MASTER

The Influence of Distribution Center Stock Outs on the Product Availability in the Stores

Verhoef, Vincent H.

Award date:
2022

The Influence of Distribution Center Stock Outs on the Product Availability in the Stores

By V.H. (Vincent) Verhoef

BSc Industrial Engineering and Management Science -- TU/e 2020
Student identity number: 1023282

In partial fulfilment of the requirements for the degree of

Master of Science
in Operations Management and Logistics

TU/e Supervisors
1st supervisor: dr. K.H. (Karel) van Donselaar
2nd supervisor: dr. W.L. (Willem) van Jaarsveld

Company Supervisor:
MSc T. (Thom) Brand

TU/e, School of Industrial Engineering
Series Master Theses Operations Management and Logistics

Subject headings: distribution center, stock outs, key performance indicators, multiple linear regression, (pre)-allocation, mixed-integer linear programming

Abstract

This research is executed in collaboration with a Dutch Supermarket Chain (DSC). DSC experiences an increasing amount of stock outs at the distribution centers (DCs) that are often caused by supplier problems (50 to 60%). DSC, however, has limited insights on the effect of the DC stock outs on the stores. This research aims to find how dispatchers at the DC can be supported to limit the effects of the DC stock outs on the stores. To answer this main research question, four distinct stock out characteristics were identified by the use of literature, like the *breadth, frequency, duration*, and *intensity* (i.e. lost sales / lost revenue). Especially the *breadth* and *frequency* KPI were found to be easy to apply and insightful to test the effects of DC stock outs. This KPI for example showed that most DC stock outs occur during the weekend, where DC stock outs starting on Saturday have the highest store out of stock rate of around 38%. In addition, a multiple linear regression model was developed to find significant drivers behind the stock out characteristics. This analysis found that primarily the weekday that the DC stock out starts and the demand velocity are important drivers. Finally, a mixed-integer linear programming model was developed to test the potential of optimizing the allocation of the remaining DC inventory before it goes out of stock. Compared to the current situation an overall revenue increase of around 8% was found, while also decreasing the overall store OOS rate from 24% to around 17%, depending on the model objective. All in all, multiple insights are presented to make DSC aware and be able to cope with the effects of DC stock outs in a smarter way.

Management Summary

This Master's Thesis is conducted at a Dutch Supermarket Chain (DSC), a discounter with the objective to deliver the highest quality products for a low price. In the Netherlands, DSC operates six distribution centers (DCs) that together supply around 420 retail stores.

Project Definition

DSC experiences an upward trend in the number of DC stock outs, where around 50 to 60% are caused by supplier problems and therefore most DC stock outs are often inevitable for DSC. The currently applied key performance indicators (KPIs) provide DSC with very limited insights into the effects of DC stock outs on the product availability in the stores. As result, it is hard for the dispatchers to be actively involved in decreasing these effects. Therefore, DSC is interested in finding KPIs that keep track of both the performance of DC and store stock outs. When such KPIs are determined and the insights have been analyzed, DSC wants to know how these insights can be used to improve its performance and support its dispatchers. Most DC stock outs at DSC are found in the long-life assortment and are therefore selected as the product group of interest. Based on this problem definition, the main research question is defined as follows:

How can the dispatchers be supported to minimize the effects of stock outs in the DC on the in-store product availability?

A literature study with a focus on identifying important elements relevant to stock outs for various supply chain actors had been conducted. This study showed that stock out literature primarily focuses on finding causes at the store level, which likely happens due to the finding that approximately 70% of the store stock out situations happen due to in-store causes (Corsten & Gruen, 2003; ECR Europe, 2003; Gruen, Corsten, & Bharadwaj, 2002). On the other hand, it was found that synchronization and communication in the supply chain are important levers to avoid out of stocks in the store (Moussaoui, Williams, Hofer, Aloysius, & Waller, 2016). Despite this finding, the research found on describing the interaction between both the DC and store actors was very limited.

Research Design

DSC is aware of the limitations of the in-store registered stock outs. Therefore, it has been chosen to estimate the store stock outs during the DC stock outs by using point of sales (POS) data. This method only works for fast-moving products and therefore only DC stock outs for the 200 fastest moving SKUs have been selected. Based on a sensitivity analysis, it was decided that if a DC stock out starts and a store has not registered any sales for 10 straight hours, a store stock out will be noted. Ultimately, this results in a total set of store stock outs during the selected DC stock outs. This created set will be used to test the performance of DSC's current situation.

Based on the literature review, a set of KPIs was found to express the performance of different stock out characteristics. First of all, the fill rate was identified as the most common way to measure the customer service level (Teunter, Syntetos, & Babai, 2017), which is defined as 'the percentage of demand which can be fulfilled directly from inventory on the shelf' (Broekmeulen & van Donselaar, 2017). In addition, the following four measures I) *breadth*, II) *frequency*, III) *duration*, and IV) *intensity* were found (Gruen & Corsten, 2008). An overview of the measures can be found in the table below.

Attribute	Measure
Breadth	$\frac{Number\ of\ different\ stockout\ items}{Total\ number\ of\ items\ in\ assortment}$
Frequency	$Item\ stockout\ frequency$
Duration	$Total\ time\ an\ item\ is\ out\ of\ stock$
Intensity	$\frac{Total\ unit\ sales\ lost\ due\ to\ an\ stockout\ item}{(Total\ units\ sold+units\ sale\ lost)}$
	$\frac{Total\ monetary\ loss\ due\ to\ stock\ outs}{Total\ monetary\ sales+Loss}$
Fill rate	$\frac{Total\ units\ sold}{Total\ demand}$

Based on the literature review and interviews with employees from the supply chain department at both DC and HQ levels, drivers were identified that could influence the above mentioned stock out characteristics. Another goal of these interviews was to find the stock out characteristics with the best fit to DSC's overall objective. Eventually, the influence of the identified drivers on DSC's main objectives was tested with a multiple linear regression model.

Finally, the performance of an optimized final allocation for the remaining DC inventory was tested. The model performance based on two different kinds of objectives were tested. First of all, DSC expresses itself as a very revenue-driven organization and therefore one objective is to maximize the sales during DC stock outs. On the other side, DSC is aware of the importance of product availability. Therefore, the second objective is focused on reducing the number of stores going out of stock during a DC stock out. The performances of the different objectives were compared in terms of the KPIs defined above.

Results

All of the defined KPIs were tested on the estimated store stock outs in times of a DC stock out. First, the *breadth* KPI was not found to be very applicable to the goal of this research. The following formula, however, is an adjusted version of the *breadth* KPI which was found to be a practical and useful KPI to describe the effect of a DC stock out on the stores. This formula is from now on referred to as *store OOS rate:*

$$\frac{Number\ of\ stores\ out\ of\ stock}{Total\ number\ of\ stores}$$

Based on the estimated store stock outs, it was found that, on average, 34% of the stores face a stock out when the DC goes out of stock. In addition, a DC stock out starting on either Friday or Saturday faces the highest store OOS rates, with approximately 38%.

Next, the *frequency* KPI showed that most DC stock outs are caused by SKUs in group 43, followed by group 72. This KPI also addressed a week pattern for the DC stock outs, where the number of stock outs starts increasing at the end of the week with the largest peak on Monday. This pattern can be explained by the fact that there are no supplier deliveries on the weekends, and thus on Monday, there might not be sufficient DC inventory left to fulfill all store orders.

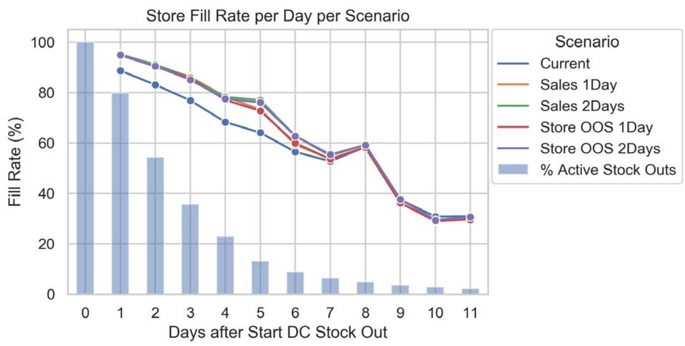
By taking the start difference of the stock outs between the DC and store actors, the *duration* KPI has been applied. This application showed that DC stock outs starting on Monday and Tuesday have, on average, the lowest start difference, where Friday and Saturday take the longest to be felt in the stores. Regarding the product groups, groups 43, 41, and 83 tend to have, on average, the lowest start difference between a DC and store stock out. This seems to occur due to small store spaces relative to their demand velocity.

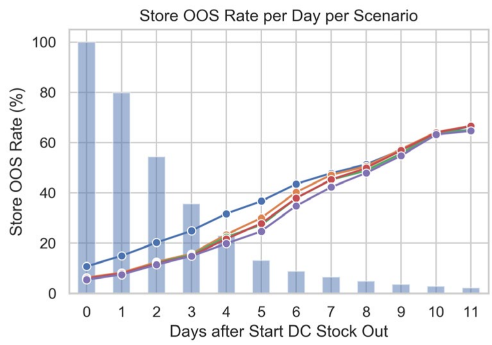
Finally, it was found that the *intensity* and *fill rate* KPI are relatively similar in their measure. Group 63 was found to have, on average, the stock outs with the highest lost revenue, followed by group 84. The highest lost sales, however, are caused by group 47, followed by group 63. This might indicate that some product groups require a potential higher stock on hand in the DCs to avoid costly DC stock outs.

The second main part of the results is the regression analysis. The identified drivers were tested on a set of different dependent variables. For each regression model both demand velocity and starting weekday of the DC stock out were found to be important drivers. The higher the demand velocity, the higher the expected lost sales and lost revenue, though the lower the DC stock out duration and store OOS rate. Regarding the weekdays, DC stock outs starting on Friday and Saturday were found to have the longest duration and also result in the highest amount of stores going out of stock. On the other side, DC stock outs that affect stores starting on either Wednesday or Thursday are the costliest, although, the differences compared to either Friday or Saturday were not found to be that large.

Finally, when implementing an optimized allocation of the remainder of the DC inventory, an improvement in the fill rate, revenue, and store OOS rate is found. A visualization of the improvements regarding the fill rate and store OOS rate can be found in the two figures below. For the total set, a revenue increase of approximately 8%, where for both the fill rate and store OOS rate the improvements are approximately 7% point, depending on the applied objective. For DC stock outs lasting between 3 and 8 days, it could be beneficial to apply a 2-day DC inventory allocating. Though, with at most a 4% point increase in comparison to the Sales 1Day scenario, the benefits are limited.

Especially for the SKUs with the highest demand velocity, the model showed a large revenue increase of approximately 11.5%, whereas the slower movers have an increase of around 7.5%.





Recommendations

Based on the obtained results, the following points describe the recommendations for DSC:

- Investigate the possibility to start accepting supplier deliveries during the weekends. This will help to prevent the peak in DC stock outs during these days. It is advised to start small with a selection of the groups with the most expensive DC stock outs during the weekend. The top 3 of these are groups 43, 44, and 45 (<u>*Appendix B: Additional KPI Figures).*</u>
- Consider implementing additional KPIs for stock out situations. The *frequency* KPI can help to gain more insights into the patterns of DC stock outs. In addition, the *store OOS rate* or *fill rate* can help to gain more understanding of the effect DC stock outs have on the store.
- Implement the proposed model for optimizing the allocation of the remaining DC inventory when the dispatchers note that a DC stock out will occur. It is advised to start with a pilot focused on the fastest moving SKUs since for these SKUs most benefits are expected.

Prologue

This Master's Thesis marks the end of my Master Operations Management and Logistics, ending a beautiful period full of hard work with ups and downs. This also ends my life as a student, but I am ready for the new challenges that lie ahead. Before heading to the body of this Master's Thesis, I would like to thank some people, because without them writing this Master's Thesis would not have been possible.

First of all, I would like to thank my first supervisor and mentor Karel van Donselaar. Thank you for connecting me to Thom, and creating a great opportunity to conduct my Master's Thesis at DSC. Thank you for always being there to provide support and feedback. Your experience, knowledge, and critical view have helped to improve the quality of this report. Next, I would like to thank my second supervisor, Willem van Jaarsveld. Your feedback gave me new insights and opened opportunities for improvement.

Of course, writing this Master's Thesis would not have been able without the help of the people from DSC. In special I would like to thank my company supervisor, Thom Brand, for providing this opportunity, your feedback, and (practical) insights throughout my Master's Thesis. Also many thanks to the other people from the supply chain team at both the headquarters and DC 5 for welcoming me and answering my questions.

I want to give a special thank you to my girlfriend for her endless and continuous support by listing to my struggles and reviewing parts over and over. Moreover, I want to thank my parents who have always supported and believed in me. Finally, I would like to thank my brothers and sister, friends, and roommates for their support during both my studies and my Master's Thesis.

Vincent Verhoef

Eindhoven, May 2022

Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Meaning
CU	Consumer Unit
DC	Distribution Center
DSC	Dutch Supermarket Chain
FMCG	Fast Moving Consumer Goods
HQ	Headquarters
MILP	Mixed-integer Linear Programming
MIS	Management Information System
OLS	Ordinary Least Squares
OOS	Out of Stock
POS	Point of Sale
PP	Percentage Point
SCM	Supply Chain Management
SKU	Stock-Keeping Unit
SOH	Stock On Hand
VIF	Variance Inflation Factors

Part 1. Project Definition

1 Introduction

This Master's Thesis project has been conducted at a Dutch Supermarket Chain, which will be referred to as DSC throughout the report. This first chapter serves as an introduction to both the company and the structure of this report. For confidentiality reasons, all results in this Master's Thesis are scaled with a factor known by DSC and the names of the product groups are left out. In addition, some appendices are intentionally left out of the public version.

1.1 Company Description

DSC is a multinational company with the goal to deliver the highest quality products for the lowest prices, both focused on food and non-food products. They have dispersed over 33 countries, which are mainly European countries, but they are also active in the United States. In total, they have around 11,200 stores employing over 300,000 people. Within the Netherlands, DSC has over 430 stores spread throughout the country, which are restocked by one of the six distribution centers (DCs). Furthermore, the Dutch branch employs over 19,000 people.

1.2 Report Structure

The goal of this project is to find solutions to the practical problems experienced by DSC. To be able to formulate a clear business problem and provide structure in solving such problems, the iterative steps of the problem-solving cycle as defined by van Aken, Berends, & van der Bij (2012) are used. In general, companies face a problem mess of interrelated problems (van Aken et al., 2012). Given this, the first step of the problem-solving cycle is to define a clear problem definition. The second step consists of analyzing the problem, its context, and diagnosing the causes of the problem. The next step is to provide a solution design, which should be designed such that it solves the most important problem causes. Within this step, also the implementation of the solution should be given. The problem-solving cycle as described by van Aken, Berends, & van der Bij (2012) concludes with an intervention and learning/evaluation steps. Though, these final two steps are out of the scope of this research.

The structure of this report is based on this problem-solving cycle and consists of four parts. The first part, the project definition, includes the first two chapters. Chapter 1 will present a general introduction to this research and covers the research motivation for the defined problem faced by DSC. Chapter 2 will follow up with DSC's desired goal, along with the scope and fitting research questions. The second part of this research will cover the research design. For each sub-question, the applied methodology and assumptions will be discussed (Chapter 3). Next, Chapter 4 will cover the data selection and cleaning phase. This second part closes with the description of the methodology for estimating the store stock outs (Chapter 5), which is required for testing the performance of the current situation. The third part covers the results, which consist of Chapters 6 till 10 which all represent a certain sub-question. Chapter 6, 7, and 8 mainly focus on analyzing the current situation, performances, and desires of DSC. Next, Chapter 9 focuses on finding significant drivers of product availability and Chapter 10 presents the results of the designed model. The final part will cover the conclusions and recommendations and consists of two chapters. Chapter 11 will present the conclusions to the research questions and the contribution to the literature. Finally, in Chapter 12 the recommendations for DSC will be given and will close with the limitations, and directions for future research.

1.3 Research Motivation

As mentioned in the introduction, DSC differentiates itself by delivering the highest quality of products for a low price. DSC is also known for its relatively bounded assortment although over the last years DSC has been expanding its assortment by adding branded items and product variants. Nevertheless, compared to its competitors, the assortment offered by DSC is still way smaller. As a result, when one of DSC's products goes out of stock, there are limited substitutes for their customers. The problem for DSC is thus that stock outs for a certain product will likely have a larger impact on the customer experience compared to stock outs at their competitors. It is therefore important for DSC to minimize the frequency of stock outs.

As stated by several sources, approximately 70% of the store stock out situations happen due to in-store causes, like ordering mistakes or inaccurate inventory levels (Corsten & Gruen, 2003; ECR Europe, 2003; Gruen et al., 2002). The remaining 30% of the store stock out situations will originate somewhere upstream, i.e. due to disruptions at the supplier, miscommunication at the headquarters, or forecast failures at the DC (Moussaoui et al., 2016). Often, this will first result in a stock out at the DC level. Based on data in internal reports, the average monthly stock outs in 2020 and 2021 for all DSC its DCs are plotted in Figure 1.1. At the start of 2020, a large peak in the DC stock outs can be noticed which is caused by the start of the Covid-19 pandemic. After this peak was resolved, a moderate upward trend of DC stock outs can be observed. DSC experiences that the Covid-19 pandemic has caused several disruptions in the supply chain, for example, due to the high absence of employees at their suppliers the production and/or the transport of goods lags behind.

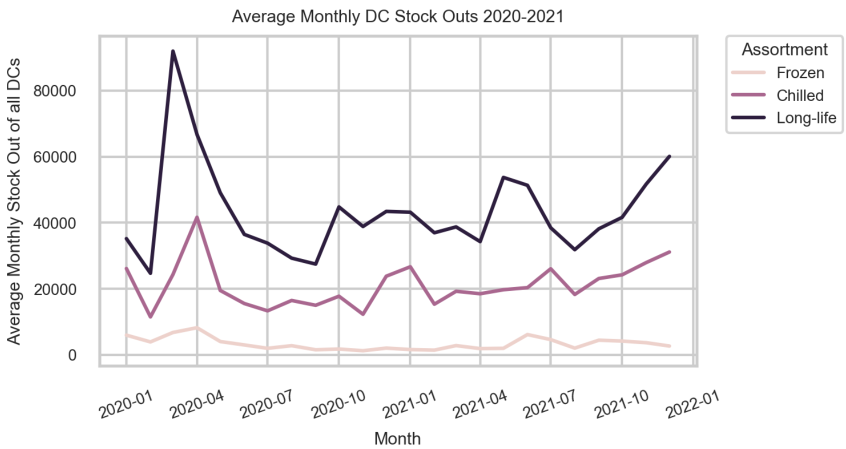


Figure 1.1: DSC's DCs Stock Out Trend 2020-2021

The causes of the DC stock outs can vary from problems at the supplier to inadequate ordering at the DC level. DSC keeps track of these reasons and an overview can be found in Figure 1.2. One main difference between the causes is the origin, which is either internal or external. As can be seen, *supplier problems* are the most often noted cause, with a share of 50 to 60%, followed by *dispatcher failure* with 10 to 15%. Many of the DC stock outs thus have an external origin, on which DSC has limited power to prevent them and are therefore often inevitable. Also, due to a wide range of disruptions in the supply chain caused by the Covid-19 pandemic, DSC does not expect that the share of *supplier problems* will drop soon. Moreover, at the start of 2022, the Russian invasion in Ukraine began and brought even more challenges in the shipments and supplies of goods, like sunflower oil (van Straaten, 2022) and wheat (Linsell, Durisin, & Anghel, 2022).

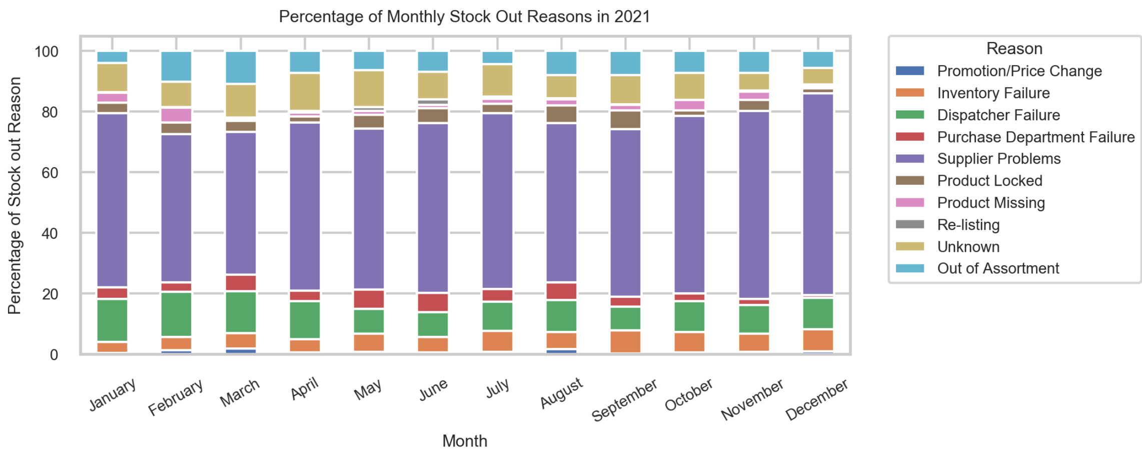


Figure 1.2: Stock Out Reasons at DC per Month

To keep track of the DC stock outs, DSC currently applies only relatively simple KPIs for both the DC and store actors. In essence, these KPIs are only based on the number of stock outs per actor. When the number of stock outs is below a certain threshold value, which is determined by DSC itself, the performance of the actor is fine. However, when the number of stock outs exceed this level, measures will be taken. The actual threshold values and measures will be further discussed in Section 6.2. By using internal reports, an overview of the current situation regarding the average stock outs on a daily level is provided in Table 1.1. Note that the start period of 01-07-2020 is chosen intentionally to avoid the high stock out peak due to the Covid-19 pandemic as seen in Figure 1.1.

