacting brand perception in full price stores. A single sell-out point, such as the outlet, would make it easier to coordinate bulk shipments and manage them efficiently. Even more so as it will be connected to the central warehouse. Given the high markdowns which can be seen in overstocked stores, both consolidating into high grade stores and to an outlet could be relevant strategies to handle the effect of the end-of-season balance to decrease the price reductions.

Store-clearing order fulfilment

Another strategy that can be worth considering relates to how online orders are fulfilled during the end of the season. If a store only holds a few remaining sizes of a product, and the central warehouse holds the same sizes or not enough to restore a full range of sizes in the store, it may be more beneficial to fulfill online orders directly from the store. This would help clear out the last few pairs from the stores with broken assortments, instead of using the warehouse stock to replenish a store that cannot offer a complete selection. The remaining inventory in the central warehouse could instead be redirected to a high performing store with a more complete size assortment, or to the outlet, which may be able to offer the full range for a longer time. This approach would reduce the number of stores with incomplete assortments to support a more effective clearance strategy. It would avoid unnecessary partial replenishments, and let the product be sold in a setting where it is more likely to be valued by customers. Hence, a higher price could be asked. However, fulfilling online orders from stores is typically more labour intensive compared to using the company's automated warehouse. For that reason, this strategy should be applied selectively, when the value of clearing out fragmented store stock outweighs the additional order fulfilment costs.

6
Conclusion

This thesis examines why stock imbalances occur in seasonal retail by looking at the inventory process at Sports Inc. It identifies which parts of the process cause the balancing issue and how the process stages can be changed to minimise the issue.

Initial allocation and replenishment are identified as key contributors to the balancing issue. The data analysis consistently links these processes to end-of-season imbalance. Within the initial allocation, the minimum value is the main issue. High minimum values drive over allocation in small stores. Another contributing factor is the lack of updating changes and assumptions during the planning window, meaning that the allocation does not reflect current circumstances. Regarding the replenishment, the main issue is that the process operates with a static reorder level which reinforces imbalances from initial allocation. Another shortcoming of the replenishment process is the failure to account for lost sales, this contributes to sub-optimised forecasting by lowering data accuracy.

To minimise the negative effects of these processes we suggest the following changes. The issues with the minimum value can be reduced by further reducing assortment width in low store grades and thereby increasing per-product volume. Alternatively, it can be done by reducing the size range in low store grades. A practice of updating store conditions, e.g. construction, prior to initial allocation should be set up. Additionally, stock from previous seasons should be systemically included by linking the product to its replacement.

To allow the replenishment process to correct possible misalignments from the initial allocation a dynamic reorder level needs to be adopted. This can be updated with the same data and methods currently used for forecasting. Moreover, censored demand should be included to improve forecasting. This can be done by utilising cross-store comparisons, approximating sales by looking at similar stores' sales.

In addition to improving the initial allocation and replenishment logic, two alternative strategies could mitigate the effect of imbalance, rather than solving the issue as such. First, end-of-season consolidation, where remaining inventory is redirected to a smaller number of larger stores. This strengthens the presentation effect, reduces excessive markdowns and supports continued sales at higher margins. This is an even more viable option if you consider the upcoming outlet. Given size and proximity to the central warehouse, logistics would be greatly simplified. Second, fulfilling online orders directly from stores with broken assortments can accelerate local stock clearance while preserving warehouse inventory for more strategic use. Both strategies improve flexibility in the latter part of the season and support a more efficient sell-through of seasonal goods.

In conclusion, this thesis has shown that stock imbalance in seasonal retail is primarily driven by static planning logic within the initial allocation and replenishment processes. By introducing more dynamic elements, such as adaptive reorder levels and further deepening the store grade differentiation, Sports Inc. can significantly reduce the imbalance. Complementary strategies like end-of-season consolidation and store-level fulfilment of online orders offer further means to mitigate the consequences when imbalance still occurs. Together, these insights provide a foundation for improving both operational efficiency and financial performance in future seasons.