Table 1.1: Average Daily Stock Outs per DC over Period 01-07-2020 till 31-12-2021

Assortment	*DC 1*	*DC 2*	*DC 3*	*DC 4*	*DC 5*	*DC 6*	Assortment share	*Stores DC 5*
Long-life	1590.04	1512.96	1005.44	1655.04	1429.12	885.12	64 %	749.44
Chilled	553.60	732.80	999.68	488.96	631.04	647.68	31 %	430.72
Frozen	120.32	171.52	104.96	146.56	129.92	144.64	5 %	177.92

Table 1.1 shows that on a daily average the long-life assortment represents most DC stock outs. Moreover, it is notable that DC 3 and DC 6 have fewer stock outs compared to the other DCs in long-life products. On the other hand, DC 3 is more sensitive to stock outs for the chilled assortment. For DSC it is remarkable that there are large differences between the performances of the DCs. Each DC has the same systems, suppliers, and, on average, experience the same demand patterns. Therefore, DSC would expect that the amount of stock outs would be relatively similar. In addition, the average inventory on hand (in weeks) for the long-life products is found to be very similar among the six DCs with the lowest value of 2.36 (DC 1) and the highest being 2.71 (DC 2). The inventory capacity is thus not necessarily the driver of the differences in stock outs.

On the right, a column is added with the average daily store stock outs based on the stores served by DC 5. This DC is chosen as the focus of this research, which will be explained in Section 2.2. Except for the frozen assortment, the average daily store stock outs seem to be way lower compared to the DC stock outs in that same assortment. This could be a first indication that the effect of DC stock outs on the stores is limited.

The store stock outs are registered manually every night after 19:00 by doing a round through the shop to check which products are out of stock at that moment in time. It is important to note that this way of working has its limitations. If there are, for example, many absent colleagues and plenty of other tasks to be done, it may happen that the responsible person will count only a few products and sent them through. There is no check on how many products are counted to make it a ‘valid’ stock out check. Secondly, it is possible that stores do not even send a stock out check through. Stores that have not sent through a check of stock outs are mentioned in the daily briefing the day after. For the stores supplied by DC 5, it is found that on average 4 to 5 stores of the 78 stores appear in this daily briefing. Finally, the stock out KPI within the store is based on the number of stock outs registered by the employees in the store themselves. Therefore, stores could count less stock outs on purpose to boost their performance. All in all, the registered store stock outs may thus be biased.

As shown there is data available about both DC and store stock outs which are used to determine the individual performance of these actors. In addition, the dispatchers at the DC can use a list with DC inventory levels, supply quantities, and future demand, to anticipate on DC stock out two days in advance. This could allow the dispatcher to allocate the remainder of the DC inventory to the stores more optimally. DSC, however, questions the actual use of this list. This could be due to the lack of KPIs showing the effect of DC stock outs on the stores. In other words, for DSC it is relatively unknown how many of the DC stock outs actually impact the product availability within the stores. A supply chain management (SCM) consultant from the headquarters (HQ) however mentioned the following:

‘.. the store stock outs are potentially disappointed customers, so these stock outs should weigh more heavily’.

This quote shows some awareness of the importance and effect of DC stock outs on the store stock outs. Though to date, DSC has not implemented any measures in this direction.

2 Problem Statement

In this chapter, first the goal of this research is provided. Based on this, the scope of the research will be defined. Finally, the end of this chapter will present the main and sub-research questions.

2.1 Goal

As mentioned in the research motivation, DSC is often not able to overcome a DC stock out. However, currently DSC takes limited measures to measure and control the effect of a DC stock out to the stores. Therefore, DSC is interested in finding alternative ways to keep control over these situations. From interviews with supply chain management (SCM) employees, it was found that DSC is interested in mainly two parts. First, DSC wants to know which different KPIs could be applied to find out more about the effects of a DC stock out on the store performance. Secondly, given these insights, DSC wants to know what actions can be taken to increase the performance compared to the current situation.

2.2 Scope

Within this section, the scope in which this research is performed will be described. A scope will be set in three different domains. The first domain will be the selection of the DC of interest. Next, a decision will be made on which time span to include. Finally, the reasoning behind the selection of the included SKUs (stock-keeping units) will be given.

2.2.1 Distribution Center

The first decision on the scope is which DC to select. Assuming that all six DCs all in general operate the same, and the time of this research is restricted, it is decided to focus on one DC. Based on the findings in Table 1.1, it can be stated that DC 5 performs as an ‘average’ DC among the six DCs. In addition, this DC is located relatively close to Eindhoven which makes it more convenient to visit. Therefore, it is chosen to focus on DC 5, which currently supplies 78 retail stores.

2.2.2 Time Span

It has been chosen to focus on the most recent available data, and thus data over 2021 has been collected. Due to habituation to the Covid-19 pandemic and the stabilization of the demand patterns compared to 2020, it is assumed that the selected data provides realistic demand patterns.

2.2.3 Products

The third decision of the scope is about the selection of the products of interest. Based on Figure 1.1 and Table 1.1, it can be concluded that most of the DC stock outs occur in the long-life assortment (64%). DSC also expects that most advantages can be gained in this assortment. In addition, given that most DSC stock outs occur in this assortment, there will likely be sufficient data to perform a proper analysis. Therefore, the long-life assortment is selected as the assortment of interest.

The long-life product assortment consists of approximately 1250 SKUs. However, this assortment varies slightly from month to month and therefore it has been decided to select only the SKUs which have been sold in the entire year of 2021. For the sake of this research, this approach has two main advantages. First, the SKU characteristic regarding the assigned store space can only be retrieved when they are being sold in the stores (see Section 4.1.2). Since all data has been collected at the end of 2021, it would not be possible to retrieve this information for a product that was in the assortment only at the start of 2021. Moreover, by filtering on the SKU number it excludes SKUs of which the SKU number has been altered during the year, resulting in cleaner data. Ultimately, this selection contained a total of 983 SKUs.

As introduced in the research motivation (Section 1.3), there are disadvantages of using the store stock outs registered by the stores themselves. To overcome these issues, the number of store stock outs will be estimated by using point of sales (POS) data. If there have been no sales for a certain period, it will be indicated as store stock out. This method will be further discussed in Section 4. However, the downside of this method is that there are only reliable results if products are sold, on average, at least a few times during the defined time range, which thus excludes slow movers. Therefore, the top 200 of the, on average, fastest movers have been selected. Gruen, Corsten, & Bharadwaj (2002) found that fast-moving consumer goods (FMCG) have a 50 to 80 percent higher stock out rate in comparison to all products. Therefore, the reduction of 983 SKUs to the fastest 200 SKUs, is assumed to provide a realistic overview of the current situation. All in all, it is found that the selection accounts for:

- 38,4% of the DC stock outs
- 44.7% of the total sales within the long-life category
- 39.0% of the total revenue within the long-life category

With a selection of approximately 20% of the SKUs, around 40% of the above numbers are explained. Therefore, this selection is assumed to be a representable sample of the long-life product assortment.

2.3 Research Questions

Now that the problem is stated, research questions will be formulated that aim for a solution to this problem. The main research question is formulated as follows:

How can the dispatchers be supported to minimize the effects of stock outs in the DC on the in-store product availability?

To provide structure and focus to this research, the following sub-questions have been set up.

- *What is the current setup of the replenishment system of both DC and stores and what are the definitions and current levels of the used KPIs?*

- *Which alternative KPIs are mentioned in the literature and what are their pros and cons?*
- *What are potential drivers of product availability in DC and/or stores?*
- *Which of the potential drivers impact the effect of the DC stock out on the product availability in the store?*
- *How to combine the gained insights into improvement suggestions and what is its potential for the product availability based on historical data?*

2.4 Literature Gap

In preparation for this Master's Thesis, a literature review (Verhoef, 2021) about stock out research has been performed. This literature review focused on identifying important elements relevant to stock outs for various supply chain actors. Although this review had a broader focus than needed for this research, it addressed important aspects and issues to identify the gap this research will try to fill.

First of all, the literature review addressed several methods to measure the performance of stock outs. These methods can, roughly, be divided into two different kinds of literature streams. Firstly, there is a stream with a focus on finding stock out causes or consumer reactions based on its characteristics. These characteristics are often expressed in one of the four measures, I) *breadth*, II) *frequency*, III) *duration* or IV) *intensity* (Gruen & Corsten, 2008). These characteristics will be explained in more detail in Chapter 7. The other literature stream focuses more on increasing the on-shelf availability by opting for an as effective as possible inventory system. The most common method in this stream is to express the number of stock outs in terms of a fill rate (Teunter et al., 2017).

Another finding of this literature review was that many studies focused mainly on issues that occur at the store level. Examples of these issues are ordering practices and forecasting errors. This main focus likely occurs because approximately 70% of the store stock out situations happen due to in-store causes (Corsten & Gruen, 2003; ECR Europe, 2003; Gruen et al., 2002). On the other side, it is remarkable that the found literature mainly focused on the store level, due to the finding that synchronization and communication in the supply chain are important levers to avoid out of stocks (OOS) in the store (Moussaoui et al., 2016). The study they refer to has a focus on synchronizing information regarding promotions (Ettouzani, Yates, & Mena, 2012), and is thus performed in a different context.

There were two studies found which considered the element of DC stock outs in their research. First of all, Avlijas, Simicevic, Avlijas, & Prodanovic (2015) found that DC stock outs increase the probability that stores will go out of stock by four to five times. Also, their analysis showed that a higher product price increases the probability of a store stock out, though not enough evidence was found to treat the finding as significant. The other research found was Usman (2008) with the insight that stock outs at the DC level have an adverse impact on the sales in the stores. His regression model found that on the category level, the Beauty-Care category caused the 'cheapest' stock outs, whereas the snacks and candy category were found to be the most expensive. In addition, Usman (2008) highlights the trade-off between the lost sales at the store level versus extra inventory holding costs at the DC. Increasing the safety stock at the DC for 'cheap' stock outs, possibly results in higher total costs in the end.

Finally, the study of Pibernik (2006) focused on (pre-)allocation of goods to customers in situations where a stock out is expected. The focus of this study was to investigate whether the remaining inventory could be allocated in such a way as to minimize the overall negative consequences for a company. They took into account effects such as lost profits and contractual penalties to quantify the negative consequences. In a stock-out situation, first-come-first-served was found not to be an adequate allocation mechanism. Switching to either a rank-based or optimization-based allocation lead to more beneficial allocations i.e. reducing the negative consequences, although the effects were limited.

This thesis aims to dive more into the drivers of DC stock outs and their effect on store stock outs, focusing on the synchronization and communication elements opted by Moussaoui et al. (2016). It will be tested whether the performance of both the DC and store actors, can be tracked using the existing KPI measures proposed by Gruen & Corsten (2008). Finally, the benefits of making (pre-)allocations for expected stock out situations will be tested to complement the findings of Pibernik (2006).

Part 2. Research Design

3 Research Design

In this chapter, the used methodologies to find an answer to the different sub-questions that were defined in Section 2.3 are described. Each subsection below focuses on one sub-question.

3.1 Sub-question 1 - What is the current setup of the replenishment system of both DC and stores and what are the definitions and current levels of the used KPIs?

The goal of this sub-question was to gain a clear understanding of the current processes within DSC, where the focus was on the setup of DSC's current replenishment system and the corresponding KPIs. This information was retrieved by the use of interviews, which were held with people from both HQ and DC 5. Ultimately six interviews were held, consisting of two dispatchers from DC 5 and three consultants plus one team leader from the HQ SCM department. Due to both the explorative nature, but also the clear focus, the interviews held were semi-structured. A semi-structured approach makes sure that on one side, the initial subjects of interest were covered, and on the other side, the sub-topics could be covered that the interviewer had not thought of (Blumberg, Cooper, & Schindler, 2014). Moreover, to gain an understanding of the processes within the store, an afternoon was scheduled to work along in the store. This observation method allowed the opportunity to ask many questions to the people in the store and to get an understanding of what the processes within the store were like.

3.2 Sub-question 2 - Which alternative KPIs are mentioned in literature and what are their pros and cons?

This sub-question served to gain another perspective on the current situation and performance of DSC her stock outs in contrast to their current applied KPIs. In preparation for this Master's Thesis, a literature review about stock outs was executed. Therefore, the first step was to reflect on these findings. Within this literature review, five KPIs were described to gain insights into the performance of the stock outs. These findings were listed and an explanation for each KPI was given. In addition, for each KPI the advantages and the disadvantages were shortly addressed.

Secondly, after a complete overview of KPIs was established, the practicality and the usability of the KPIs were tested. These KPIs were tested on data from 2021. Some KPIs were easy to implement using data retrieved from DSC her management information system (MIS). However, some KPIs described in Verhoef (2021) required a more data-intensive approach, for example, one KPI required the actual duration of a store stock out. Given that store stock outs are only registered once a day, and store stock outs can be solved during the day, estimating the duration of using registered store stock out would be very inaccurate. To overcome these limitations, POS data was used to estimate the store stock outs in times of a DC stock out for the 200 SKUs as defined in the scope (Section 2.2). The setup of this estimation model can be found in Chapter 5. By the use of the estimated store stock outs, each KPI was demonstrated to reflect the current stock out performance of DSC.

3.3 Sub-question 3 - What are potential drivers of product availability in DC and/or stores?

The goal of this sub-question was twofold. On the one side, DSC's main objective regarding product availability had to be determined, whereas on the other side potential drivers of product availability had to be defined.

First of all, the performance and potential of the previously described KPIs were discussed with DSC. The goal of this discussion was to find out the main objective(s) for DSC during a DC stock out. For example, does DSC has the main priority to minimize the lost sales, the lost revenue, or do they prefer to limit the amount of store going out of stock. Clarifying this objective was important for the follow-up of the research as it had to be used as input for both models used in sub-question 4 and 5.

Secondly, DSC wanted to find out what kind of drivers significantly influences product availability. To gain an extensive, but appropriate list of potential drivers, three sources were consulted. First, the gained insights retrieved during the interviews were sorted out. The elements of the current processes as discussed in sub-question 1 were listed as potential drivers. These drivers were based on the experiences and current activities executed by DSC and were thus assumed to be highly relevant. The second consulted source was the results of the KPIs that were described in sub-question 2. These KPIs were applied to the current situation of DSC and indicated weekly patterns or large differences between product groups. The underlying elements of these patterns were listed as potential drivers of product availability. Finally, the literature review of Verhoef (2021) discussed a wide range of potential drivers. Therefore, this review was studied thoroughly to include the most important drivers. Though, one criterion of this final source was that required data had to be available at DSC.

When the collection of drivers was found to be extensive enough, the data of these drivers were collected. Finally, the drivers were combined in a table including a short description, their source, and their measurement.

3.4 Sub-question 4 - Which of the potential drivers impact the effect of the DC stock out on the product availability in the stores?

As mentioned in the previous sub-question, one of DSC's desires was to find which drivers significantly influence their product availability objective(s). Now that an extensive list of drivers was constructed in sub-question 3, this sub-question applied a multiple linear regression model to explain the significance and strength between the dependent and multiple independent variables, i.e. the potential drivers. The main idea behind such a linear regression model is that for the independent variables X, it is estimated how much they affect the chosen dependent variable y. In other words, it will test how much variance in y is explained by the independent variables X. This can be summarized in the following formula:

$$y = \alpha + X\beta + \varepsilon$$

In this formula, $\alpha + X\beta$ represents the explained variance, whereas ε, the error term, represents the unexplained variance. These tests were performed using R Studios, which is software used for statistical computing (RStudio Team, 2022). The input data for this linear regression was the dataset containing the estimated stock outs, which will be described in Chapter 5 and is thus scoped according to the boundaries in Section 2.2. The overview and explanations of both the dependent and independent variables can be found in Chapter 8. Below, the first step reflects on the number of required observations. Next, the assumptions of linear regression are discussed, followed by a section about multicollinearity. Before the results can be determined (Chapter 9), these assumptions first had to be checked.

3.4.1 Number of Observations

While building a linear regression model, it is important to make sure that there are enough observations in the data set. The required amount of observations is based on the number of independent variables. Based on the findings of Green (1991), the number of observations depends on the goal of the regression analysis. According to Green (1991) there should be at least $N \geq 50 + 8 * K$, with N the number of observations and K the number of independent variables, when testing for multiple correlations. If the testing of partial correlation is the goal, the formula $N \geq 104 + K$, should be used. To be able to perform a reliable regression, it is decided to always use the highest of both methods. Within the result section, it will be reflected whether there are enough observations.

3.4.2 Assumptions

The linear regression executed in this research was done with the ordinary least squares (OLS) method, which is an often-used method. However, to obtain a reliable estimation, first several assumptions (Hair, Black, Babin, & Anderson, 2014) have to be verified. These assumptions are discussed below.

3.4.2.1 Linearity

The name *linear regression* suggests that the relation between the dependent and the independent variable must be linear. When this assumption is not met, the model is invalid. By creating regression scatterplots, this can be tested and checked visually for each independent variable. If one of the scatterplots shows a polynomial or exponential trend, a log transformation could be applied to potentially solve the problem.

3.4.2.2 Normally Distributed Error Term

The second assumption that has to be checked concerns the error term. This assumption states that the error term must have a normal distribution. Given that the central limit theorem also applies to regression coefficients, it can be assumed that the error term is normally distributed. Only for small datasets, this assumption must be checked.

3.4.2.3 Constant Variance of the Error Term

The next assumption states that the error term has a constant variance, which would indicate homoskedasticity. Whether this assumption holds, can tested by the Breusch-Pagan test (Breusch & Pagan, 1979). If the null hypothesis is rejected, it will indicate that the data is heteroskedastic. If there is heteroskedasticity, the estimated coefficients are still valid, but the standard errors are not and thus have to be corrected. A way of correcting this is to apply Newey-West standard deviations, which are robust to heteroskedasticity (Newey & West, 1987).

3.4.2.4 Explanatory Variables Independent of the Error Term

The final assumptions concerns that the explanatory variables must be independent of the error term. Only if this assumption is true, the regression parameters can be interpreted as causal effects (Hair et al., 2014). However, in business one can almost always think of omitted variables, and thus it is decided that this assumption is beyond the scope of this project to analyze this completely. Despite a causal interpretation is not possible, the main goal, namely a descriptive analysis, can still be performed without this assumption.

3.4.3 Multicollinearity

There should be no perfect linear relationship between the independent variables in the model (Field, 2013), since this could mean overlap in explaining the variance of the dependent variable. As a result, the isolated effects of independent variables can be hindered, which is an undesirable property. This phenomenon is checked with the presence of multicollinearity.

In order to check for multicollinearity for each independent variable, the variance inflation factors (VIFs) are determined. The rule of thumb is to drop the variable if the VIF score is greater than 10 (Hair et al., 2014). However, for categorical variables a Generalized VIF (GVIF) must be determined to suite multiple degrees of freedom (Fox & Monette, 1992). To be exact, it is GVIF(1/(2*df)), where df are the degrees of freedom. When squaring the resulting GVIF(1/(2*df)) value, the general rule of thumb can be applied.

3.5 Sub-question 5 - How to combine the gained insights into improvement suggestions and what is its potential for the product availability based on historical data?

This sub-question applied a deterministic optimization model to test the potential of allocating the remaining DC inventory before going out of stock to the stores in a smarter way. In addition, the influence of the most important drivers gained during the previous sub-questions was tested. First, a general introduction to the model setup will be given, where Chapter 10 will provide a complete overview of the model setup, assumptions, and objectives.

3.5.1 Model Setup

The goal of this optimization model was to optimize the final allocation of the DC inventory based on the desires, i.e. main objectives, of DSC. By using DC inventory levels, supply quantities, and future demand, dispatchers are able to anticipate on a DC stock out two days in advance. Therefore, when being aware that an SKU will go out of stock, a dispatcher can act on it. Although the demand in the stores was stochastic, it was chosen to assume a deterministic demand. This assumption was made to better fit with the current ordering strategy of the dispatcher (i.e. single input value for the demand) and therefore makes the model easier to understand. The deterministic demand was determined by taking the 8-week average of demand per specific weekday. This is relatively long, but due to high variation in sales over a short time period, a longer time period provides better forecasting results (Zotteri, Kalchschmidt, & Caniato,2005).

Eventually, by the use of this deterministic demand, the inventory levels of the stores could be tracked relatively easily during a DC stock out. Using these varying store inventory levels, the model determined which stores were in most need of a final allocation. This final allocation also depended on the model objectives, which were based on the findings of sub-question 3. This resulted in a set of different allocation scenarios focused on either maximizing the sales or reducing the store OOS rate.

3.5.2 Model Execution

Each DC stock out was a single event and could therefore be optimized on its own, which resulted in a relatively static and easy to solve problem. Given the goal of optimization, a 'static' problem, and the deterministic demand, this problem was solved using a Mixed-Integer Linear Program (MILP). Due to a large amount of DC stock outs in the dataset, the model was built using the Gurobi Solver implementation in Python (Gurobi Optimization, 2022). This setup was chosen since Gurobi is a powerful solver for such kinds of problems and the integration in Python makes it easy to solve a set of multiple DC stock outs in one row. Finally, Gurobi supports the use of constraint helper functions to ease the implementation of the MILP within Python. The idea behind the model could also be relatively easily implemented in an Excel tool to solve a single allocation problem, which could support the dispatchers in their daily activities.

3.5.3 Performance Testing

The performances of the different scenarios were compared to the performance of the current allocation method, i.e. first-come-first-served, of DSC. These performances were expressed in terms based on the desired objectives of DSC and the most useable KPIs found in the literature. Moreover, interesting findings from the KPIs and the linear regression, like product characteristics, were used to broaden the analysis of the performance differences of the different scenarios.

4 Data Preparation

As introduced in the research design for each sub-question, both qualitative and quantitative data had to be gathered to be able to answer the (sub)-questions. The qualitative was retrieved through interviews and eventually, interesting quotes were used throughout the report. This chapter, however, will focus on how the required quantitative data was gathered and cleaned.

4.1 Data Gathering

Various data elements from the included SKUs, DC, and individual stores were needed. Below it will be listed which source at DSC was used to extract the necessary data.

4.1.1 DC

For the DC stock outs, data from two sources had to be extracted. First of all, the data was extracted from DSC MIS (Management Information System). Within this data, most of the DC stock outs were found. Though, this data did not contain the actual time of the start and end of the DC stock out. This information could eventually be extracted from daily stored files. Due to synchronization issues between the two sources, the data retrieved from daily stored files contained additional DC stock outs for the included SKUs. These were also included in the total set of DC stock outs.

The lead time from the supplier to the DC and the corresponding MOQs were gathered manually from the program called 'DIS', which is the program used by the dispatchers to place their orders.

4.1.2 Stores

For the stores, multiple sources within DSC had to be consulted to gather all necessary data. Many data could be extracted from MIS. This was done for the daily sales data, last sales time, and the delivered quantities towards the stores. The granularity of the daily sales data was on an hourly level, whereas the last sales time was specific to the minute.

The inventory levels within MIS are the theoretical inventory levels of the stores. This inventory level was simply the sum of the supplies to the stores minus the sales and waste. Three times a year, the inventory levels are fully counted and corrected. Due to these limitations, it was chosen to use inventory levels stored in a different source, namely 'Store Data Application'. This data had more corrections throughout the year and in addition, this data was also used for the financial settlements. Therefore, it was assumed that this data was more accurate.

Also, an overview of the registered store stock out was needed. The purpose of this data was to tweak the estimations of the store stock outs. Data regarding these store stock out were stored in CSV files of which a new one was created every day. These were eventually combined to get a yearly overview.

Finally, information regarding the store space allocated and the minimum order quantities (MOQ) per store per individual SKU were extracted from, again, another database, which contained information about SKU-related store settings. Unfortunately, information in this database was not saved over time and therefore this data only represented a specific moment in time. It was therefore assumed that the space allocation and the MOQs in the stores do not change largely over the year. The data was extracted on 14-01-2021.

4.1.3 Product Characteristics

Finally, information about product characteristics was needed to make comparisons based on these characteristics. Most of the information could easily be extracted from the monthly updated file. The following information was extracted from this file:

- Retail Price
- Ordering Strategy (see Section 6.1)
- Case-pack Size
- Product Group

4.2 Data Cleaning

Data cleaning aims to highlight inconsistencies, detecting, and removing errors in the data to increase the data quality and therefore make it usable for further analysis (Grossmann & Rinderle-Ma, 2015). To provide some structure in cleaning the data, the applied cleaning process was based on the steps described by Blumberg et al. (2014). Their process focuses on correcting missing data, outliers, and obvious mistakes.

4.2.1 Missing Data

In some cases, the start and ending time of the DC stock out was missing. Given that the amount of DC stock outs was relatively limited, it was not desired to delete this data. Therefore it was chosen to adapt the missing data with the time that most DC stock outs either occurred or were finished. It was found that most stock outs were caused between 10 and 11 AM, therefore, when the start time of the stock out was missing, it was set to 10:30 AM. On the other side, most DC stock outs were solved between 12 and 13 PM, therefore, when the stock out solving time was missing, the time was set to 12:30 PM.

The data about the store space allocation and the MOQ data in the store also had some missing data. This problem appeared if a certain SKU was temporarily, but relatively long, out of stock at the DC. As a result, the space allocated in the store was removed and filled with different products. Therefore, on 15-02-2022, a second try was performed to retrieve the missing data. This did solve the missing data for three SKUs, although data was still missing for 5 SKUs. Given that this data was only used for the regression analysis, it was been decided only to drop these 5 SKUs in the regression analysis.

4.2.2 Outliers

The total amount of registered store stock outs seemed to differ largely between the stores. Two of the 78 stores really stood out with a low number of stock out registrations. Further analysis showed that these two stores were opened somewhere in mid-2021. The sales data over 2021 was thus not complete for these two stores, and therefore it was chosen to exclude the two stores during the full analysis throughout this report.

Sales data could be heavily influenced by promotion and thus had to be corrected for these events. Information about the promotion dates for each SKU was retrieved from an internal program. To correct the sales data for the promotion, the average sales in the prior eight weeks of the same weekday were taken and substituted for the promotion sales. An example of this can be seen in Figure 4.1, which demonstrates the effect of correction for promotion for a random 'sauce' SKU. The blue line represents the data where promotion was active, which is characterized by a large peak. Only where the promotion was active, the data was replaced with the average of the past eight weeks. Thus, except for where the blue line is visible, the orange line represents the actual sales on that day.

In total 44 SKUs had one or more promotions in 2021. Ultimately, these 44 SKUs were found to be good for 110 individual promotions. These events all were corrected using the above-described method.

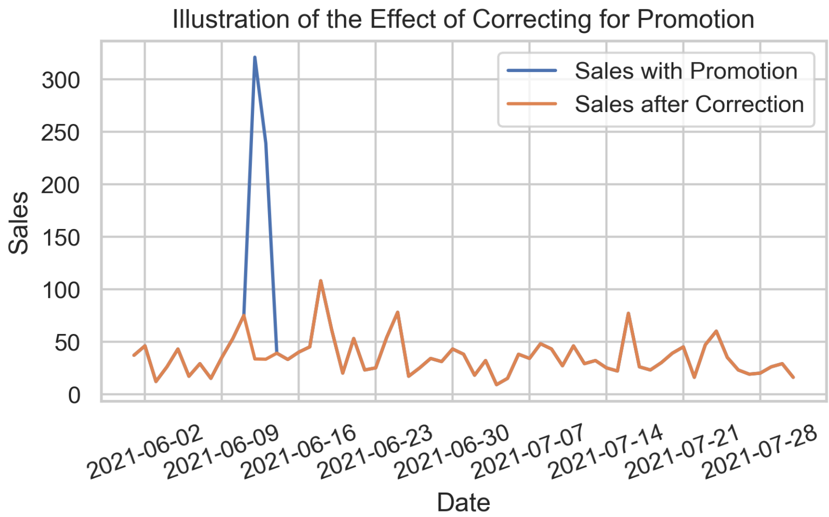


Figure 4.1: Effect of Promotion Correction for a Single SKU

4.2.3 Obvious Mistakes

4.2.3.1 MOQ and Space Allocation

For the allocated space and MOQ in the stores also some adjustments had to be made. Most of the SKUs are being ordered per box and thus both the space allocated and MOQ are expressed in a multiple of these boxes. However, there are two kinds of products with an exception, namely 1) SKUs shipped per EU pallet and 2) SKUs shipped per 'Düsseldorfer' (Approximately ½ EU pallet). Most stores could fit either a full EU pallet or 'Düsseldorfer' in their stores, but sometimes due to space limitations the SKU were ordered per layer. After transformation, both the allocated space and MOQ were expressed in consumer units (CUs) to work with a uniform and easily comparable unit.

4.2.3.2 Opening Hours

During nights the stores are closed. It was thus not possible to have any sales during a certain timeframe and therefore, the stock out duration had to be corrected for opening hours. Due to the varying opening hours per store, it was chosen to create one uniform opening hour scheme. The following opening hours were used for all stores:

- Monday until Saturday: 08:00 - 21:00
- Sunday: 09:00 - 18:00

The store stock out duration were used to approximate the number of lost sales. Therefore, when a store was actually opened till 22:00, instead of 21:00, it was assumed that this would not make a huge difference given that these last hours are very quiet. The same applies to when a store opens earlier, for example at 07:00. In the end, the differences were therefore be assumed to be neglectable.

Also, for the stock out duration on the DC level, it was chosen to correct them for the openings hours. Though, on the DC level, the opening hours are less strict compared to the stores. Based on the interviews with the dispatchers and by studying the stock out data, it was chosen to use the same openings hours of 06:00 – 17:00 for every weekday.

4.2.3.3 Inventory Levels

The inventory levels from the stores contained some negative values. For the optimization problem, the inventory values were extracted two days before the start of a DC stock out. When this inventory value appeared to be negative, the inventory level was set to zero.

4.2.3.4 Sales Data

When retrieving and analyzing the sales data, it sometimes occurred that there were negative sales. This is obviously not possible and these few events were replaced by zero.

4.2.3.5 DC Stock Outs

Due to the combination of data from MIS and the daily stored files, sometimes an overlap between DC stock outs for the same SKU occurred. It was chosen to stick with the DC stock out with the longest duration. Eventually, the total number of DC stock outs was reduced by 32.

5 Estimating Stock Outs

As mentioned in the research motivation, DSC is hesitant about the completeness of stock out registered by the stores themselves. Therefore, for this research, it was chosen to estimate the store stock outs by using POS data during DC stock outs. This chapter will first elaborate on which store stock outs were considered to be influenced by the DC stock outs. Next, the method of parameter tuning and its limitations will be mentioned. Finally, it will be elaborated on how the lost sales are determined based on the gained data.

5.1 Scope

It was important to apply a set of boundaries of when a store stock out was assumed to happen due to a DC stock out. This way of working improves the transparency of the research, as well as the reproducibility of this research. In Figure 5.1, an overview is given of which situations were included and which were not. The values for the two variables 'N' and 'X' were determined after data was gathered and cleaned.

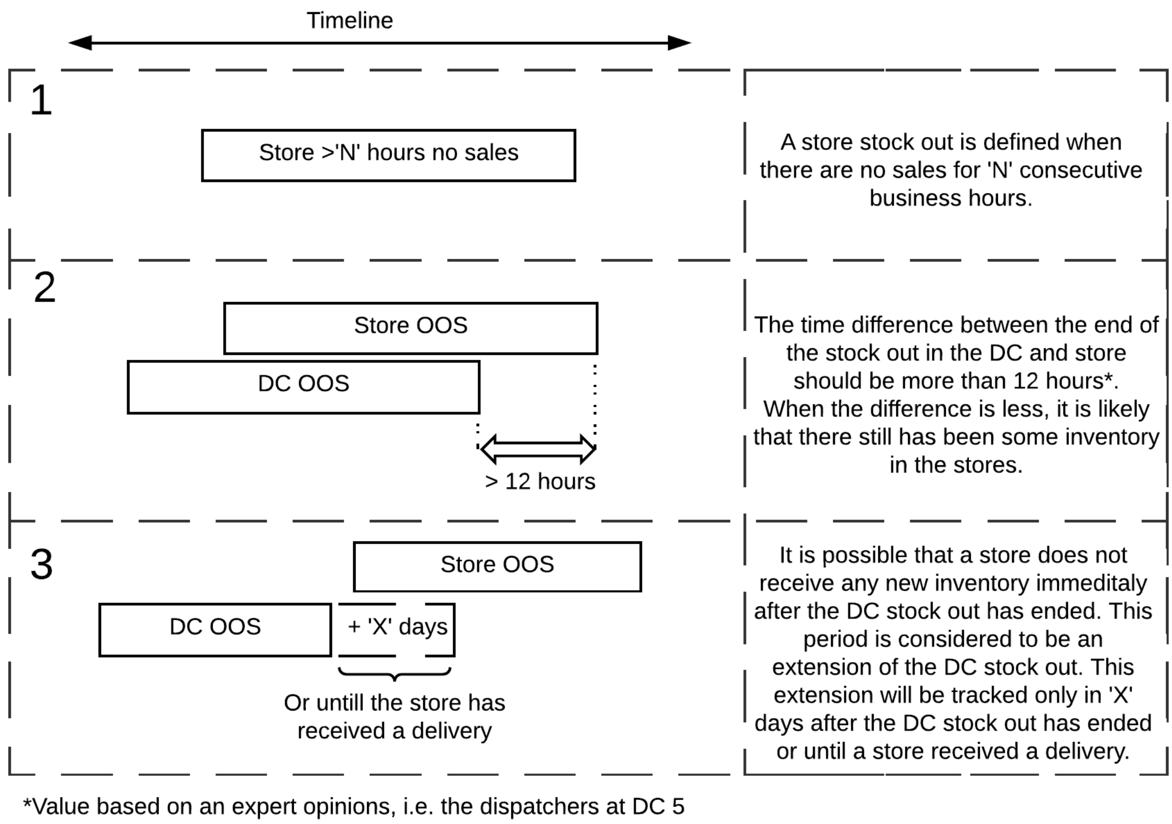


Figure 5.1: Set of Boundaries to Determine Store Stock Outs

Situations as shown in Figure 5.2 are not taken into account for the estimation of the stock outs. This assumption was made because DSC uses a tool that if a store registers a store stock out, this SKU is automatically added to the next delivery of the store (see Section 6.1). Therefore, it was not likely that the shown scenario would often occur.

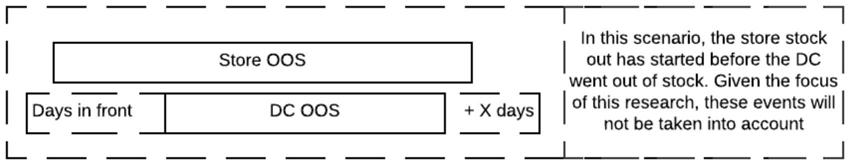


Figure 5.2: Not Included Boundary to Determine Store Stock Out

Ultimately, the model presented for each of the included DC stock outs which of the 76 stores went out of stock. Due to the use of POS data, the duration of the store stock out could easily and accurately be determined. This is one of the main advantages compared to using the registered store stock outs. In Table 5.1 the layout of the model output is given.

Table 5.1: Lay-out of the Stock Out Estimation Dataset

Product	Start DC OOS	End DC OOS	Store	Stock Out?	Store Last Sell	Store First Sell	Duration (hours)
1	02-01-2021 10:00	04-01-2021 12:00	1	1	03-01-2021 17:02	05-01-2021 10:17	19.05
1	02-01-2021 10:00	04-01-2021 12:00	2	0	n/a	n/a	n/a

5.2 Parameter Tuning

For both the variables 'N' (hours between a sale) and 'X' (days after the end of DC stock out), the parameters had to be tuned. This tuning was done by the use of a sensitivity analysis. For the number of hours between a sale, the tested variables ranged from 1 to 12 hours, to determine its effect on the model. For the number of days after a DC stock outs, the effect was tested to immediately stop after the DC stock out was solved or to wait for a maximum of four days. Eventually, the following set of parameters were tested:

- 'N' hours no sale: 1, 6, 10 and 12
- 'X' days after DC stock out ended: 0,1,2,3 and 4.

Each combination of parameters was run to retrieve a set of estimated store stock outs. The performance of these results was judged by the similarity with the registered store stock outs, and thus the manual audits were used to tune the estimation model. The results of this analysis can be found in *Appendix A: Parameter Tuning Results.* For the parameter combination N = 10 and X = 2, the highest similarity was found. Also, the total number of estimated store stock duration seemed reasonable compared to the registered stock outs, which will be explained in more depth below Table 5.2.

Finally, the expert opinion about the 12-hour difference between the DC end and store end was checked on the best performing parameter combination (N = 10 and X = 2). It was chosen to check the parameter values 1, 6, 12, and 18, of which the results can be found in *Appendix A: Parameter Tuning Results*. The conclusion was that the performance of the model varied only slightly among these parameters and therefore it was chosen to stick with the expert opinion of 12 hours.

All in all, in Table 5.2 the final chosen parameters and the corresponding results can be found.

Table 5.2: Result Overview of the Chosen Parameters

Parameters			Registered		Estimated		
N (hours)	X (days)	End Difference (hours)	Number of stock outs	Avg. Duration (days)	Number of stock outs	Avg. Duration (days)	Similarity*
10	2	12	1102464	1.71	5630208	3.38	77.82 %

*Similarity based on % estimated also part of registered

By estimating the number of daily store stock outs, more than five times as many store stock outs were found in comparison with the registered store stock outs. The average duration of the store stock out almost doubled because by using POS it is not possible to forget to register a store stock out in a few consecutive days. Next, the similarity between the estimated and registered store stock outs is 77.82%. This implies that more than 20% of the registered store stock outs does not appear in the set of estimated stockouts. It has been tried to increase this similarity, but no real patterns, for example, lower similarity in small stores or within slower moving SKUs, could be found. Below some reasons are listed why these above-mentioned differences occur:

I. The data of the registered stock outs is relatively messy. Consider the actual example (Table 5.3) below during a DC stock out, where two of the limitations are visible. Using the registered stock out data, it displays two stock outs (indicated by X), whereas using the estimation model it results in four hits. This difference is caused by two factors. First, on the third of January, the store forgot to register the stock out. Next, given that on the fifth of January the stock out was already solved in the morning, no stock out is registered on that day. Both of these suggestions together explain a part of the increase in stock out hits and why the average duration of the estimated stock outs increases.

Table 5.3: Illustration of Errors Caused by using Registered Store Stock Outs

	Date							
	2 January		3 January		4 January		5 January	
Registered	19:00	X	Missing		19:00	X	Missing	
Estimated	15:08	X	-	X	-	X	09:00	X

II. In Figure 5.3 a scatterplot illustrates the relation between the total registered stock outs per store and the similarity percentage between the registered and estimated store stock outs. It can be seen there is a clear trend that when stores have more stock out registrations, the similarity increases. It thus looks like that the stores with low stock out registrations register fewer stock outs than actually occur within the store, and thus 'boost' their own performance.

Figure 5.3: Stock Out Registrations versus the Overlap with the Model

III. When stores were already out of stock when the DC goes out of stock, the store stock out is not taken into account. Although the assumption (Figure 5.2) was made that this is not possible, further analysis showed that this sometimes does occur. As a result, there are some inaccuracies in estimating the store stock outs.

All in all, based on the argumentation above it was assumed that the model produces realistically enough results to use for further analysis.

5.3 Lost Sales

For each DC stock out it was now indicated which store went out of stock, including an accurate duration of this event. This opens the possibilities for some additions to the model. By using the historical demand for the products in combination with the duration of the store stock out the lost sales per store can be estimated.

After the sales data was corrected for promotion, the 8-week average was taken per weekday to be used as an estimation for the expected demand. For example, for each Monday, the average over the previous eight Mondays was taken as the expected demand for the ninth Monday. A relatively long time period has been chosen given the finding of Zotteri et al. (2005) that due to high variation in sales over a short time period, a longer time period provides better forecasting results.

Given that store stock outs may start and end somewhere during the day, the expected demand can not immediately be used as the expected lost sales. Therefore, the expected demand had to be corrected for the actual hours the store was out of stock on that day. First, the daily expected demand was divided by the number of hours a store is open on that day. It was assumed that for Monday until Saturday the stores were open 13 hours a day, whereas on Sunday the stores were open for 9 hours. This provides an expected demand per hour and this was multiplied by the number of hours the stock out had lasted on a specific day. This approach, however, assumed that there are no differences in demand patterns during the day. This is, of course, a phenomenon that does occur and is therefore known as a limitation of this method.

Table 5.4 provides an example of an actual event in the dataset of how the lost sales was determined. On the 28th of July at 15:24 a store stock out started for a certain SKU. On the 30th of July at 13:00 the first next sale was made. The duration of the store stock out per specific day was determined and multiplied by the expected hourly sales on that day, resulting in the following numbers.

Table 5.4: Example of Determining the Lost Sales

Day	**Weekday**	**Start**	**End**	**Stock out Duration (Hours)**	**Expected hourly sales**	**Estimated lost sales**
28 July	Wednesday	15:24	21:00	6.35	3.84	24.38
29 July	Thursday	08:00	21:00	13	3.85	50.05
30 July	Friday	08:00	13:00	5	6.27	31.35

Thus, in total, it was estimated that the lost sales of this specific store stock out accounts for 105.78 consumer units. Multiplying this with the retail price of €0.64 results in an estimated lost revenue of €67.70.

Part 3. Results

6 Relevant Processes Regarding Stock Outs

Within this chapter, an overview and explanations of the current situation of DSC will be given. First, the current replenishment processes relevant to this research will be explained. Secondly, the currently applied KPIs and performance levels regarding stock outs will be highlighted.

6.1 Replenishment Processes

6.1.1 Distribution Center

The products that are sold by DSC can be roughly divided into two groups, namely *direct* products and *international* products. In the case of *direct* products, the DCs are in direct contact with the suppliers. DSC's buying department at HQ is free to search and choose suppliers for products to include in DSCs regular assortment. The advantage of this ordering method is that dispatchers at the DCs can easily contact the suppliers themselves, for example, when there are problems with a delivery they can call them to ask when to expect the goods. Most suppliers have a lead time of one week with strict ordering and delivery days, whereas some suppliers have a lead time of two weeks. Moreover, there are no set review moments for the *direct* product. Some dispatchers review the products every day, except for the weekends, resulting in a review period of 0.2 weeks for the *direct* products.

This is in contrast with *international* products, where the DCs are not in contact with the suppliers. The orders of all DCs are combined and checked by someone at HQ and then sent to the international HQ. At the international HQ, the orders from all the different countries are combined, after which orders at the suppliers are placed. This method provides economies of scale letting DSC have very competitive prices. In Figure 6.1 an overview of this scheme can be found. *International* products can be ordered approximately once a week and are not reviewed in the meantime. Therefore, the review period of all *international* products is equal to 1 week.

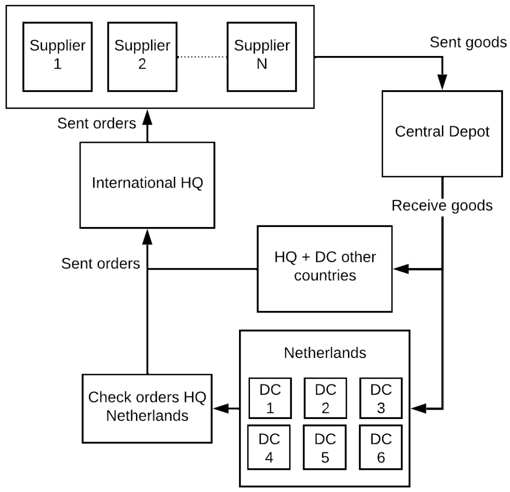


Figure 6.1: Ordering Scheme of International Products

In addition, DSC also offers both branded as well as house brand SKUs to its customers. Out of the 983 SKUs offered in the regular assortment, approximately 10% can be considered a branded item. DSC mentions that every year more branded items are added to the regular assortment.