7
Future Research

There are several paths to go down regarding future research in relation to this thesis. One avenue concerns the alternative strategies suggested, end-of-season consolidation and store-clearing order fulfilment. Future research could assess the practical viability and economic impact of these strategies. For example, a pilot program testing store-based fulfilment of online orders could evaluate its effect on clearance rates. Similarly, the potential benefits and trade-offs of consolidating residual stock to selected high-performing stores or outlets could be analysed in terms of markdown necessity, sales velocity, and operational complexity. Moreover, the optimal point within the season to initiate these concepts is an interesting query. Addressing these questions would help determine whether such strategies provide a viable complement to the other structural process changes suggested in this thesis.

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A
Appendix 1

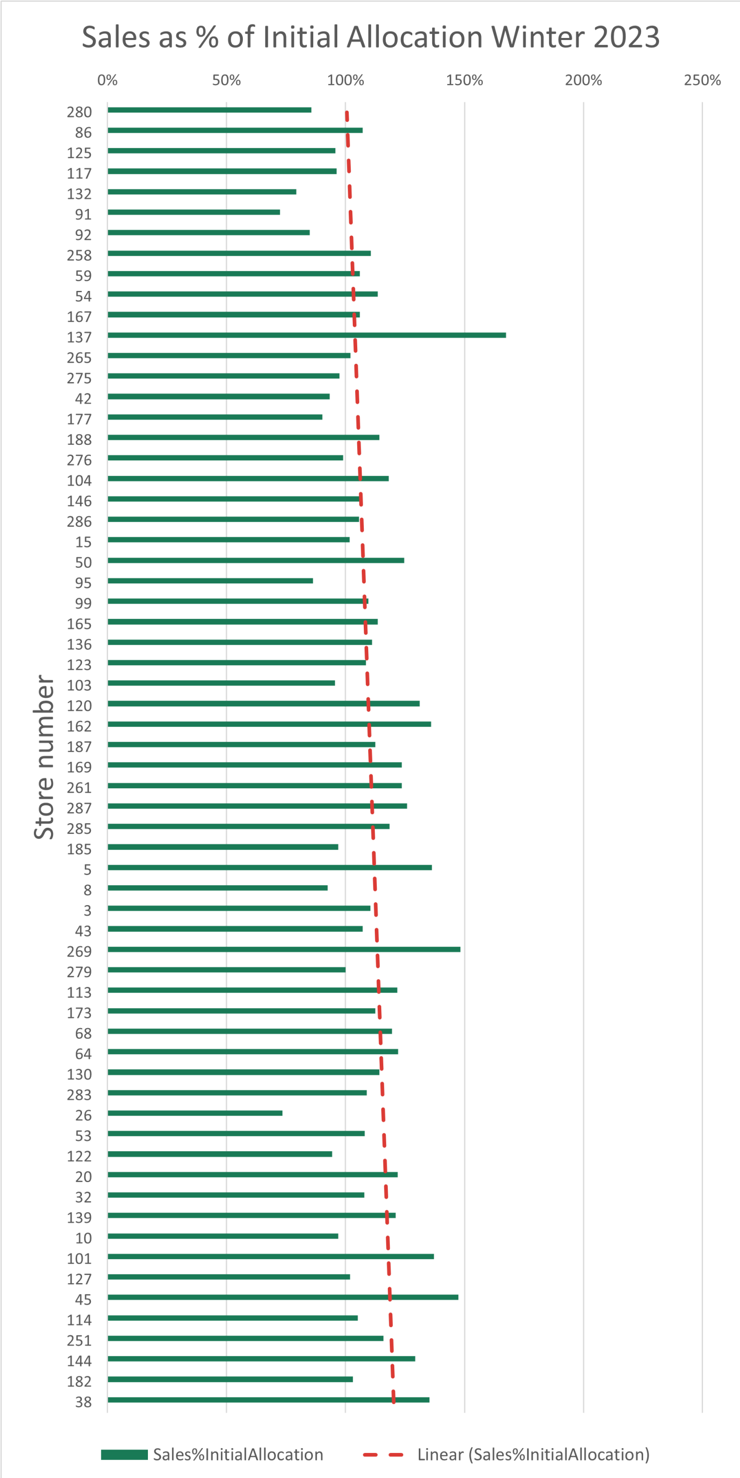

Figure A.1: Sales of winter products 2023 within intended season as a percentage of the initial allocation by store, with stores ranked in ascending order of their average store grade.