To determine when a dispatcher should reorder an SKU, DSC makes use of a so-called stock on hand (SOH) level. This level expresses how many weeks of DC inventory of that SKU is left and when a certain threshold value is reached the dispatcher should trigger a new order. DSC uses to following formula to determine these levels:

$$SOH = \frac{Inventory\ on\ hand\ +\ Outstanding\ orders}{Expected\ weekly\ demand}$$

The SKU-specific SOH threshold values are determined by the dispatchers themselves, where the main driver is the lead-time of the SKU. For example, a dispatcher can set the threshold value for a certain SKU on 2. Thus, when the SOH for this product drops below 2, the dispatcher knows to trigger a new order. When the supplier of this SKU is known to be an 'unreliable' supplier, the dispatcher can set the threshold value at, for example, 3 instead of 2. By doing this, the DC will have a larger safety stock which may help to avoid a DC stock out. However, there are no guidelines for increasing the threshold value based on supplier reliability. According to a dispatcher, the most important driver is his feeling:

'It is primarily just a feeling that says to increase a certain SOH, and if that feeling occurs, I increase it' – Dispatcher at DC 5

Also, the *expected weekly demand* input value must be determined by the dispatchers themselves. The dispatchers are thus expected to use historical demand information, their experience, and common sense to determine a realistic input value. For example, when the outside temperature increases, the dispatcher should change the expected demand input accordingly. Given that a reorder is triggered based on this value, it is important that this input value reflects a realistically expected demand.

Furthermore, it is expected that every morning the dispatcher checks the 'Expected Negative Stock' list. On this list, the dispatchers can quickly see which SKUs are expected to go out of stock based on the DC inventory level, incoming supplies, and outgoing orders. Using this list, two kinds of actions must be undertaken. First, when a DC sees that a product will go out of stock just before delivery, they should contact the supplier to get the replenishment sooner, or when there are larger issues, they should contact HQ. When the first option is not a possibility, the DC could cancel the outstanding store orders and allocate the remainder of the inventory to stores that would need it the most. During the interviews, it was noted that only for the chilled assortment this allocating is done actively. The assortment for the long-life products is said to be too large to continuously re-allocate the inventory in such situations and therefore would require too much of the dispatcher's time. When the allocation is not adjusted, it will just be picked in a first-come-first-served order until the DC inventory runs out.

Moreover, one consultant from HQ stated that the list 'Expected Negative Stock' list is *'one of the most important lists within the operations of the DC'.* Whereas on the other side, a dispatcher ordering long-life products mentioned that he '*only takes a look at it twice a week to see what is on the list'.* Thus, the actually achieved effectiveness of this list can be questioned for long-life products.

6.1.2 Store

Stores must order long-life products 'A for C', which means that products ordered on Monday are delivered on Wednesday, implying a lead time of 2 days. Stores are able to order each SKU every day. Though, there are two exceptions to the ordering and delivery schemes. First, on Sunday the stores are not able to make an order, although they receive a delivery on Tuesday. This order must therefore already be created on Saturday evening, implying a slightly longer lead time. Moreover, on Sunday stores do not receive delivery of long-life products. The store orders made on Friday will therefore be received on Monday.

As mentioned in the research motivation (Section 1.3), stores have to register their stock outs every night after 19:00. The overview of these registered store stock outs is sent to the supply chain department at the DC. Every morning at the DC these overviews are checked and compared to the store orders. If a certain SKU is registered as a stock out, but is not included in the next store order, the SKU will be added to this new order. Therefore, as long as there is DC inventory and the store registers all the stock outs correctly, store stock outs can be prevented.

6.2 Stock Outs and KPIs

6.2.1 Distribution Center

The DC performance regarding stock outs is tracked by the use of a so-called traffic light system. The input for these KPIs is extracted from DSCs MIS every Monday. Though, since the sheets are made only once a week, some stock out events might already be outdated. For example, a DC stock out that originated on Monday, will eventually be discussed a week later after the sheets have been constructed. It could thus well be possible that this stock out is already solved and therefore discussing this stock out is of limited use.

Regarding the traffic light system, the number of stock outs can be either good (green), should be watched (orange) or intervention is needed (red). If the color is orange, a bi-weekly meeting with the managing board is scheduled to discuss the results, whereas if the color is red a weekly meeting is arranged. The threshold value per color is reviewed on a yearly basis to see whether the goals are still realistic and if it is still possible to score a green light. Moreover, it is notable that DSC has decided to use such a method themselves and they are unaware whether the branches in other countries also apply similar methods or KPIs.

The general thought of the currently applied KPIs is that when there are store stock outs, these will be a derivative of a DC stock out. Thus, when there are many DC stock outs, DSC assumes that the stores also register more stock outs.

> '*DC stock outs are used as a degree of measurement whether the stores are properly filled'* – Consultant SCM HQ

DSC currently applies the following goals per assortment for the DC stock outs.

Table 6.1: Current KPI Measure of DSC and the Corresponding Performance of DC 5 in 2021

Assortment Group	**Green**	**Orange**	**Red**	**Daily Average DC 5**	**Std. Deviation**
Long-life	<1472	1472-1728	>=1728	1538.56	635.52
Chilled	<640	640-832	>=832	660.48	378.88
Frozen	64	128	>=192	134.4	85.12
Total	<2240	2240-2752	>=2752	2301.44	830.08

As can be seen in Table 6.1, DC 5 scores, on average, just in the range of the orange traffic light. However, the standard deviations of the daily stock outs are relatively large, indicating that the number of stock outs is relatively volatile. Therefore, it is likely that every 'traffic light' can indeed be achieved, which is also the goal for DSC:

> '*The set threshold value must be acceptable for us [HQ], but should also be realistic and achievable for the DCs'* – Team leader SCM HQ

Although there is a quite large division between *direct* and *international* SKUs, DSC does not apply separate KPIs for these products. This also applies to branded and house-branded items. The only separation made in the current KPIs is the different assortments, like chilled, frozen, and long-life products as shown in Table 6.1. Chapter 9 will test if there are significant differences between such product characteristics, which will show whether this limited distinction is righteous or whether DSC should consider implementing separate KPIs.

6.2.2 Stores

The store stock outs are also measured purely on the number of stock outs. The applied KPI is even more simple compared to the DC since there is only one threshold value to indicate the level of performance. If stores exceed the accepted number of stock outs, the regional manager will address and discuss the problem with the store managers. As mentioned in the research motivation, given that stores count their own stock outs, the stores themselves have a large influence on their 'visual' performance level. The maximum allowed stock outs of the stores per assortment group are listed in Table 6.2. The added daily store averages are based on registered stock outs, which is done to be able to show the current performance of the stores for all assortments. Secondly, note that the assortments 'Ultra-fresh' and 'Meat' were missing at the DC stock outs, because DSC does not keep track of DC stock outs in these assortments.

Table 6.2: Maximum Allowed Store Stock Outs and Performances over 2021

Assortment group	Maximum allowed	Daily average per store	Std. deviation
Ultra-fresh	384	421.12	332.8
Meat	384	449.28	400
Frozen	320	177.92	178.56
Chilled	704	430.72	426.88
Long-life	1024	749.44	520.96

For the assortments 'Frozen', 'Chilled', and 'Long-life' it is noteworthy that the averages per store are way lower compared to the maximum allowed stock outs. Also, the standard deviations for all assortments are very high compared to the daily average. This indicates that the number of stock outs differs largely, either from day to day or between the stores.

Another interesting finding was found during the interview with a store manager. He mentioned that there is limited opportunity for stores to compare their stock out performance with the other stores in the same region. Although the stores are able to see the number of stock outs in their own region, they cannot see the revenue of these stores. This makes it hard for the stores to compare themselves to similar stores based on their 'stock out' performance.

7 Stock out KPIs

In this chapter, the KPIs found in the literature review (Verhoef, 2021) are used to provide an overview of the characteristics of the DC and store stock outs at DSC. Each KPI will first shortly be elaborated, after which the KPIs are applied to test the current performance of DSC using the estimated store stock outs. In Table 7.1 an overview of the KPIs can be found, which are primarily based on the suggestions of Gruen & Corsten (2008). For a more in-depth elaboration of the KPIs, the reader is referred to the literature review of Verhoef (2021).

Table 7.1: Overview of Stock Out KPIs

Attribute	Level	Measure
Breadth	Category	$\frac{Number\ of\ different\ stockout\ items}{Total\ number\ of\ items\ in\ assortment}$
Frequency	Item	$Item\ stockout\ frequency$
Duration	Item	$Total\ time\ an\ item\ is\ out\ of\ stock$
Intensity	Item	$\frac{Total\ unit\ sales\ lost\ due\ to\ an\ stockout\ item}{(Total\ units\ sold+units\ sale\ lost)}$
	Item (value)	$\frac{Total\ monetary\ loss\ due\ to\ stock\ outs}{Total\ monetary\ sales+Loss}$
Fill rate	Item	$\frac{Total\ units\ sold}{Total\ demand}$

7.1 Breadth

7.1.1 Explanation

The first and also most often used attribute type in stock out literature is the *breadth* (Celebi, 2019). The *breadth* level is calculated by dividing the number of stock out items by the total number in that specific assortment. By applying this method, it can, for example, be used to compare the performance between different assortments, stores, or manufacturers. It is important to note that this is the only measure that focuses on a group of products (i.e. assortments), whereas the other KPIs focus on individual SKUs. Finally, this method only captures a certain snapshot in time, ignoring the element of stock out duration. Note that the chosen scope focuses on a limited amount of SKUs in one assortment, so the actual use of the KPI for this research is limited. However, with some adjustments, the KPI can be applied to the setting of interest.

7.1.2 In practice

In a way, this KPI is relatively similar to the currently applied KPI based on the number of stock outs as described in Section 6.2. The *breadth* KPI, however, has one additional step where the total stock outs are divided by the total number of SKUs in that assortment. Given that DSC has been expanding its assortment over the year and is likely to continue this way, dividing the total stock outs by the total assortment, might provide easier to compare performances over the years. For illustration purposes consider the following fictive example in Table 7.2. DSC can choose to either use the amount of (daily) stock outs or *breadth* level to compare the performance over the years. Due to the growing number of SKUs in DSC's assortments, a comparison of the total stock outs might not provide a 'fair' reflection of the actual performance. Setting a certain *breadth* level will correct for the increase in the amount of products and therefore might be more 'fair'. In the example, the allowed stock outs increase from 20 to 22 to 24 with the same *breadth* level of 2 over the years.

Table 7.2: Illustration of the Breadth KPI

Month & Year	Assortment size	Daily Stock outs	Breadth
January 2021	1000	20	2%
January 2022	1100	20	1.8%
		22	2%
January 2023	1200	20	1.67%
		24	2%

Next, one could alter the formula of *breadth* slightly to fit better to goal of this research. Instead of focusing on assortments, the focus will be on how many stores have gone out of stock during a DC stock out. This can be expressed with the following formula, which will from now on be referred to as store OOS (out of stock) rate.

$$\frac{Number\ of\ stores\ out\ of\ stock}{Total\ number\ of\ stores}$$

When applying this formula to the estimated store stock outs, it shows that on average 34.24% of the 76 stores will experience a store stock out when a DC goes out of stock. When specifying this per weekday, the pattern visible in Figure 7.1 occurs. This pattern shows that a DC stock out starting on either Friday or Saturday results in a higher store OOS rate. In other words, a DC stock out starting on either Friday or Saturday is more crucial for DSC in terms of product availability in the stores. In <u>*Appendix B: Additional KPI Figures,*</u> a similar figure about the store OOS rate is, but with a focus on comparing the effect of the different product groups.

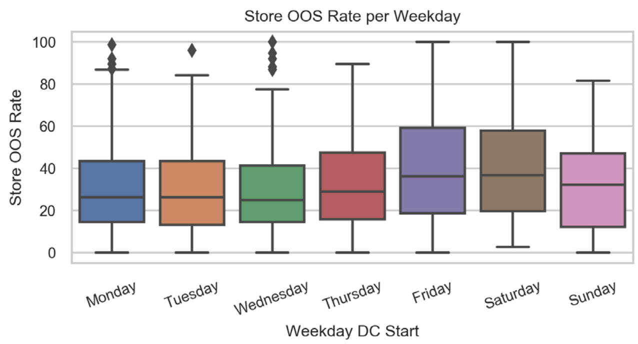


Figure 7.1: Store OOS Rate per Weekday

7.2 Frequency

7.2.1 Explanation

The *frequency* attribute is about the number of stock out occurrences during a specific amount of time. The first step in applying this method is to clearly state the time length since otherwise it will be hard to make fair comparisons. Again, like the *breadth* attribute, nothing about the duration of the stock out can be concluded. However, this method is useful to provide insights into comparing availabilities over different time patterns. For example, different product groups can be compared on their stock out frequencies during a certain year.

7.2.2 In practice

First, in Figure 7.2 the stock out frequency of all included SKUs summed per product group is shown. The taken time length is the full year of 2021. This shows that both group 43 and group 72 account for many of the DC stock outs, indicating which product groups DSC should focus on to reduce most DC stock outs. For group 49 DC stock outs are found to be a rarity, followed by group 46 and group 40. Moreover, the estimated store stock outs are most of the time well in proportion to the number of DC stock outs, which strengthens the trust in the store stock out estimation model.

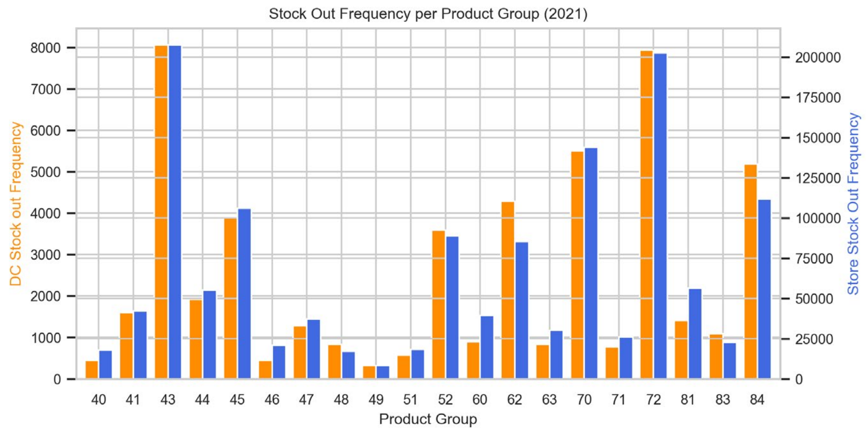


Figure 7.2: Stock Out Frequency for DC and Store per Product Group (2021)

Next, for Figure 7.3 and Figure 7.4 the chosen time range are the weekdays. The orange line represents the newly started stock outs per weekday, whereas the blue lines represent the sum of active stock outs on that weekday.

Figure 7.3 represents the week pattern for the stock outs on the DC level. As can be seen, by far most DC stock outs start Monday, followed by Friday and Saturday. In addition, most DC stock outs are active during the weekends, with the peak on Monday followed by a relatively steep drop on Tuesday. The high number of active stock outs during the weekend is caused by the fact that there are limited supplier deliveries during the weekends. The peak on Monday is reinforced by the fact that many store orders come in and order pickers start around 8:00 with picking the store orders. The suppliers, however, can deliver their goods until 14:00, causing SKUs to go out of stock. This finding is confirmed by a manager at DC 5. This would indicate that on Monday there will be, on average, shorter DC stock outs. Moreover, is noticeable that on Sunday the overall stock outs tend to increase, whereas the newly started DC stock out decreases on Sunday. This pattern occurs because on Sunday there are limited orders sent out to the stores.

Next, Figure 7.4 represents the pattern for the store stock outs influenced by the DC stock outs. Here it can be seen that the peak of stock out occurs are the highest on the first three days of the week, after which it lowers till Friday and then stays stable. This pattern is very well expected due to the high number and higher store OOS rate (Figure 7.1) of DC stock outs at the end of the week.

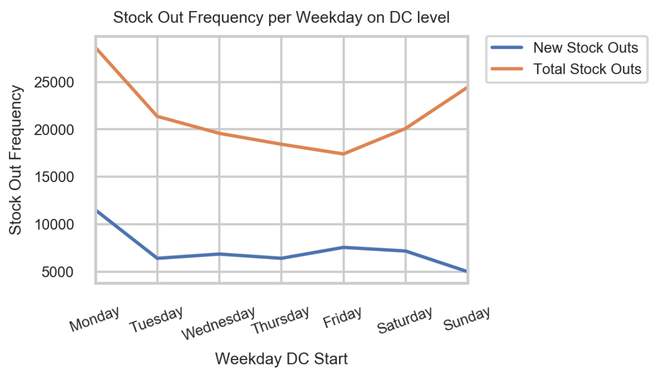


Figure 7.3: Frequency of Stock Out Hits per Weekday on DC Level

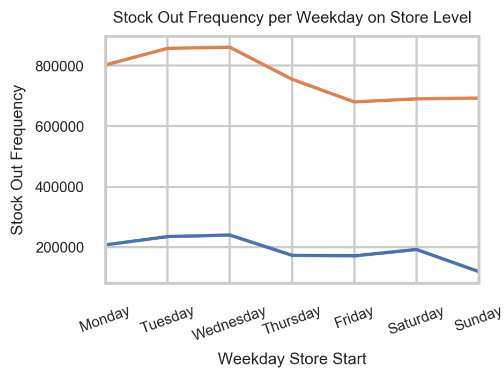


Figure 7.4: Frequency of Stock Out Hits per Weekday on Store Level

Next, the proportions of the stock outs per assortment over the weekdays are analyzed and shown in Figure 7.5. For each weekday, the top eight assortments with the highest share were included to check if week patterns based on the product group could be found. It appears that often the same product groups represent the large shares of stock outs per weekday. For example, group 43 represents a relatively stable percentage of the stock outs over the week with a peak on Friday. Next, it is notable that the share of group 72 and group 70 increases towards the end of the week and on Monday. These product groups cover SKUs with a typical high demand during the weekends and thus the observed pattern is found to be quite logical. This finding is also found to be in line with the pattern presented in Figure 7.3. Finally, the sudden appearance of group 81 on Wednesday is remarkable, for which no explanation could be found. Given these insights, DSC can focus more precisely on which product group might need the most attention, instead of looking at the full long-life assortment.

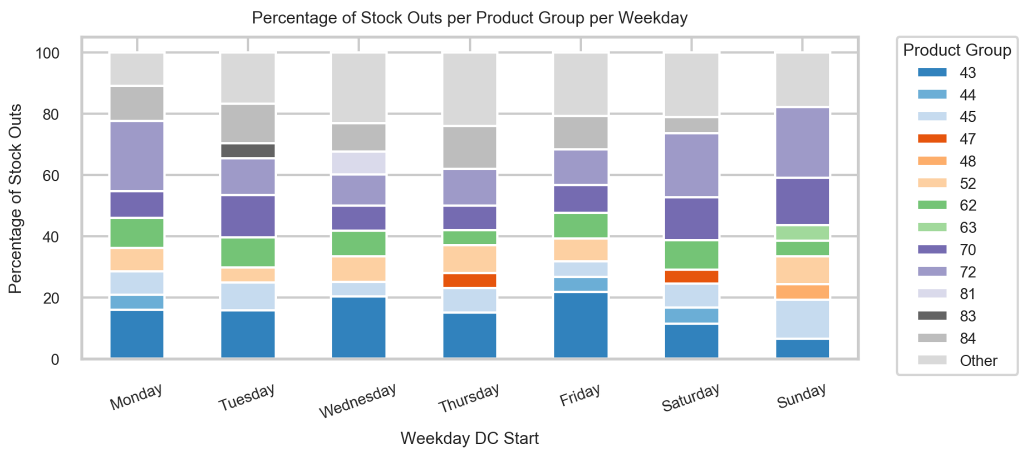


Figure 7.5: Percentage of Stock Outs per Product Group per Weekday

7.3 Duration

7.3.1 Explanation

The third attribute type is *duration,* which concerns the time that an SKU is not available to the consumer. Within the literature, this is found to be the least common measure (Celebi, 2019). In the case of manual auditing of the store stock outs the actual duration is very inaccurate. Therefore, to gain an accurate impression of the stock out duration point of sales (POS) data is required. Due to the need for POS data, this KPI is way more data-intensive compared to the previous two KPIs and therefore harder to implement.

7.3.2 In practice

The first approach to using this KPI is a relatively straightforward one. The actual duration of both the DC and corresponding store stock out for each individual SKU can be determined. Note that these results only take into account store stock outs caused by a DC stock out. This retrieves the following results (Table 7.3).

Table 7.3: Descriptive Statistics Stock Out Duration (in Business Hours)

Level	Mean	Min	Max	Standard Deviation
DC Stock Out (Hours)	25.61	0.05	486	34.25
Store Stock Out (Hours)	42.99	10	699.44	60.74

These statistics show that, on average, a DC stock out lasts 25.61 business hours, which equals approximately 2.5 days. On the other hand, the average duration of the corresponding store stock outs is around 43 business hours, which is approximately 3.5 working days. A store stock out thus has, on average, a longer duration when rescaled to days. For both DC and store, the standard deviations of the stock outs are very large indicating that the duration of the stock out differs largely among each other. This approach, however, again only focuses on expressing the performance of the single actors, like the currently applied KPI of DSC.

To make a combination of the two, one could apply the *duration* KPI in a slightly different manner. For example, one can determine how fast a DC stock out is felt in the stores. This will be expressed in the start difference in hours between the DC and the store stock out. On average, it is found that store stock outs start 3.3 days after the DC went out of stock, with a standard deviation of 2.7 days.

One could also check the influence of the DC stock out start day on this start difference, which is visualized in Figure 7.6. The average start difference seems to increase during the week. On Sunday and Monday, the average start difference is the lowest, whereas the start difference on both Friday and Saturday seems to be the longest. However, there are many outliers in durations, and therefore it is hard to draw real conclusions. The weekday pattern will therefore be investigated further in the regression analysis in Chapter 9.

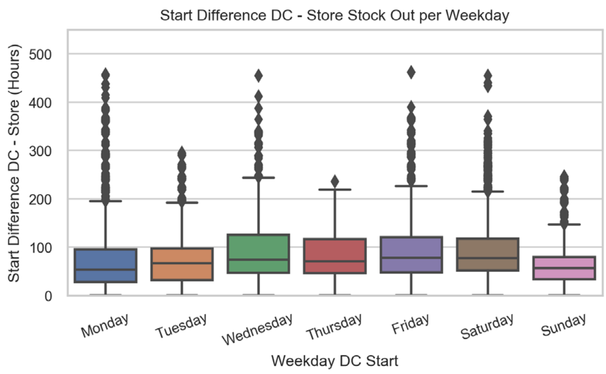


Figure 7.6: Week Pattern Start Difference Between DC and Store Stock Out

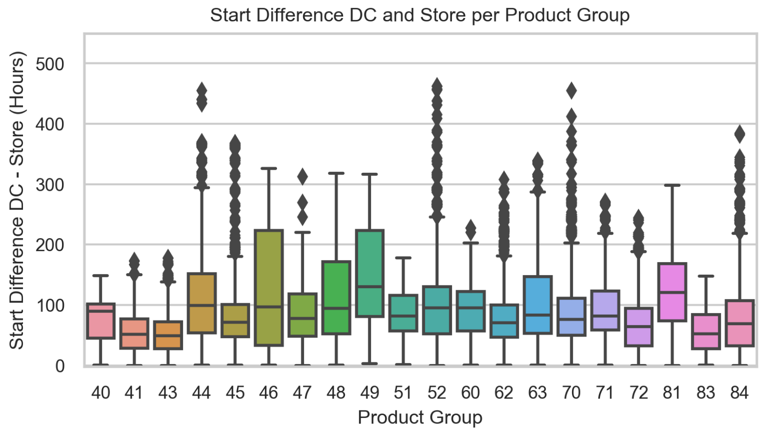


Figure 7.7: Start Difference DC and Store per Product Group

Next, a similar comparison is made, but now with a focus on the effect on the different product groups. Within Figure 7.7 one can see that, for example, group 49 and group 81 are the product groups with, on average, the largest start differences. Groups 43, 41, and 83 tend to have, on average, a low start difference. DC stock outs in these last three groups are thus relatively sensitive for DC stock outs. Further analysis showed that there is a high correlation between the in-store SOH levels with the average start difference per product group, which provides a possible explanation of the findings. This correlation is visualized in Figure 7.8 and shows that for the SKUs within group 43 and 41 the assigned store space has, on average, the least capacity to cover disruptions in the form of a DC stock outs. On the other hand, the SKUs within the groups 49, 46, and 81 are expected, and also can survive longer based on their assigned store space.

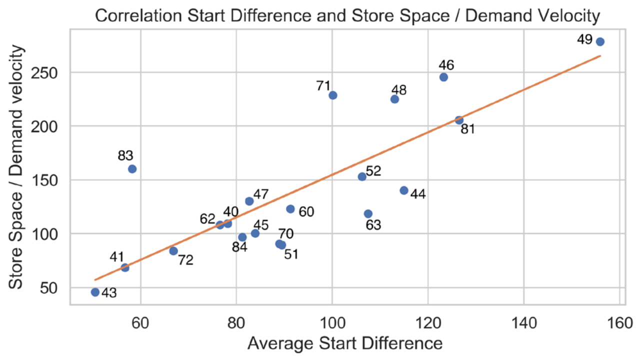


Figure 7.8: Correlation Start Difference and Store Space / Demand Velocity

7.4 Intensity and Fill Rate

7.4.1 Explanation

The last attribute *intensity* tries to capture the percentage of lost sales, which can be determined either in terms of consumer units or monetary values. However, this method is found to be relatively similar to determining the *fill rate*, which is 'the percentage of demand which can be fulfilled directly from inventory on the shelf' (Broekmeulen & van Donselaar, 2017). In essence, when looking at a single item, the fill rate is equal to 1 minus *intensity.* Both methods also have the same limitation, namely that in environments where only the sales are registered the actual performance must be estimated with an expected demand (Broekmeulen & Van Donselaar, 2016). Given that the fill rate is the most common method to measure the customer service level (Teunter et al., 2017), it is chosen to use this as the main definition.

7.4.2 In practice

The idea behind the *fill rate* can be perfectly used to describe the percentage of (expected) store demand fulfilled in times of a DC stock out. The range in which the fill rate for this research is determined is only equal to the period of the DC stock out. Therefore, this differs from the usual definition of the fill rate in the literature, where the period in which the fill rate is determined is much larger, i.e. describing the overall performance.

To be able to apply the fill rate formula, the total (expected) demand in a certain time period is required. The range in which the total (expected) demands must be determined is between the start of the DC stock out and the end of the store stock out, and thus the range varies per store. This range can be divided into two parts. The first part consists of the start of the DC stock out till the start of the store stock out, in which the total demand is known. The second part is the time between the start and the end of the store stock out. For this second part, the lost sales have to be estimated (See Section 5.3). Both parts together equal the total (expected) demand. Finally, to find the fill rate, the total sales are divided by the sum of both parts. For the stores that did not experience a store stock out, the fill rate is equal to 1.

On average, the fill rate level is found to be 0.82, implying that, on average, 18% of the demand is missed when a DC stock out occurs. In Figure 7.9, the DC stock outs are divided into four groups of DC stock outs. These lines show that the longer the DC stock out, the lower the average fill rate. Overall, for each group the deviations among the weekdays are relatively stable indicating no real week pattern.

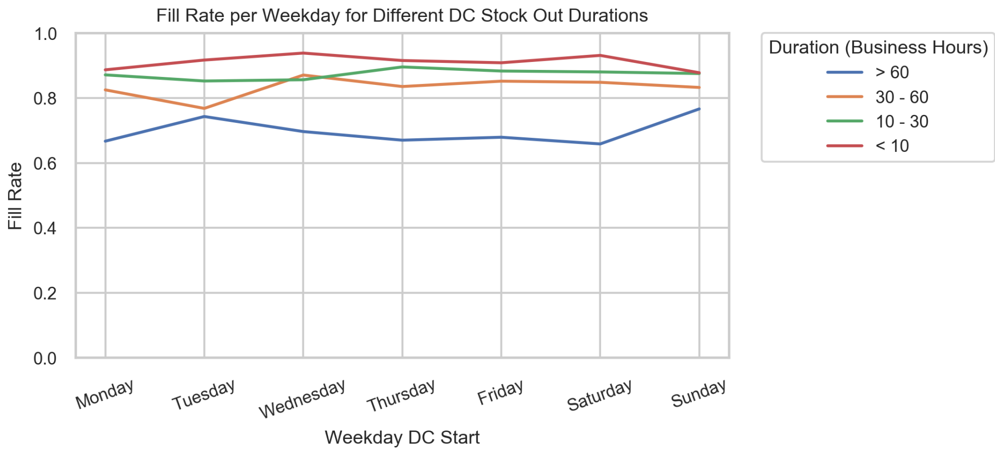


Figure 7.9: Fill Rate per Weekday for Different DC Stock Out Durations

Another focus of the *intensity* KPI is the monetary aspect of the DC stock outs. This could provide new insights for DSC, given that during the interviews a SCM consultant from HQ mentioned that:

> '*But you do not think about the revenue number, you only think about the number of pieces*' – Consultant SCM HQ

Therefore, in Figure 7.10 an overview is given of the average lost revenue and lost sales per DC stock out per product group. The perspective of the lost sales is added to show that the lost revenue and lost sales are not always in proportion indicating that not only the revenue part should be considered. This shows the group 47 results in by far the most lost sales, followed by group 63 and group 52 on the third place. The highest lost revenues are found for group 63, followed by group 84 and at the third place group 43. DSC should consider to take measure to minimize the DC stock outs within these product groups by, for example, increasing the SOH levels or reduce the lead times.

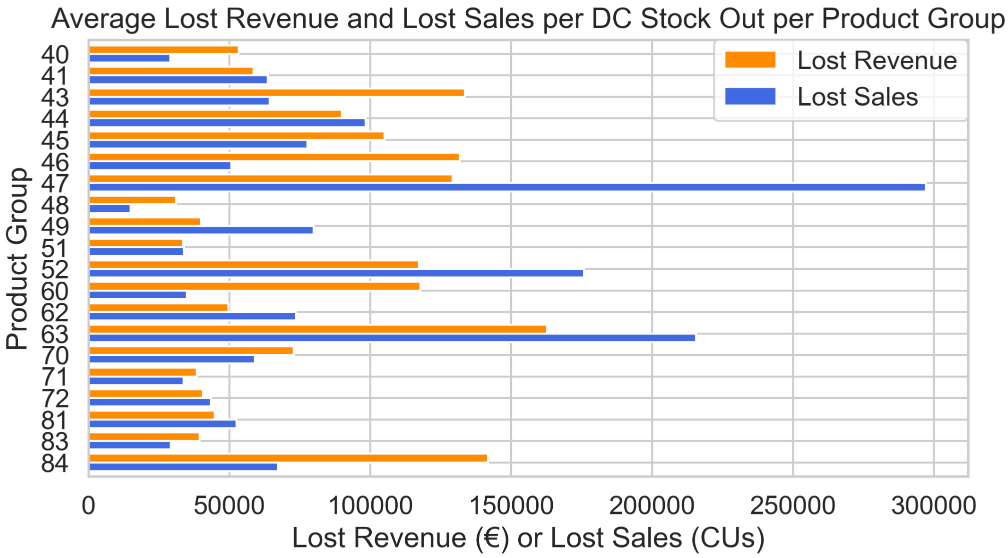


Figure 7.10: Average Lost Revenue and Lost Sales per Product Group for DC Stock Outs

In Figure 7.11, the average cost of a stock out per weekday can be seen. The blue line represents the average lost revenue for all DC stock outs, also including when the stores that not result in a store stock out. This line shows that near the end of the week, there is an increase in the DC stock out costs, but Sunday seems to be a 'cheap' day for out of stocks. The three days with the highest lost revenue (Thursday, Friday, and Saturday) were already found to have the largest store OOS rate, which likely explains these associated costs. Now, when only including the stores that have gone out of stock (Green), the stock outs are associated with higher costs, but the pattern also shifts a little. Here, a DC stock out occurring on Thursday leads to the highest average lost revenue. This is likely caused by both a relatively high store OOS rate on Thursday in combination with the fact that these DC stock outs are already felt in-store on both Friday and Saturday, two days with usually the highest revenues. After this peak, a large drop can be observed, where Sunday represents the lowest lost revenue. Finally, regarding the start day within the stores, the most expensive day to go out of stock is Friday, followed by Saturday. This can be logically reasoned by the fact that those two days are usually the days with the highest revenue.

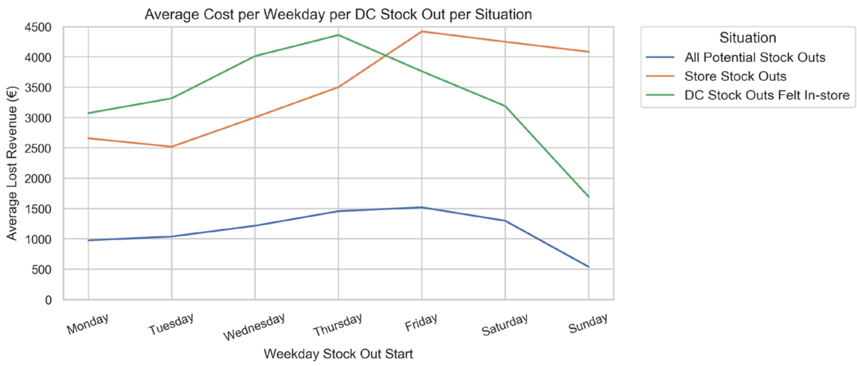


Figure 7.11: Average Cost per Weekday per Stock Out at DC and Store Level

In *Appendix B: Additional KPI Figures*, two additional figures are included about the eight product groups with the most lost revenue and lost sales per weekday. As expected based on Figure 7.10, the share of product groups differs between the two figures. These figures are mainly to provide some additional insights for DSC.

7.5 Conclusion

Within this chapter, many alternative KPIs have been demonstrated to describe the performance of DSC. All KPIs have their strengths, but also their weaknesses. The general *breadth* KPI was found to be the least useful KPI for the goal of this research, though DSC could take the provided insight into practice. The *store OOS rate* was easily applicable and can provide DSC with real insights into the influence of DC stock outs on the stores. Next, the *frequency* KPI provided useful insights into the weekly patterns. However, this KPI is less intuitive to use in order to keep track of the influence of DC stock outs. The adjustment of the *duration* KPI to track the start difference does contribute to the goal of this research. However, the practicality of this method is questioned. Finally, the *intensity* or *fill rate* KPI fits well for this goal and did gain additional insights about the stock outs of DSC. The downside though, is that given the requirement to estimate the expected total sales, implementing is way more challenging compared to the others.

8 DSC Focus and Potential Drivers

This chapter will first present the objectives and goals that DSC is currently most interested in when facing a DC stock out. Secondly, a list of potential product availability drivers based on findings of both DSC's current situation and literature will be constructed.

8.1 Focus

The previously described KPIs (Chapter 7) were discussed with the SCM team from both HQ and DC. The first direction mentioned by every interviewee was that decreasing the lost revenue should be the main focus, indicating that DSC is a very revenue-driven organization.

'At first the revenue is most important, this is what makes the managing board most happy' - Manager SCM DC

'Revenue is by far the most important factor, so when a choice should be made, this must be the focus' - Team leader SCM HQ

Though, when only focusing on the lost revenue, it would highlight the SKUs with a high retail price. This issue was already visualized in Figure 7.10. For example, the SKUs in group 47 often have a relatively low retail price, but many sales. Whereas the SKUs in group 84 often have a higher retail price but in total fewer sales. Thus, the proportions between lost revenue and lost sales are totally different for these two product groups. However,

'.., those products are not less important when it comes to customer satisfaction' – Team leader SCM HQ

Therefore, to account for this phenomenon, the lost sales will also be included as a dependent variable of focus.

Another often mentioned element during the interviews is the duration of the DC stock out.

'I think the duration of a DC stock out also plays an important role in how to handle DC stock outs ' - Manager SCM DC

Chapter 7 already introduced the *duration* KPI, conforming that literature also highlights this characteristic as an important element. By the use of this KPI, some insights about these characteristics were already introduced. However, by testing potential drivers that influence the DC stock out duration with, for example, linear regression, it can be checked which (additional) drivers significantly influence this duration.

Finally, another goal of DSC is to have a high product availability for its customers. The idea behind the currently applied KPIs is that the store stock outs are a derivative of the DC stock outs. DSC thus assumes that the DC stock outs are felt in many stores. The number of stores going out of stock might, however, differ between DC stock outs based on, for example, the weekdays (as seen in *Figure 7.1: Store OOS Rate per Weekday*). DSC is interested in which factors affect this store OOS rate, and is therefore included as a dependent variable.

In addition, an employee mentioned the following during the interview:

'It should not be the case that the percentage of stock outs differ largely between the store, as that would give a distorted store image' – Consultant SCM HQ

Due to the fact that there is no control over the final allocations, this store image might be distorted in the current situation. One store could possibly bridge another few days during a DC stock out without a final allocation, whereas another store cannot. When stores go out of stock during a DC stock out, it might be interesting to find out what drivers influence the start difference between the DC and store stock out. DSC could try to take fitting actions when it is known what affects this phenomenon. Therefore, this will also be listed as an independent variable of interest.

All in all, five dependent variables are indicated to be of interest for DSC, which are listed in Table 8.1.

Table 8.1: List of Dependent Variables

Dependent Variable	**Unit**
Lost Revenue	€
Lost Sales	Consumer units
DC Duration	Hours
Start Difference	Hours
Store OOS Rate	Percentage

8.2 Drivers

The insights from the current situation, KPIs, and literature have been combined and analyzed to indicate potential drivers behind the dependent variables (Table 8.1). Some of the drivers are specific to the environment of DSC and were already discussed in the previous chapters. In addition, the literature review of Verhoef (2021) had listed a wide set of variables that were used by other studies focusing on stock outs. An overview of these drivers is given in Table 8.2, including a small description, some additional information, and the source.

Table 8.2: List of Independent Variables

Variable	**Description**	**Measurement***	**Scale**	**Source**
DC Level				
Lead-time	Duration from ordering at the supplier till delivery at the DC	Weeks	Scale	Section 6.1.1
SOH Level	Desired stock on hand at the DC before a new order should be triggered	Weeks	Scale	Section 6.1.1
Store Level				
Backroom	Size of the backroom of each store	m2	Scale	(Milićević & Grubor, 2015)
Sales Floor	Size of the sales floor of each store	m2	Scale	(Milićević & Grubor, 2015)

Average Revenue	Average weekly revenue of each store taken over the year 2021	Euro's	Scale	(Milićević & Grubor, 2015)
Average Sales	Average weekly amount of consumer units sold in each store taken over the year 2021	CUs	Scale	(Avlijas, Milicevic, & Golijanin, 2018; Milićević & Grubor, 2015)
SKU Characteristics				
Product Group	Dummies indicating to which product group a product belongs	(0,1)	Nominal	Section 8.1
Case-pack Size	Number of consumer units in a box	CUs	Scale	(Eroglu, Williams, & Waller, 2011)
Retail Price	The retail price of each SKU	Euro's	Scale	(Corsten & Gruen, 2003)
Ordering Strategy	Dummy indicating if SKU is ordered via Direct or internationally	(0,1)	Nominal	Section 6.1.1
Brand	Dummy indicating if the SKU is a house brand or branded item	(0,1)	Nominal	Section 6.1.1
Store dependent SKU characteristics				
MOQ	Minimal order quantity per order per store	CUs	Scale	(Corsten & Gruen, 2003)
Space Allocation	Amount of space allocated to a certain SKU	CUs	Scale	(Corsten & Gruen, 2003)
Final Supply	Dummy indicating if the store received a final delivery	(0, 1)	Nominal	Section 6.1.1
Demand Velocity (Hourly)	Average sales per hour taken over the 8 week average	CUs	Scale	(Avlijas et al., 2018; Milićević & Grubor, 2015)
Weekday				
DC Stock Out	Dummies indicating which weekday the DC stock out started	(0,1)	Nominal	Section 7.2
Store Stock Out	Dummies indicating which weekday the store stock out started	(0,1)	Nominal	Section 7.2

*For confidentially reasons the measurement intervals are hidden (See *Appendix C: Information Table Dependent Variables*)

9 Testing Drivers of Stock Outs

In the previous chapter, a list of to be investigated dependent variables was given (Table 8.1). Afterwards, an overview of the to-be-included independent variables was given (Table 8.2). In this chapter, each of these independent variables will be tested against the selected dependent variables. To make it easier to compare the standardized variables (Pallant, 2016), all the independent variables have been converted to the same scale. First, the regression results regarding the DC duration and store OOS rate will be discussed. Secondly, the results of the other three dependent variables, I) lost revenue, II) lost sales, and III) start difference, will be talked through.

9.1 DC Duration and Store OOS Rate

Both the DC duration and store OOS rate cannot be influenced by the characteristics of individual stores. Therefore, some independent variables have to be excluded, ultimately resulting in the following list (Table 9.1).

Table 9.1: Set of Dependent Variables for DC Duration and Store OOS Rate

Variable	**Description**
DC Level	
Lead-time	The duration from ordering at the supplier till delivery at the DC
SOH Level	The desired stock on hand at the DC before a new order should be triggered
SKU Characteristics	
Product Group	Dummy indicating to which product group a product belongs
Case-pack Size	Number of consumer units in a box
Retail Price	The retail price of each SKU
Ordering Strategy	Dummy indicating if SKU is either *direct* or *international*
Brand	Dummy indicating if the SKU is a branded item or a house brand
Demand Velocity*	Average sales per hour taken over the 8-week average *over all 76 stores*
Weekday	
DC Stock Out	Dummies indicating which weekday the DC stock out started

*Slightly adjusted in comparison to Table 8.2

Before proceeding to the results the discussed assumptions in Section 3.4.2 had to be checked. First, the linearity assumption for all included variables is checked by visually interpreting the regression scatterplots. For each plot, it is concluded that a linear relation is visible and thus complies with the linearity assumption. Due to the large number of plots, it is chosen not to include them in the report.

The next step in the analysis is to check which independent variables are not significantly related to both the DC duration and the store OOS rate, which resulted in the drop of four independent variables. Next, the DC duration and store OOS rate independent variables are tested on 27 dependent variables. According to Green (1991), this requires at least 266 observations. The total incorporated DC stock outs are larger than 266 and therefore it is assumed that there are enough observations to perform this regression analysis.

Finally, for multicollinearity reasons, the VIF values were checked for the included variables. The highest VIF value found is 2.67 for the SOH variable, which is thus well within the limit of 10 (Hair et al., 2014). An overview of the VIF scores can be found in *Appendix D: VIF Values*. Finally, it is checked whether the error is heteroskedastic or homoscedastic by using the Breusch-Pagan test (Breusch & Pagan, 1979). This test is found to be non-significant and therefore no corrections must be made (Section 3.4.2). Table 9.2 provides an overview of the included variables and the corresponding results of the regression analysis.

Table 9.2: Regression Results DC Duration and Store OOS Rate

Dependent variable:	***DC Stock Out Duration***		***Store OOS Rate***	
	Estimate	*Std. Error*	*Estimate*	*Std. Error*
Intercept	N.S.	N.S.	N.S.	N.S.
Lead-time	N.S.	N.S.	-0.191	0.068**
Stock on hand (SOH)	0.231	0.054*	0.266	0.089**
Brand (ref= House Brand)	0.304	0.133**	0.310	0.132**
Demand Velocity (Hourly)	-0.099	0.037*	-0.245	0.037*
Weekday DC Start (Reference = Friday)				

Monday	-0.401	0.111*	-0.374	0.111*
Tuesday	-0.471	0.128*	-0.461	0.128*
Wednesday	-0.379	0.125**	-0.547	0.125*
Thursday	-0.406	0.127**	-0.322	0.127**
Saturday	N.S.	N.S.	N.S.	N.S.
Sunday	-0.492	0.139*	-0.425	0.138*
Product Group (Reference = Group 62)				
Group 44	0.830	0.211*	N.S.	N.S.
Group 47	0.597	0.244**	0.492	0.237**
Group 81	0.730	0.235**	0.870	0.235*
Group 84	0.374	0.172**	N.S.	N.S.
Group 60	N.S.	N.S.	0.970	0.279*
Group 63	N.S.	N.S.	0.727	0.289**
Others	N.S.	N.S.	N.S.	N.S.
Adjusted R^2	0.151		0.153	
** = significant at 0.001 significance level ** = significant at 0.05 significance level N.S. = not significant*				

When comparing the regression results for both the DC duration and the store OOS rate, it can be noted that the effect of the drivers is relatively the same. Though, the lead-time is found to have a significant negative effect on the store OOS rate, whereas for the DC duration this dependent variable is not found to be significant. Moreover, Avlijas et al. (2015) found that a higher product price increases the probability of a store stock out. This regression analysis, however, did not find any significant relation between the store OOS rate and the retail price.