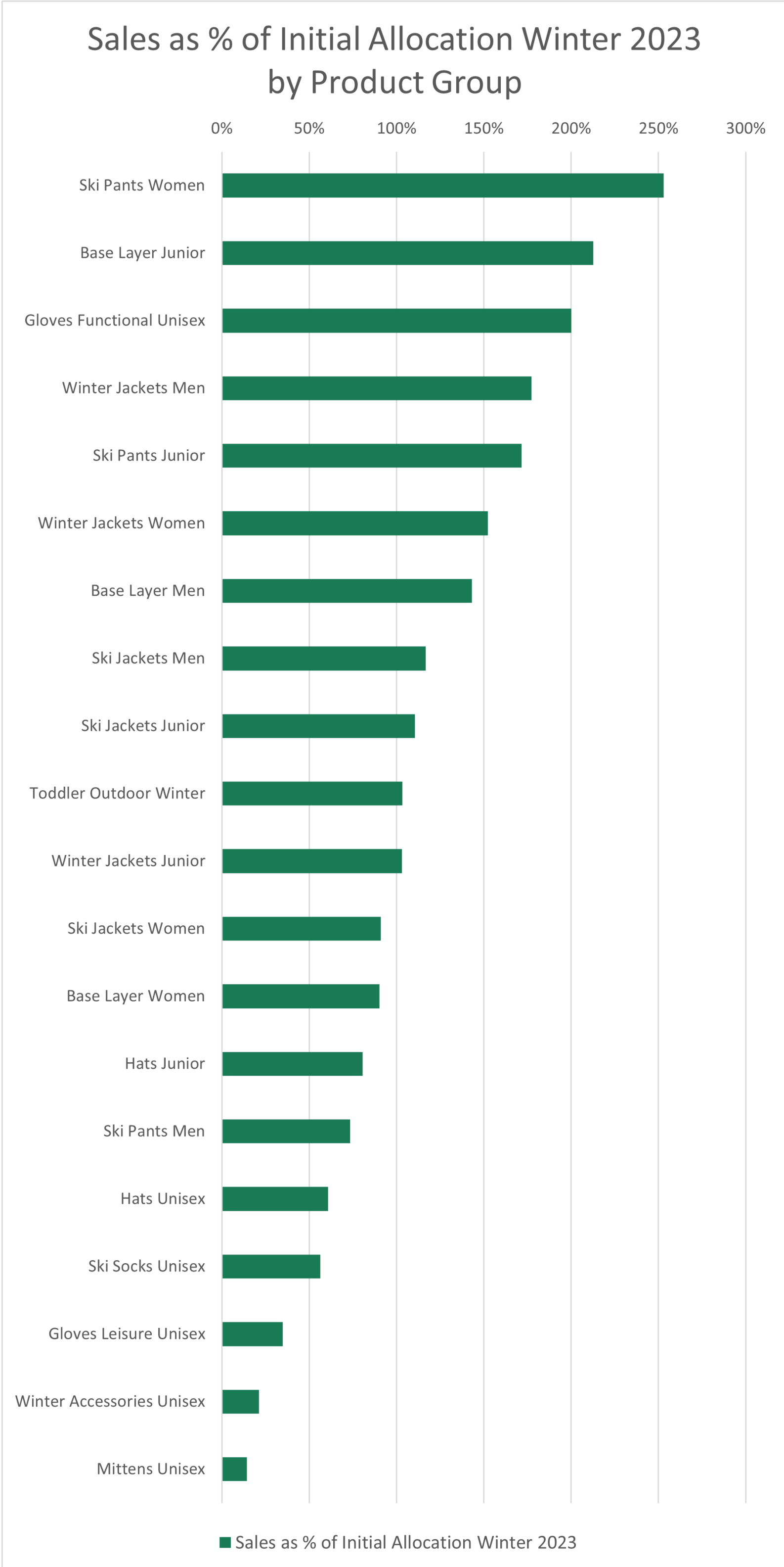

Figure A.2: Sales of winter products 2023 within intended season as a percentage of the initial allocation by product group.

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