Next, the SOH level was found to have a highly significant positive correlation for both drivers, with a relatively low standard error. SKUs with higher SOH levels, thus tend to have a longer stock out duration and result in a higher store OOS rate. When DSC experienced problems with certain SKUs in the past, the corresponding SOH levels are increased. It could be the case that the set SOH levels are still not high enough to handle disruptions, resulting in longer DC stock outs.

Moreover, there is a relatively large significant difference between branded and house brand SKUs, where branded items are found to result in longer DC stock outs and also a higher store OOS rate. This could be an indication that it would be smart for DSC to add a separate KPI for this product characteristic.

Next, a significant negative correlation for demand velocity is found, with a stronger effect on the store OOS rate. A higher demand velocity will likely result in a shorter duration of the DC stock out. A possible explanation could be that dispatchers are monitoring these SKUs more closely to prevent these stock out situations. An explanation for the lower store OOS rate for faster movers could be that the store spaces are relatively well set, so that disruptions, like DC stock outs, can be partly absorbed by the store inventory.

The weekday variables are found to be important estimators of the DC stock out duration and store OOS rate. Except for Saturday, each weekday shows a significant negative effect on the independent variables. It can thus be concluded that a DC stock out starting on either Friday or Saturday, on average, has the longest duration and the highest store OOS rate. These findings can be explained by the fact that there are limited supplier deliveries during the weekends, making it impossible to solve DC stock outs during these days. DC stock outs starting on either Sunday, Monday, or Tuesday result in the largest negative effect, given that many stock outs can be solved relatively quickly with supplier deliveries. This finding was opted in Section 7.2.2 about the *frequency* KPI and is thus confirmed by the results of this regression model.

Finally, some product groups are found to have a significant effect on the dependent variables. Four product groups were found to have a significant effect on the DC stock out duration. Group 44 is found to have the longest stock out durations, followed by the groups 81, 47, 84. Only the effect of group 81 was not expected, since Figure 7.5 showed that the other groups are good for a relatively large percentage of the stock outs on the weekdays with the longest DC stock out durations (Friday and Saturday). In addition groups 81 and 47 are also found to result in a high store OOS rate, and thus might need to be treated with some more caution by the dispatchers. Finally, also groups 63 and 60 area found to result in a high store OOS rate.

9.2 Lost Revenue, Lost Sales & Start Difference

In this section the drivers behind the lost revenue, lost sales, and start difference will be discussed. To get a uniform collection of drivers to test on each three of the dependent variable, the independent variables are selected based on their significance. The variables 'Average sales at store level' and 'Backroom space' are not found to be significant for any of the dependent variables and are therefore excluded from the models. Next, the VIF values are checked. The variable 'Product group' is found to affect the VIF values of some variables largely. To avoid skewed results, it is decided to exclude this variable from the analysis. The VIF values of the final included set are found to be well below 10, with an acceptable overall average VIF value of 1.84 (Hair et al., 2014). An overview of all VIF scores can be found in *Appendix C: Information Table Dependent Variables.*

After excluding the above-mentioned variables, a total of 24 independent variables remain. Based on the requirements of Green (1991), at least 242 observations are required. Given that approximately 34% of the store went out of stock during all DC stock outs, around one-third of the total data set remains. Also, due to missing values within the variables MOQ and the store space allocation, 620 observations are eventually dropped. Though, the number of observations exceeds the required 242 observations easily, allowing to assume that there are enough observations to test the variables. Finally, the errors term are checked on heteroskedasticity. The Breusch-Pagan test was found to be significant and therefore corrections are made to the standard errors, see Section 3.4.2.3.

To maintain a clear overview of the results, the findings of the regression analysis will be discussed in two parts. First, there will be an overview of some single variables (Table 9.3), which will be followed by the results for the different weekdays (Table 9.4).

Table 9.3: Results Regression Analysis

	Lost Sales		**Lost Revenue**		**Start Difference**	
Variable	*Estimate*	*Std. Error*	*Estimate*	*Std. Error*	*Estimate*	*Std. Error*
Intercept	*0.079*	0.022*	*0.085*	0.025*	0.164	0.028*
DC Level						
Stock on hand (SOH)	-0.029	0.010**	-0.036	0.009*	0.194	0.013*
Lead-time	0.220	0.022*	0.103	0.012*	N.S.	N.S.
Store Level						
Average Store Revenue	0.047	0.009*	0.081	0.010*	N.S.	N.S.
Sales Floor	-0.017	0.006**	N.S.	N.S.	N.S.	N.S.
Product Characteristics						
Retail Price	-0.050	0.007*	0.227	0.008*	-0.077	0.006*
Branded Items	0.101	0.019*	0.069	0.023*	0.381	0.028*

(Ref = House Brand)						
Ordering Strategy (Ref = *Direct*)	-0.040	0.012**	0.057	0.012*	0.205	0.014**
Case-pack Size	N.S.	N.S.	0.214	0.027*	0.087	0.007*
Store Dependent Product Characteristics						
MOQ	-0.122	0.037*	0.111	0.025*	-0.097	0.014*
Store Space	0.136	0.033*	-0.135	0.021*	0.200	0.016*
Demand Velocity (Hourly)	0.505	0.026*	0.414	0.022*	-0.201	0.011*
Final Supply	-0.014	0.006**	N.S.	N.S.	0.054	0.006*
Adjusted R^2	0.369		0.336		0.158	
** = significant at 0.001 significance level*						
*** = significant at 0.05 significance level*						
N.S. = not significant						

9.2.1 DC and store level

The SOH levels are found to have a significant effect on all three dependent variables. SKUs with a higher SOH level are expected to result in higher lost sales and lost revenue. Likely, this has to do with the finding of the regression analysis in Section 9.1, that SKUs with a higher SOH, on average, have a longer DC stock out. Moreover, a higher SOH level also leads to a longer start difference. Next, the lead-time is found to be a strong predictor of both lost sales and lost revenue. The longer the lead-time of an SKU, the higher the expected lost sales and lost revenue. Though, the lead-time has no significant effect on the start difference.

Store characteristics are not found to be very good predictors for the dependent variables. For the two included variables, the found effect is either limited or non-significant. The ‘Average Store Revenue’ has a small positive effect on the lost revenue and lost sales. Finally, for the size of the sales floor, a small negative effect is found on the lost sales.

9.2.2 Product Characteristics

For the lost revenue the retail price is, as expected, one of the most important factors. SKUs with a higher price, result in higher expected lost revenue. For both the lost sales and start difference the effect of the retail price is also found to be significant, but the effect is rather limited.

Next, whether the SKU is a house or branded item seems to be important for the dependent variables, especially for the start difference. It is remarkable that the branded items result in significantly higher lost sales and lost revenue compared to DSC’s own brand. The start difference, however, is found to be longer for branded items. It is not really clear why this trend occurs, but this again indicates that it could be smart for DSC to make a separate comparison in their KPIs for this product characteristic.

For the ordering strategy, a small negative effect is found on the lost sales, but a small positive effect is found in the lost revenue. This pattern is found because, on average, the price of *international* SKUs is slightly higher, but creates less volume. *International* SKUs also seem to have a longer start difference compared to *direct* items. Further analysis showed that, on average, the store space for *international* products is larger, which likely explains this effect.

The case-pack size seems to be important an important driver to determine the lost revenue. The more CUs in a case, the higher the lost revenue. For the lost sales, no significant effect is found whereas the effect on the start difference is limited.

For the lost sales, the MOQ has a significant negative effect, whereas the store space has a significant positive effect. For the MOQ, this can be explained by the fact that stores have to order more at once and therefore have more inventory left, leading to overall lower lost sales. The effect of the store space can be explained by the fact that SKUs with higher mean sales have a larger store space. Thus, when the store goes out of stock, the lost sales will be higher due to higher expected demand. This same way of reasoning can be explained for the start difference. However, for the lost revenue, the results were contradictory. After doing some further analysis, it was found that SKUs with a larger store space have, on average, a lower retail price, and therefore result in lower lost revenue.

The independent variable with the highest effect on all dependent variables is the demand velocity. The higher the mean sales, the higher both the lost revenue and the lost sales. Moreover, the start difference for SKUs with a higher demand velocity is also smaller. These results are found to be self-explanatory.

Finally, it is surprising that a final allocation for the stores has only a very small effect on the lost sales and the start difference. A store receiving a final supply will, on average, take longer to go out of stock and have lower lost sales, but the effect is very minimal. No significant influence on the lost revenue was found. This could be an indication that the current strategy of the allocation of the remaining DC inventory is done relatively well. In Chapter 10, the effect of an optimized final allocation strategy will be tested and compared to the current situation.

9.2.3 Weekday

In this section, the results about the influence of the different weekdays are shown (Table 9.4). Note that these results belong to the same regression analysis as performed in Table 9.3.

Table 9.4: Weekday Regression Analysis Results

	Lost sales		**Lost revenue**		**Start difference**	
Variable	*Estimate*	*Std. Error*	*Estimate*	*Std. Error*	*Estimate*	*Std. Error*
Weekday DC Start (Reference = Friday)						
Monday	N.S.	N.S.	N.S.	N.S.	-0.292	0.023*
Tuesday	-0.065	0.022**	N.S.	N.S.	-0.516	0.024*
Wednesday	0.175	0.028*	0.101	0.023*	-0.192	0.027*
Thursday	0.093	0.021*	0.053	0.025**	-0.218	0.024*
Saturday	N.S.	N.S.	N.S	N.S.	0.131	0.023*
Sunday	N.S.	N.S.	N.S.	N.S.	-0.384	0.023*
Weekday Store Start (Reference = Friday)						
Monday	-0.167	0.022*	-0.254	0.024*	-0.453	0.026*
Tuesday	-0.149	0.021*	-0.230	0.023*	-0.204	0.025*
Wednesday	-0.049	0.021**	-0.141	0.025*	N.S.	N.S.
Thursday	-0.055	0.022**	-0.110	0.024*	N.S.	N.S.
Saturday	-0.058	0.022**	-0.052	0.026**	-0.134	0.028*
Sunday	-0.088	0.026*	-0.120	0.031*	-0.223	0.030*
** = significant at 0.001 significance level ** = significant at 0.05 significance level N.S. = not significant*						

A DC stock out occurring on a Wednesday results in both the highest expected lost sales and lost revenue, followed by Thursday. This finding can be explained by the fact that the first store stock outs resulting from these DC stock outs likely occur on the busiest days in the store, namely Friday and Saturday. This finding also confirms the patterns found in Figure 7.11.

The largest start differences are found on both Friday and Saturday. This sounds reasonable, given that these DC stock outs occur after the busiest days in the store. The shortest start difference appears to be for DC stock outs starting on Sunday, followed by Tuesday and eventually Monday. Recall that store orders are placed two days in advance, thus orders placed on Friday are picked on Sunday. These orders need to restock the peak demand that occurred during the weekend, resulting in low inventory levels in the store. Thus, when a DC stock out occurs on Sunday, and many of these restocks were very necessary, the store stock outs will start sooner. This reasoning is supported by the fact that most store stock outs start on both Monday and Sunday (Figure 7.4). An explanation for the peak on Tuesday could not really be found. It could have something to do with that store orders for Tuesday must already be ordered on Saturday, implying a slightly longer lead-time of 3 instead of the normal 2 days. This could have less accurate store orders as a result, but whether this really holds is unknown.

For the weekday of the store start, it was found that stock outs starting on Friday and Saturday result in the highest lost sales and lost revenue. Monday is found to have the least effect on the lost sales and revenue, however, store stock outs starting on Monday have the shortest start difference. This is likely caused by a combination of the aftermath of the store's peak demand and limited supplier deliveries during the weekends.

10 Testing of Improvement Suggestions

All in all, the previous sub-questions provided many insights into both the current performance of DSC and drivers of product availability. Based on the introduced KPIs in Chapter 7, DSC has better insights into the performance of DC stock outs. However, DSC is also interested in how to minimize the effect of DC stock outs on the stores. This chapter will introduce how DSC could set up a smarter allocation method for the remaining DC inventory and the performance improvements this can achieve.

10.1 Model Setup

As introduced in Section 6.1.1, the dispatchers at the DC feature a so-called 'expected negative stock' list. This lists provides an overview of which SKUs are expected to go out of stock in the next two days, based on the current DC inventory, incoming store orders, and supplier deliveries. Often dispatchers can very well estimate the duration of a DC stock out. Next, by extracting the current store inventory levels and determining the expected demand for the stores during the expected duration of the DC stock out, dispatchers could optimize the allocation of the remainder of the goods. In this research, solving this allocation problem will be done with a mixed-integer linear problem (MILP). This allocation problem relies on a set of assumptions and objectives which will be discussed in the next section.

10.1.1 Assumptions

10.1.1.1 Inventory and Demand

As mentioned before, the 'expected negative stock' list can help dispatchers anticipate a DC stock out two days before it actually starts. The day that the dispatchers become aware of an upcoming DC stock out will be seen as the start of the model and is indicated with t = -2. The moment that the DC stock out actually occurs is defined as t=0. Due to the known outgoing orders at t = -2 and t = -1 are at, at t = -2 the dispatchers know the remaining DC inventory at t=0. In addition, the store orders are preferred to be in the system two days before the actual order picking starts. Therefore, at t=-2 the optimized allocation must already be determined. The dispatcher needs the following information to estimate the flow of the inventory levels in the store, I) outstanding store orders, II) expected DC stock out duration, III) the inventory levels of the stores, and IV) the expected demand per weekday.

The expected demand is assumed to be deterministic and will be used to keep track of the inventory flows of the stores during the DC stock out period. For this model, it is assumed that the 8-week average provides a good estimation of the expected demand. This expected demand is needed for the total time period of the expected duration of the DC stock out, which also includes t=-2 and t=-1. In this model, historical data is used to define the time periods (i.e. duration in days) per DC stock out event. Each stock out duration is extended with one extra day to have a small buffer for accuracy reasons.

For the two days prior to the DC stock out (t=-2 and t=1), the stores may receive deliveries from the DC. These deliveries should thus be used to update the inventory levels. Finally, at t=0 the stores may receive the final delivery that is determined by the model. For these deliveries, it is assumed that they are always added at the end of the day. Thus, the supply will be added after all the demand of that day is extracted. Finally, for stores it is not possible to have a negative inventory, thus the minimum value of the inventory is zero. An overview of the above processes can be found in Figure 10.1.

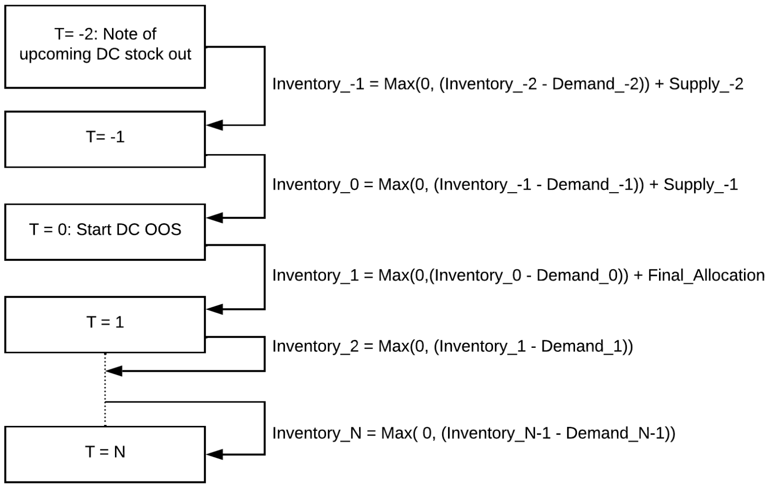


Figure 10.1: Store Inventory Update Scheme

10.1.1.2 Allocation

Next, the SKUs have to be allocated to the store based on a certain minimum order quantity (MOQ). It is not possible to allocate the inventory per individual consumer unit, because this would be very inefficient for the order pickers at the DC. When stores make the orders on their own, their orders must comply with a store-dependent MOQ set for each SKU. This MOQ is primarily based on the in-store space allocated to this SKU and is implemented to increase efficiency at the DC. However, for this final allocation, these store-dependent MOQ levels are ignored to be more flexible in the final allocation. Instead, the MOQ in the model will be the minimal quantity of CUs that can be shipped to the stores, which is determined by the case-pack size. For example, if a case for a certain SKU contains eight CUs, the MOQ constraint for that SKU will be set to eight.

10.1.1.3 Scenarios

As found in Chapter 8, DSC is a revenue-based organization, and therefore, one of DSCs objectives is to reduce the lost revenue as much as possible. Due to optimizing one DC stock out at a time, maximizing the revenue is equal to maximizing the sales.

Another desire opted by DSC in Chapter 8 is to reduce the number of stores going out of stock during the DC stock out. In this scenario, DSC wants to allocate the goods to the stores that are expected to be out of stock the soonest. To achieve this, it is assumed that there is a fictive cost linked to going out of stock. By applying a decreasing cost curve, going out of stock a few days after the DC stock out will be cheaper than going out of stock immediately. By minimizing these fictive costs, the model can be used to optimize this objective.

Earlier in this section, it was mentioned that the store orders for t=-1 are already scheduled for the order pickers at t=0. However, DSC has mentioned that there is some flexibility in rescheduling these orders. Therefore, it could be possible for DSC to combine the remaining inventory at t=-1 and t=0 for an optimized allocation to the stores. This idea will be applied to both the desires of maximizing the sales and minimizing the penalty costs, resulting in a total of four different scenarios.

10.2 Mathematical Model

The model elements discussed in the previous section can be divided into three groups, namely parameters, the decision variables, and other variables (Table 10.1). Next, the objective must be defined based on these parameters and variables. Finally, the objective must satisfy a set of requirements and constraints to result in a realistic optimized solution.

Table 10.1: Model Parameters and (Decision) Variables

Parameters	
I	$\{Set\ of\ Stores\ \}$
T	$\{Set\ of\ Time\ periods\ during\ DC\ stock\ out\}$
C	$\{Amount\ of\ CUs\ in\ package\}$
D_{it}	$\{Forecasted\ demand\ at\ Store\ i\ on\ Day\ t\ \}$
SI_{it_0}	$\{Set\ of\ Inital\ available\ inventory\ at\ each\ Store\ \}$
DCI_{t_0}	$\{Amount\ of\ packages\ to\ be\ allocated\ \}$
$PenC_t$	$\{Penalty\ costs\ per\ time\ period\ (t)\}$
Decision Variable	
q_i	$Amount\ of\ CUs\ allocated\ to\ Store\ (i)$
Variables	
I_{it}	$Inventory\ level\ at\ each\ Store\ (i)\ at\ the\ end\ of\ each\ Period\ (t)$
S_{it}	$Amount\ of\ CUs\ sold\ at\ Store\ (i)\ at\ per\ Period\ (t)$
P_{it}	$\begin{cases} 1, & if\ store\ went\ out\ of\ stock \\ 0, & store\ did\ not\ go\ out\ of\ stock \end{cases}$
PC_{it}	$Amount\ of\ Penalty\ costs\ assigned\ at\ Store\ (i)\ at\ Period\ (t)$

10.2.1 Objective

Based on the description of the scenarios and the set of parameters, the objectives of the MILP can be defined. The first one will be to maximize the number of sales during the DC stock out, whereas the other one will be to minimize the penalty costs of premature stock outs. This results in the following two objectives:

$$(1)\ Maximize\ Sales{:}\ Max \sum_t \sum_i S_{ti}$$

$$(2)\ Minimize\ Penalty\ Costs{:}\ \ Min \sum_t \sum_i P_{ti}$$

One limitation of a MILP is that the behavior is a little unpredictable when there are multiple optimal solutions. Consider the following simple example in Table 10.2, where a DC has 5 units left that must be allocated to two stores. Both stores have a starting inventory of 10 and a total demand of 15 spread over two days (D1 and D2). The penalty cost of going out of stock at D1 is 2 and at D2 is 1.

Table 10.2: Explanation Scenario of a Single Objective Setting

				Option 1: Maximize Sales			*Option 2: Minimize Penalty Cost*		
Store	**Inventory**	**Dem D1**	**Dem D2**	**Allocation**	**Inv D1**	**Inv D2**	**Allocation**	**Inv D1**	**Inv D2**
1	10	5	10	5	10	0	0	5	0
2	10	10	5	0	0	0	5	5	0

In this example, the total demand is higher than the total inventory. Therefore, when solving this example to maximize the sales, it does not matter which store will receive the goods. Likely, the MILP will just send the goods towards store 1, given that is the first on the list, as illustrated in option 1. Though, DSC will likely prefer option 2, in which the same amount of sales is achieved and both stores go out of stock on the second day.

Therefore, to gain more control over the allocations, a combination of both objectives, i.e. a multi-objective problem, will be used. This setup will be implemented by using a priority rule, which means that the objective function with the highest priority will be optimized first. Next, the objective with the second-highest priority will be optimized, where the optimized value of the first objective should remain the same. In the case of the provided example, a multi-objective problem with the highest priority of maximizing sales and secondly the penalty costs will work as follows. As mentioned before, the total sum of inventory equals 25 units and the total demand is 30 units. This results in the maximum sales, i.e. the objective with the highest priority, of 25. Next, when holding the amount of 25 sold units equal, the penalty costs have to be minimized. In option 1, the total penalty costs are equal to 4 (=2 + 1 + 1), whereas for option 2 the penalty costs are minimized and equal to 2 (=1+1). Thus, based on the application of the multi-objective, option 2 will be chosen as the optimal solution. Note that if there are again multiple optimal solutions, this model will, like the above-mentioned single objective models, just pick a random optimal solution.

The given priority will interchange between objectives 1 and 2 resulting in two different objective functions, namely one with a priority to maximize the sales and the second one to minimize the penalty costs, i.e. reducing the number of stores going out of stock. These two scenarios will from now on be referred to as I) Priority Sales and II) Priority Store OOS, both with the option to allocate either 1 or 2 days of DC inventory.

10.2.2 Constraints

The following constraints apply for optimizing the above stated multi-objective problem.

Table 10.3: Overview of the MILP Constraints

Number	**Constraints**
If t = 0	
(1)	$SI_{it_o} + (q_i * C) = I_{it_0}, \quad \forall\, i \in I, t \in T$
(2)	$\sum_I q_i <= DCI\ ,$
if t > 0	
(3)*	$I_{ti} = \max\left(I_{(t-1)i} - D_{ti}, 0\right), \quad \forall\, i \in I, t \in T$
(4a)	$S_{ti} \leq D_{ti}\,, \quad \forall\, i \in I, t \in T$
(4b)	$S_{ti} \leq I_{(t-1)i}\,, \quad \forall\, i \in I, t \in T$
(4c)	$S_{ti} = I_{(t-1)i} - I_{ti}, \quad \forall\, i \in I, t \in T$

(5a)*	$P_{ti} = \begin{cases} 1, & if\ I_{ti} = 0 \\ 0, & else \end{cases}, \qquad \forall\, i \in I, t \in T$
(5b)	$PC_{it} = P_{ti} * PenC_t\,, \qquad \forall\, i \in I, t \in T$

*By definition not linear, but can be converted to a linear expression. See <u>*Appendix E: Linear Formulations*</u>

In constraint 1 the number of allocated packages is added to the initial inventory of the stores. Since the store inventory is measured in CUs, the allocated packages have to be multiplied by the amount of CUs in the package. The total amount of allocated packages cannot be larger than the amount of inventory available at the DC (constraint 2).

There are no backorders possible for the stores. Therefore, the stores cannot have a negative inventory level, which is prevented by the use of constraint 3. Next, constraint 4 makes sure that the amount of CUs sold cannot be larger than the actual demand (4a) and cannot be larger than the available inventory (4b). Given these two constraints, it can be stated that the amount of sold CUs are equal to the difference in inventories between two consecutive time periods (4c).

Constraint 5 is about assigning penalty costs for stores going out of stock at a certain time period. First, a binary variable is introduced to indicate a store stock out (5a). When the store inventory is equal to zero at a certain time period, it will be labeled as a store stock out for all successive time periods for the whole period of the DC stock out. Next, the corresponding penalty score for the periods that the store has been out of stock will be added (5b).

10.3 Model Performance

The model introduced in the previous section has been applied to the same set of DC stock outs as used for estimating the store stock outs. In total, all the DC stock out situations for the 200 selected unique SKUs have been optimized. Below the performance of the different scenarios are listed and compared to the current situation. After this general performance overview of the different scenarios, there will be a more in-depth analysis based on important prior findings, like the effect of the weekdays and SKU characteristics. The used performance measures are based on the KPI findings and the objectives of DSC.

Two notes have to be made according to the performance measures.

- In Chapter 7, the KPI values were determined by using POS data. However, for the allocation model, the use of expected demand and an inventory level per store was required. To be able to compare the performances, the current situation is estimated using the same expected demand and inventory levels. This, however, leads to differences between the 'current' KPI values in this section and the 'current' KPI values found in Chapter 7.
- In essence, a 2-day inventory allocation starts 1 day prior to the actual DC stock out. Though, to keep a fair performance comparison between the allocation strategies and the current situation, the performance measures are always determined over the weekdays of the actual DC duration.

Table 10.4: Performance Comparison between the Scenarios

	Current	**Priority Sales**		**Priority Store OOS**	
		1 Day	2 Days	1 Day	2 Days
Overall Fill Rate (%)	76.65	83.68	84.10	82.47	83.60
Overall Store OOS Rate (%)	24.44	18.36	17.35	17.64	16.54
Revenue Increase (%)		8.61	9.25	7.97	8.50

When 1-day of inventory is allocated to the store, the overall fill rate in times of a DC stock out, increases from 76.65% to well over 82% for both objectives. In addition, a decrease in the store OOS rate, from 24% to around 18%, can be observed. Altogether, the total revenue increases by approximately 8%. Next, with a 2-day inventory allocation, the overall fill rate improves even further, with approximately 0.5% point. The store OOS rate decreases by around 1% point and the revenue increases also slightly compared to a 1-day inventory allocation. Though, the additional improvements of switching from a 1-day to a 2-day scenario are relatively limited.

10.3.1 Weekday

As found in Chapter 7, patterns could be observed based on the weekdays. Therefore, the overall results of the fill rates and store OOS percentages have been plotted against each other, which can be found in Figure 10.2 and Figure 10.3, respectively. In general, it can be concluded that a smarter allocation method is beneficial for every weekday. Though a few findings are remarkable.

First of all, in Figure 10.2 it is found that for most weekdays a 2-day inventory allocation performs slightly better than a 1-day inventory allocation, whereas Sunday seems to benefit the most. However, on both Monday and Saturday this pattern is reversed. For Saturday, this pattern likely occurs given that the inventory will be added at the end of Friday. Therefore, this inventory can already be sold on Saturday, a day with high demand. Based on the calculation for the 2-day inventory allocation, this day is not included, resulting in lower start inventories, ultimately resulting in a lower Fill rate. Though, this reasoning cannot be applied for Monday and the reason why this occurs was not found.

In Figure 10.3, the percentage of stores going out of stock based on the weekday that the DC started can be found. In comparison with the current situation, the number of stores going out of stock can be largely decreased. Especially for the DC stock outs that occur on Sunday and a 2-day allocation is applied, the OOS percentage can be decreased significantly. For the other weekdays, the OOS percentage difference between the 1-day and 2-day allocation is limited. Finally, Saturday shows some contradictory results because the switch from a 1-day to a 2-day allocation shows no positive effect. This finding can be explained with the same reasoning used for the fill rate.

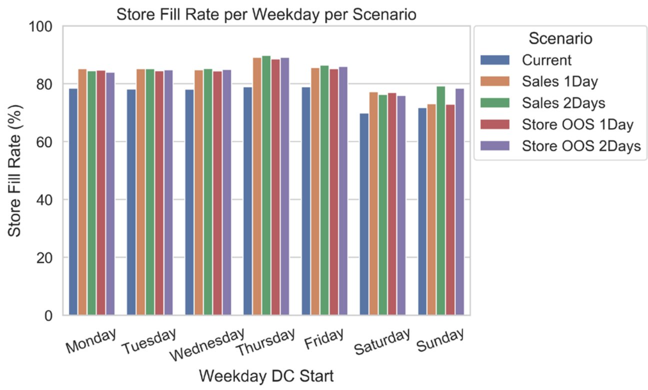


Figure 10.2: Store Fill Rate per Weekday per Scenario

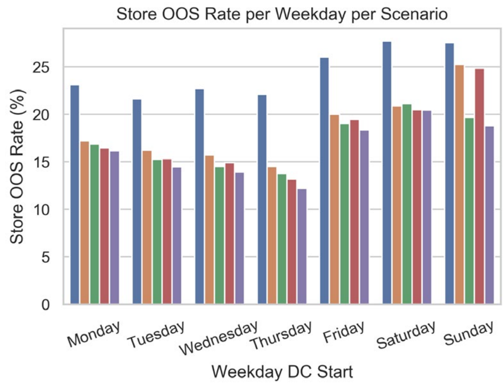


Figure 10.3: Store OOS Rate per Weekday per Scenario

10.3.2 Duration

Another interesting element is how the different scenarios behave given the duration of the stock outs. This idea is plotted for both the fill rate and the store OOS rate in Figure 10.4 and Figure 7.5 respectively. Note that the fill rate starts at t=1, because of the assumption that inventory is added after the demand of that day, as shown in Figure 10.1. The included bar graph represents the number of active stock outs at that time period. Using this line, it can be seen that around 50% of the stock outs have a duration of a maximum of 2 days, whereas there is only a very small percentage of DC stock outs that lasts 11 days.

Based on the fill rate it can be seen until the 4th day, the performances among the different scenarios are very similar. However, after the fourth day, both scenarios with a 1-day inventory allocation have a heavier drop in the fill rate compared to the 2-day inventory allocation. This phenomenon lasts until day 7, where also the current scenario seems to catch up. On day 8, there is also a strange spike in the fill rate, for which no actual reason could be found. Possibly, the number of active stock outs is too low to represent a representative behavior.

For the store OOS rate, in the first few days, the scenarios perform all relatively similarly. However, after the third, a deviation between the scenarios is observed. At this moment, the difference in store OOS rate between the Sales 1Day scenario (orange) and Store OOS 2Days scenario (purple) starts to increase, with a maximum of 6% point on the sixth day. After the sixth day, the performance difference decreases. On the 8th day, the performances of all scenarios, including the current situation, are comparatively. The performance of the two 'middle' lines between the third and 8th are approximately the average of the purple and orange line. Next, when comparing the current situation with the Store OOS 2Days scenario (purple), the maximum performance difference can be seen on the fourth and fifth days. For both days the difference in OOS rate is 12% point.

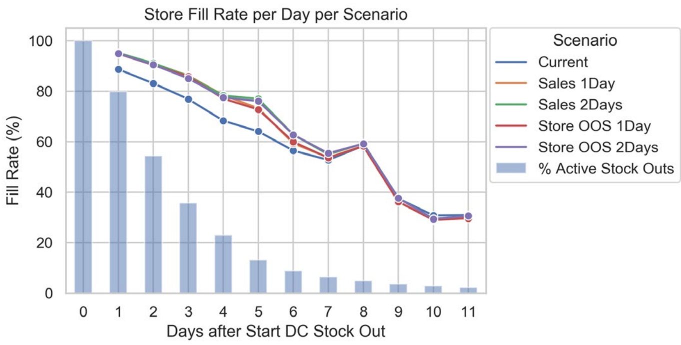


Figure 10.4: Store Fill Rate per Scenario 'n' Days after DC Stock Out

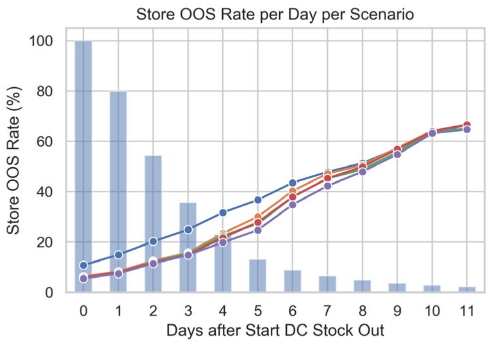


Figure 10.5: Store OOS Rate per Scenario 'n' Days after DC Stock Out

10.3.3 Product groups

Next, the effect of a smarter allocation on both the fill rate and store OOS rate per product group has been checked. This is visualized in Figure 10.6 and Figure 10.7 where the differences in percentage points between the current situation and the scenario are expressed. The actual realized fill rate and OOS rate per product group can be found in <u>*Appendix F: Fill Rates and OOS Rates per Product Group*</u>.

First of all, in Figure 10.6 it can be seen that both groups 49 and 47 seem to benefit largely from a smarter allocation, with respectively an increase of approx. 17.5% and approx. 15% in the fill rate. Though, for group 49 the number of DC stock outs is rather limited, and might therefore not be fully representable. For group 47, the large increase can likely be explained by the fact that this product group consists of many fast movers, resulting in large improvements in terms of the fill rate. The finding of this phenomenon can be found in Table 10.5.

Secondly, both groups 49 and 47, but also group 43 do not benefit from a 2-day inventory allocation. It was already found that many stock outs occur for groups 43 and 47 occur on Saturday (Figure 7.5), and therefore likely reflects the same pattern for the Saturday as seen in Figure 10.2. For group 49 no real conclusion can be drawn.

Moreover, the fill rate for group 63 increases largely when a 2-day inventory allocation is applied. This performance increase likely has to do with the fact that many stock outs of this product group occur on Sunday, which was found in Figure 7.5 and therefore likely reflects the benefit of a 2-day allocation on Sunday as seen in Figure 10.2.

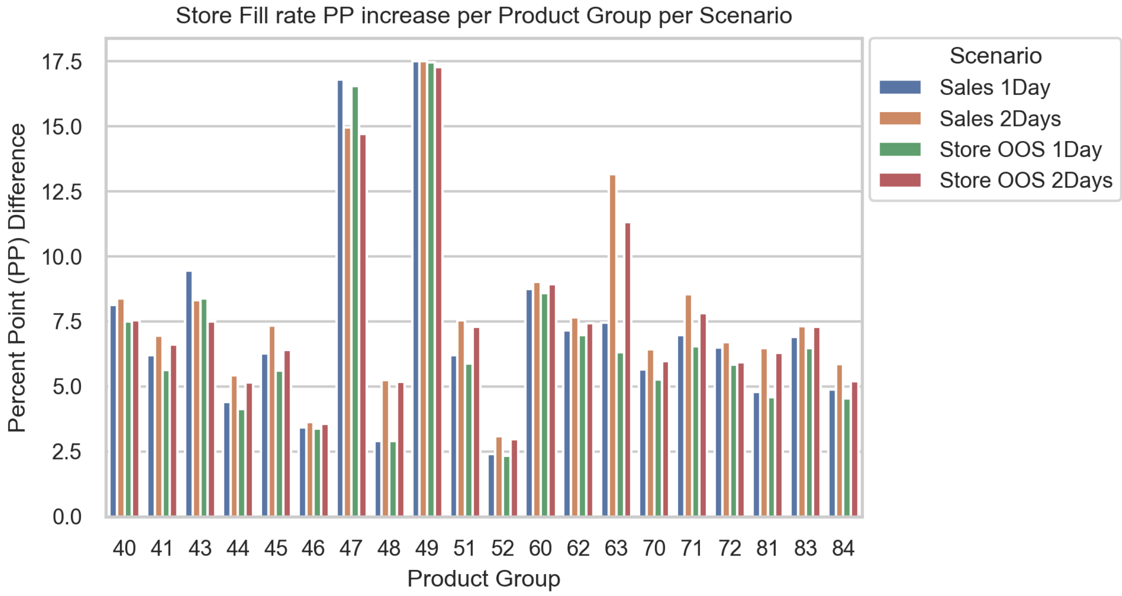


Figure 10.6: Store Fill Rate PP Increase per Product Group per Scenario

Next, when comparing the decrease in store OOS rate per product (Figure 10.7), the overall trend is very similar to the findings for the fill rate. However, it is remarkable that every product group benefits from a 2-day inventory allocation, despite the decrease in the fill rate for groups 43, 47, and 49. The overall store OOS rate during a DC stock out can thus always be improved, whereas it might not benefit the fill rate. In Table 10.5 this same pattern is found for the fastest-moving SKUs. This likely explains the large difference between the fill rate and store OOS rate for group 47 in which many fast movers are present (Figure 7.10), and to a lesser extent for group 49 and group 43.

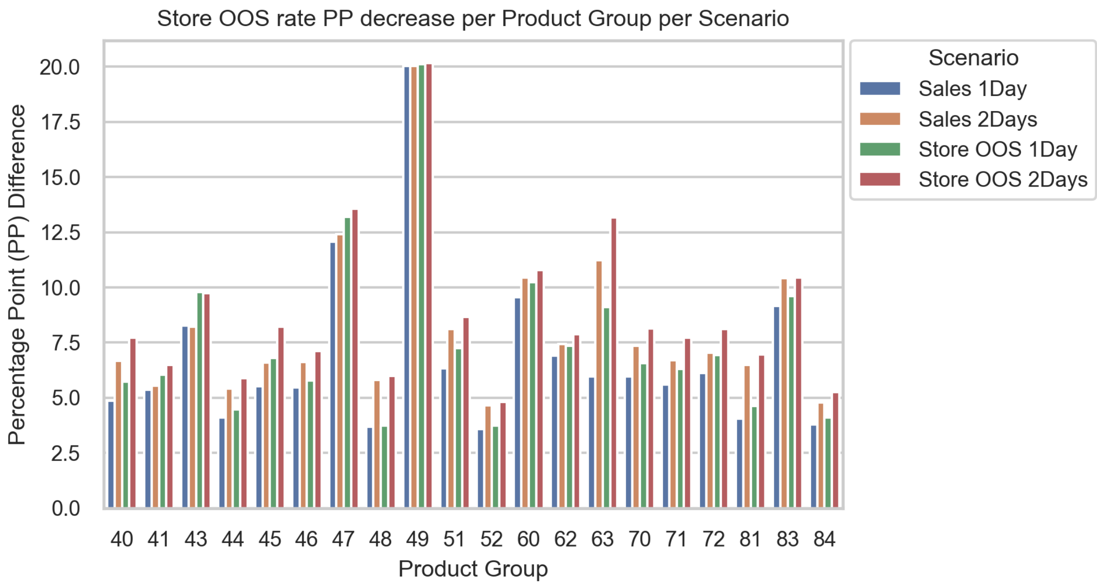


Figure 10.7: Store OOS Rate PP Decrease per Weekday per Scenario

10.3.4 Performance Analysis of Product Characteristics

Finally, the three variables with the largest influence on all three dependent variables found in Chapter 9 have been chosen for further comparison on the model performance. These three variables are I) Demand velocity, II) SKU Brand Space and III) Store Space.

Table 10.5: Model Performances based on Demand Velocity, SKU Brand, and Store Space

		Current	Priority Sales		Priority Store OOS	
			1 Day	2 Days	1 Day	2 Days
Demand Velocity (Hourly)						
Overall Fill Rate (%)	< 1	72.72	78.26	79.02	77.88	78.63
	1 - 4	78.09	84.29	85.06	83.72	84.34
	> 4	80.63	91.65	90.85	91.35	90.60
Overall Store OOS Rate (%)	< 1	26.09	20.31	19.14	18.72	18.51
	1 - 4	20.92	15.09	14.23	14.11	13.07
	> 4	22.02	9.83	10.18	8.74	9.01
Revenue Increase (%)	< 1		7.88	8.79	7.28	8.18
	1 - 4		8.01	9.07	7.32	8.07
	> 4		12.04	10.89	11.48	10.46
SKU Brand						
Overall Fill Rate (%)	House	77.26	84.49	84.90	84.05	84.40
	Branded	65.42	68.64	69.32	68.29	68.88
Overall Store OOS Rate (%)	House	24.03	17.73	16.79	17.01	15.97
	Branded	29.01	25.37	23.55	24.66	22.86
Revenue Increase (%)	House		8.82	9.44	8.18	8.68
	Branded		5.07	6.12	4.60	5.48
Store Space*						
Overall Fill Rate (%)	Large	79.44	86.57	86.94	86.16	86.40
	Small	71.17	78.13	78.63	77.63	78.21
Overall Store OOS Rate (%)	Large	20.61	14.87	13.99	14.39	13.45
	Small	27.49	21.04	19.99	20.13	18.97
Revenue Increase (%)	Large		7.29	7.93	6.74	7.14
	Small		10.15	10.78	9.34	10.08

*Size split made on the median (= 80 CUs)

The results show that most improvements can be made for SKUs with a higher demand velocity. SKUs with a demand velocity of more than 4, always result in an improvement in the fill rate of over 10% point compared to the current situation, which is also observed in a large revenue increase. The OOS rate even has an improvement of at least 12% point. Though, for the fastest-moving SKUs, a 2-day inventory allocation seems to perform worse than a 1-day inventory allocation. This, however, occurs because both scenarios are compared on the same weekdays, whereas the 2-day inventory allocation starts 1 day before this. These faster-moving items thus seem to be demanded in such quantities on the day that is not included, that it skews the results a little. For the two other groups of the demand velocity, both the fill rate and the OOS rate improve by approximately 5 to 7% points, depending on the scenario. The revenue increase for these two groups is expected to be around 8%.

When optimizing the final allocation, the house brand seems to benefit more based on the fill rate and OOS rate with an improvement of around the 7% point. The branded items, however, only improve with around the 3% point. This difference is also observed for the revenue increase, where focusing on the house brands would result in a better revenue increase. Next, based on the fill rate and the OOS rate, the difference between the improvements for either large or small store spaces is relatively small.

For both cases, the improvements are around the 7% point. However, for the SKUs with a smaller store space, the revenue increase is around 10%, whereas for the larger store space it is ‘only’ around 7%.

10.3.5 Conclusion

All in all, the performances of the scenarios have been tested on various drivers, i.e. weekdays, product groups, and some product characteristics. It can be concluded that any form of smart allocation has been proven to be beneficial for DSC. The gained improvements do not differ largely between the weekdays, though most gains are found for DC stock outs starting on Thursday. On the other hand, the improvements between the product groups do differ largely. Both group 49 and group 47 seem to benefit the most in terms of both fill rate (over 14% point increase) and store OOS rate (over 12% point decrease) compared to the current situation. Moreover, it was found that especially SKUs with a high demand velocity benefit from an optimized allocation strategy with a revenue increase of over 12%.

The difference between either a sales or OOS rate-focused approach is found to be minimal in terms of the applied KPIs. This is especially true for DC stock outs with a duration of 1 to 3 days. Although the KPIs often show improvements when distributing a 2-day inventory compared to a 1-day inventory, the improvements are found to be limited. Finally, for DC stock outs with an expected duration of more than 3 days, there are some larger differences between the scenarios. Optimizing the store OOS rate when distributing a 2-day inventory is found to perform best in terms of store OOS rate and nearly the best in terms of the fill rate.

Part 4. Conclusion and Recommendations

11 Conclusion

In this chapter, the main findings of this research are described. First, an answer to the main research question will be given based on the answers to the five sub-questions. Secondly, the contribution of this research to the literature will be discussed.

11.1 Answer to Research Question

The main goal of this study was to find an answer to the main research question. A summary of the sub-questions will serve as an answer to this research question, which was defined as follows:

How can the dispatchers be supported to minimize the effects of stock outs in the DC on the in-store product availability?

The first research question focused on the current situation of DSC. In the current replenishment system, it was found that there are two different ordering strategies, namely *direct* and *international*. Moreover, answering this sub-question provided insight into the currently applied KPIs, which are found to be relatively simple. Both on DC and store level the number of stock outs are just summed together within their assortment and compared to a certain threshold value set by DSC. In addition, it was found that the current threshold values are attainable for both the DC and store actors, and are therefore well set.

Next, the literature was studied to find other applicable KPIs for stock out situations. This resulted in an overview of four KPI directions, namely I) *breadth*, II) *frequency*, III) *duration* and IV) *intensity / fill rate*. The *breadth* KPI was eventually used to express the store out of stock rate per DC stock out. This KPI was found to be an easily applicable, but also insightful KPI to check the influence of DC stock outs on the performance in the stores. In addition, the *frequency* KPI was useful in indicating large differences in stock outs between the weekdays, but not so well in describing the effect of DC stock outs on the stores. Thirdly, the d*uration* KPI was used to express the difference in start time between the DC and store stock outs. Further analysis pointed out that this start difference can be estimated by dividing the assigned store space by the average demand velocity. This showed that likely for SKUs in product groups 43 and 41 the assigned store spaces can be optimized to better handle DC stock outs. Finally, the KPI direction of the *intensity / fill rate* provided insights in a different direction than DSC is used to. This KPI namely expressed the performance expression in either lost sales or lost revenue, instead of the number of stock outs. Though, due to the way of working at DSC, implementing this KPI will be harder compared to the other ones.

For the third sub-question, it was found that DSC is a very revenue-driven organization. Though, during the interviews, it also became clear that the out of stock rate of the stores is rather important. Eventually, the main objectives of DSC were found to be the DC duration, store OOS rate, lost sales, lost revenue, and the start difference between DC and store stock outs. By using insights into the current replenishment strategies, KPI results over the current situation, and a literature study a list of potential drivers was constructed. Eventually, the 17 listed drivers were divided into five subsections, namely I) DC level, II) Store level, III) SKU characteristics, IV) Store dependent SKU characteristics, and finally, V) Weekdays.

By performing a regression analysis on these drivers an answer on the fourth sub-question was formulated. It found that especially the weekday that the DC stock out starts is an important driver. DC stock outs starting on Friday and Saturday are found to have the longest duration and result in the highest store OOS rate, which highlights the main bottleneck of the DC stock outs. Moreover, SKUs with a high demand velocity were found to result in higher lost sales and revenue. Finally, also the finding of the house brands differed significantly from the branded SKU, which may opt for DSC to make a separation in the KPIs for this product characteristic.

Eventually, all the insights were combined to create and test an optimized allocation of the remaining DC inventory. Two different model objectives were tested based on the desire of DSC and both showed a lot of potentials to minimize the store effects. For the total set of included DC stock outs, the model showed an overall increase of around 8% in revenue and reduced the store OOS rate from around 24% to 18%. Especially for the fastest-moving SKUs, DSC can gain the most improvements compared to the current situation, with a revenue increase of up to 12%.

11.2 Contribution to Literature

As indicated in the literature gap (Section 2.4), many studies with a focus on stock outs center around the store actor, where this research has focused on the stock outs of the DC actor and its influence on the stores. Moussaoui et al. (2016) concluded that synchronization and communication in the supply chain are important levers to improve on-shelf availability. They, however, refer to a paper with a focus on synchronizing information regarding promotions (Ettouzani et al., 2012), whereas this study has addressed synchronization and communication differently, namely during a DC stock out.

This synchronization has been tested with a set of KPIs to track the 'shared' performance of the DC and store actors. These KPIs were based on the proposed measures by Gruen & Corsten (2008) and were found to be very insightful for the performance tracking between the two actors. In addition, these KPIs also served as a synchronization tool, which for example showed that DC stock outs starting on Friday and Saturday result in the highest store OOS rate.

In addition, this research has opted for a model to optimize the final allocation of the DC inventory before it goes out of stock. Such a tool is a great example of how to improve the synchronization between both the store and DC actors. In contradiction to the study of Pibernik (2006), this study found that the smarter final allocation significantly improves the performance compared to a first-come, first-served allocation (i.e. current situation in this research) method.

12 Recommendations

In this final chapter, the recommendations for DSC are given based on the results of this research. Thereafter, the limitations of this research will be addressed and directions for future research will be given.

12.1 Recommendations

The recommendations for DSC are divided into the two main directions of this research, namely the KPIs and the replenishment strategies.

12.1.1 KPIs

Due to the expanding assortment of DSC and the current setup of the KPIs, the threshold value of acceptance must be reviewed every year. Also, due to the expression of the performance in the number of stock outs, it is hard to compare the performance of the stock outs over the years. Therefore, it is recommended for DSC to start using the *breadth* KPI, which will correct the number of stock outs based on the increase in the assortment. This very easy adjustment that could be implemented right away.

Next, the current KPIs in use by DSC have limited power in explaining the patterns behind DC stock outs and their influences on the stores. It is therefore highly recommended for DSC to implement the store OOS rate KPI to keep track of how many stores have gone out of stock due to a DC stock out. This

KPI could also be implemented by the use of the in-store registered stock out, which would make this KPI easy to implement. Although it might be less accurate in comparison to estimated store stock outs, it will likely provide new insights for the dispatchers when they can track the influence / behavior of the DC stock outs. Furthermore, this research found that the, for example, house brand and branded items differ significantly in the different product availability elements. It is therefore also recommended to make more structural separate analyses to compare the performance of different product characteristics.

Secondly, DSC expresses itself as a revenue-driven organization. However, the current applied KPIs regarding stock outs are not centered around this objective. It is therefore suggested for DSC to implement the *intensity* KPI to reflect on the lost revenue involved with DC stock outs. This implementation is more challenging compared to the previous two KPIs. This happens due to the lack of detailed information about the duration of the store stock out when using the in-store registered stock outs, which will lead to very rough estimations of the lost revenue. Therefore, when DSC desires better estimations of the lost revenue, they would have to link the registration of a store stock out with the last selling time of that day, until a new sale is registered. This KPI will require some effort to implement, but the additional insights will likely create more awareness of DSCs main objective for its supply chain employees and how their daily activities can be of influence.

12.1.2 Replenishment

The *frequency* KPI highlighted there is a peak of DC stock outs during the weekends. Taking into account that the stock outs occurring on Saturday result in a relatively high store OOS rate, it is recommended for DSC to investigate the opportunity of accepting supplier deliveries during the weekend. Accepting immediately all different assortments or product groups might be challenging, due to scheduling and resource challenges. Therefore, it is recommended for DSC to start with (some of) the top four most expensive stock outs during the weekends, which are I) group 43, II) group 44, III) group 45, and IV) group 47.

Moreover, the *intensity* KPI provided an overview of the average lost revenue and lost sales per product group when a DC stock out occurred. It is recommended for DSC to first focus on minimizing the DC stock outs for the product groups with the most expensive stock outs, of which the top five are I) group 63, II) group 84, III) group 43, IV) group 46, and V) group 47. For both group 43 and group 47, it was already recommended to start accepting supplier deliveries during the weekends, which will likely reduce the effect of these DC stock outs. Next, most DC stock outs are caused by supplier problems (50 to 60%) which is an external factor. Therefore, another option for DSC is to increase the safety stock in the DC for these product groups to be better able to absorb disruptions in the supply chain. When inventory space in the DC is an issue, DSC could opt to lower the safety stock for 'cheap' DC stock outs to create space for the more expensive ones.

Finally, DSC can also reduce the costs of the DC stock outs by implementing a smarter final allocation method. Reflecting on the product groups with the most expensive stock outs, especially for group 47 and group 43 it is found to be an effective method to reduce the DC stock out costs.

First, it is recommended for DSC to actively encourage the dispatchers to start using the 'expected negative stock', since this provides great insights into the upcoming DC stock outs. Then, the next step is to implement a tool to allocate the remaining DC inventory more smartly, based on the model used in this research. For stock outs with an expected duration of zero to three days, the shown allocation scenarios only differ a little from each other and any will perform better compared to the current situation. For simplicity reasons, it is advised to just use a 1-day allocation method. This setup requires the least changes in the current replenishment processes. Next, for stock outs with an expected duration of more than three days, it is recommended for DSC to allocate the final 2-day DC inventory to the stores while optimizing the store OOS rate. This, however, requires some additional adjustments in the replenishment strategy, since the dispatchers have to cancel the outstanding store orders for two days instead of only one. Finally, the fastest-moving SKUs seem to benefit the most by optimizing the final allocation. It is therefore recommended for DSC to start a smart allocation pilot first for these very fast-moving SKUs.

12.2 Limitations and Future Research

This research has been focusing on only one specific DC, with the assumption that all DCs operate in roughly the same way. Though, as shown in the research motivation there are some large differences in the number of DC stock outs. Especially given that the average inventory on hand is relatively equal between the DC, it is remarkable that these large differences occur. It is therefore interesting for DSC to further investigate why these similarities occur. In addition, due to the large differences between the number of DC stock outs, it would be interesting to find out if similar results (KPIs, stock out estimations, and final allocation) would be found for the other DCs.

Next, this study has used a selection of the 200 fastest moving items in the long-life assortment. This selection accounted for around 40% of the total revenue for the long-life assortment and is assumed to provide a realistic overview of the DSC's situation. Moreover, due to the focus on fast-moving items, POS data could be used. This raises two options for future research. First of all, it could be interesting to find out how to track the performance of slower-moving items. The second option could be to find out whether similar patterns occur for different assortments like chilled or frozen SKUs. Especially tracking the performance of the chilled assortment can be interesting for DSC. This assortment has the second most stock outs on both DC and store levels and two employees at the DC mentioned that these SKUs are more actively allocated in times of (expected) DC stock outs.

Moussaoui et al. (2016) indicate the importance of communication to decrease the number of store stock outs. One important communication stream at DSC between the DCs and stores is the registered store stock outs. This study has tried to avoid this communication element by estimating the store stock outs, where it was found that the accuracy of the estimated store stock outs increases when their stores register more stock outs. It might therefore be interesting to find out how stores can be stimulated to improve their registered stock outs, and thereby increase the communication level between the store and DC.

Moreover, there are some limitations and options for future research regarding the allocation model. One of the decision variables for the final allocation is the store inventory levels. The inventory levels, however, were not always found to be accurate, indicated by for example negative inventory values. Each scenario, including the current situation, has been tested with the same inventory levels, which has limited the effect of this problem. However, it is still very likely that this has influenced the actual results. Furthermore, the applied allocation model can also be extended. First of all, the multi-objective model is currently based on two objectives, namely maximizing sales, and minimizing the penalty costs. This could, however, be extended by adding store rankings to include preferences for certain stores and limit the number of optimal solutions even further. Secondly, the current model is built by using deterministic expected demand, which has been chosen to be more easily implementable by DSC. The in-store demand is, however, stochastic and therefore a deterministic model might be inaccurate with the actual demand patterns. A model based on stochastic demand likely provides more accurate predictions of the expected store inventory levels, resulting in better final store allocation. The benefits of applying a stochastic model could therefore be an interesting direction for future research.

Finally, in the regression analysis, the store level independent factors were found to be either not significant or have a very small effect on the independent variables. Therefore, in the performance analysis of the allocation scenarios, the effect on the allocation differences to the stores was not very well examined. Eventually, the assigned store space was the only store-dependent characteristic that was tested, which did show an interesting change in performance improvement. Moreover, the assigned store space in combination with the SKU demand velocity seems to be a good predictor of the average start duration between the DC and store stock out. All in all, the store effect is therefore likely larger than investigated in this research and thus would be an interesting direction for future research.

13 References

Avlijas, G., Milicevic, N., & Golijanin, D. (2018). Influence of store characteristics on product availability in retail business. *E+M Ekonomie a Management*, *21*(4), 195–206. https://doi.org/10.15240/tul/001/2018-4-013

Avlijas, G., Simicevic, A., Avlijas, R., & Prodanovic, M. (2015). Measuring the impact of stock-keeping unit attributes on retail stock-out performance. *Operations Management Research*, *8*(3–4), 131–141. https://doi.org/10.1007/s12063-015-0104-6

Blumberg, B. F., Cooper, D. R., & Schindler, P. S. (2014). *Business Research Methods* (4th ed.). London: McGraw-Hill Education.

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, *47*(5), 1287. https://doi.org/10.2307/1911963

Broekmeulen, R. A. C. M., & van Donselaar, K. H. (2017). Quantifying the potential to improve on food waste, freshness and sales for perishables in supermarkets. *International Journal of Production Economics*. https://doi.org/10.1016/j.ijpe.2017.10.003

Broekmeulen, R. A. C. M., & Van Donselaar, K. H. (2016). Lecture Notes Stochastic Inventory Models.

Celebi, H. (2019). Antecedents and Effects of Retail Shelf Availability. Retrieved from https://drum.lib.umd.edu/handle/1903/25149

Corsten, D., & Gruen, T. (2003). Desperately seeking shelf availability: An examination of the extent, the causes, and the efforts to address retail out-of-stocks. *International Journal of Retail & Distribution Management*, *31*(12), 605–617. https://doi.org/10.1108/09590550310507731

ECR Europe. (2003). Optimal Shelf Availability: Increasing Shopper Satisfaction at the Moment of Truth, 64.

Eroglu, C., Williams, B. D., & Waller, M. A. (2011). Consumer-driven retail operations. *International Journal of Physical Distribution & Logistics Management*, *41*(5), 420–434. https://doi.org/10.1108/09600031111138808

Ettouzani, Y., Yates, N., & Mena, C. (2012). Examining retail on shelf availability: Promotional impact and a call for research. *International Journal of Physical Distribution & Logistics Management*, *42*(3), 213–243. https://doi.org/10.1108/09600031211225945

Fox, J., & Monette, G. (1992). Generalized Collinearity Diagnostics. *Journal of the American Statistical Association*, *87*(417), 178–183. https://doi.org/10.1080/01621459.1992.10475190

Green, S. B. (1991). How Many Subjects Does It Take To Do A Regression Analysis. *Multivariate Behavioral Research*, *26*(3), 499–510. https://doi.org/10.1207/s15327906mbr2603_7

Grossmann, W., & Rinderle-Ma, S. (2015). *Fundamentals of Business Intelligence*. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-662-46531-8

Gruen, T. W., & Corsten, D. (2008). *A Comprehensive Guide Reduction In the Fast-Moving To Retail Out-of-Stock Consumer Goods Industry*. *Proctor & Gamble Company research study*.

Gruen, T. W., Corsten, D. S., & Bharadwaj, S. (2002). A Worldwide Examination of Extent, Causes and Consmer Responses. *Retail Out-of-Stocks*, *1*(1), 1–80.

Gurobi Optimization, L. (2022). Gurobi Optimizer Reference Manual. Retrieved from https://www.gurobi.com

Hair, J. J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis* (7th ed.).

Harlow : Pearson Education Limited.

Linsell, K., Durisin, M., & Anghel, I. (2022, April 1). Ukraine Sunflower Oil Crisis Hits Food From Chips to Cookies. *Bloomberg News*. Retrieved from https://www.bloomberg.com/news/articles/2022-04-01/ukraine-sunflower-oil-shortage-hits-food-from-chips-to-cookies

Milićević, N., & Grubor, A. (2015). The effect of backroom size on retail product availability – operational and technological solutions. *Amfiteatru Economic*, *17*(39), 661–675.

Moussaoui, I., Williams, B. D., Hofer, C., Aloysius, J. A., & Waller, M. A. (2016). Drivers of retail on-shelf availability: Systematic review, critical assessment, and reflections on the road ahead. *International Journal of Physical Distribution and Logistics Management*, *46*(5), 516–535. https://doi.org/10.1108/IJPDLM-11-2014-0284

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703. https://doi.org/10.2307/1913610

Pallant, J. (2016). *SPSS Survival Manual: A Step By Step Guide to Data Analysis Using SPSS Program* (6th ed.). London: McGraw-Hill Education.

Pibernik, R. (2006). Managing stock-outs effectively with order fulfilment systems. *Journal of Manufacturing Technology Management*, *17*(6), 721–736. https://doi.org/10.1108/17410380610678765

RStudio Team. (2022). RStudio: Integrated Development Environment for R. Boston, MA: RStudio, PBC. Retrieved from http://www.rstudio.com/

Teunter, R. H., Syntetos, A. A., & Babai, M. Z. (2017). Stock keeping unit fill rate specification. *European Journal of Operational Research*, *259*(3), 917–925. https://doi.org/10.1016/j.ejor.2016.11.017

Usman, K. (2008). Determination of Drivers of Stock-Out Performance of Retail Stores using Data Mining Techniques.

van Aken, J., Berends, H., & van der Bij, H. (2012). *Problem Solving in Organizations*. *Problem Solving in Organizations* (Second Edi). New York: Cambridge University Press. https://doi.org/10.1017/cbo9781139094351

van Straaten, F. (2022, March 8). Oorlog leidt tot explosie van tarweprijs: minder brood op de plank bij miljoenen mensen in de wereld. *NRC*. Retrieved from https://www.nrc.nl/nieuws/2022/03/08/oorlog-leidt-tot-explosie-van-tarweprijs-a4098533

Verhoef, V. H. (2021). Preparation Master Thesis: Literature Study.

Zotteri, G., Kalchschmidt, M., & Caniato, F. (2005). The impact of aggregation level on forecasting performance. *International Journal of Production Economics*, *93–94*, 479–491. https://doi.org/10.1016/j.ijpe.2004.06.044

14 Appendices

14.1 Appendix A: Parameter Tuning Results

Intentionally left out due to confidentiality

14.2 Appendix B: Additional KPI Figures

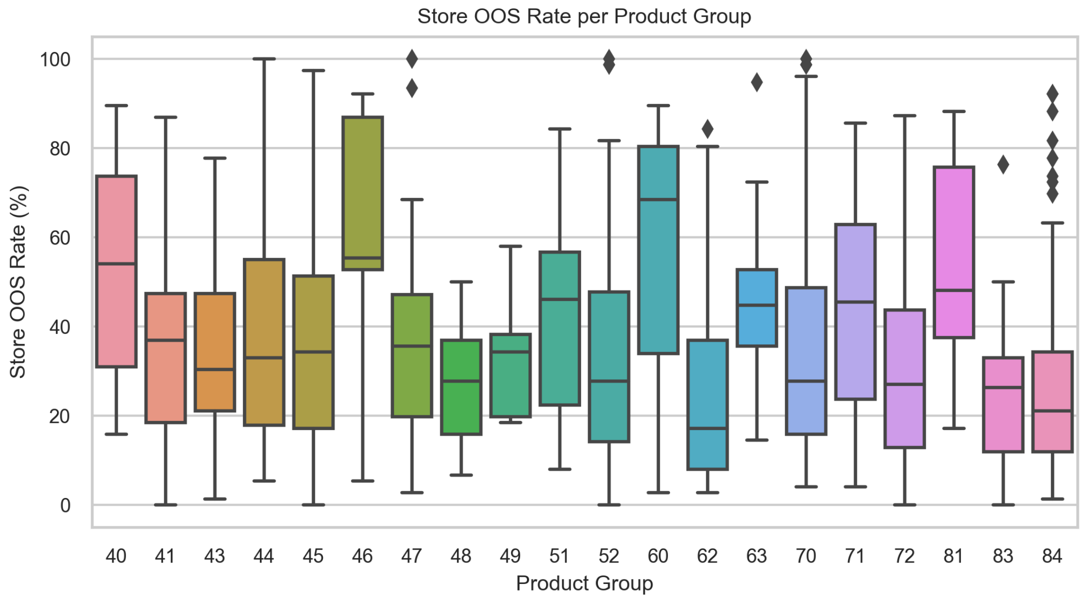


Figure 14.1: Store OOS Rate per Product Group

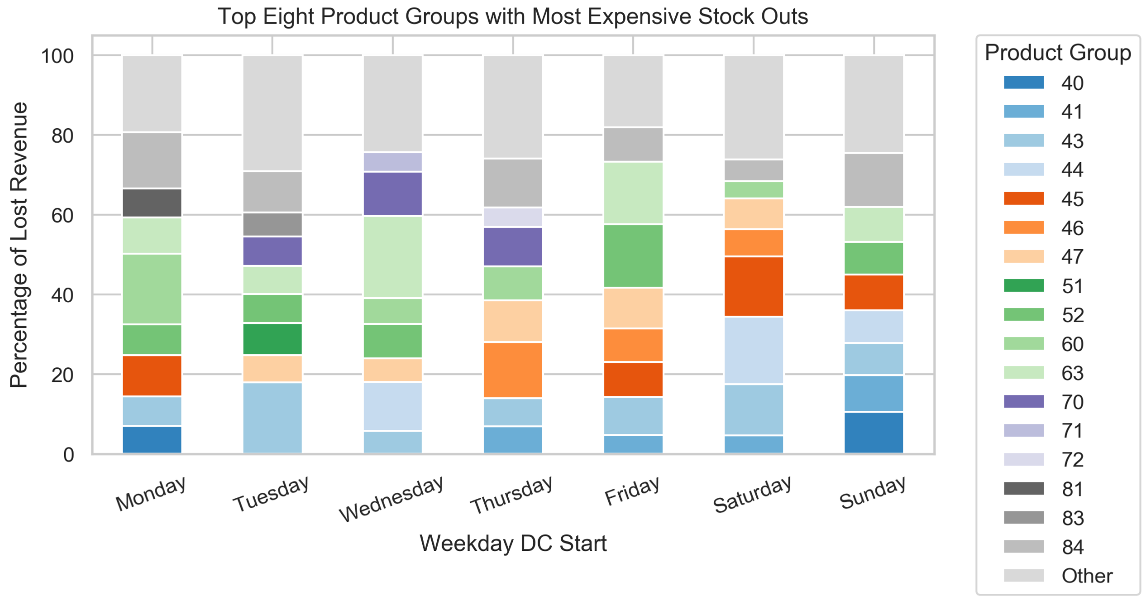


Figure 14.2: Top Eight Product Groups with the Most Expensive Stock Outs

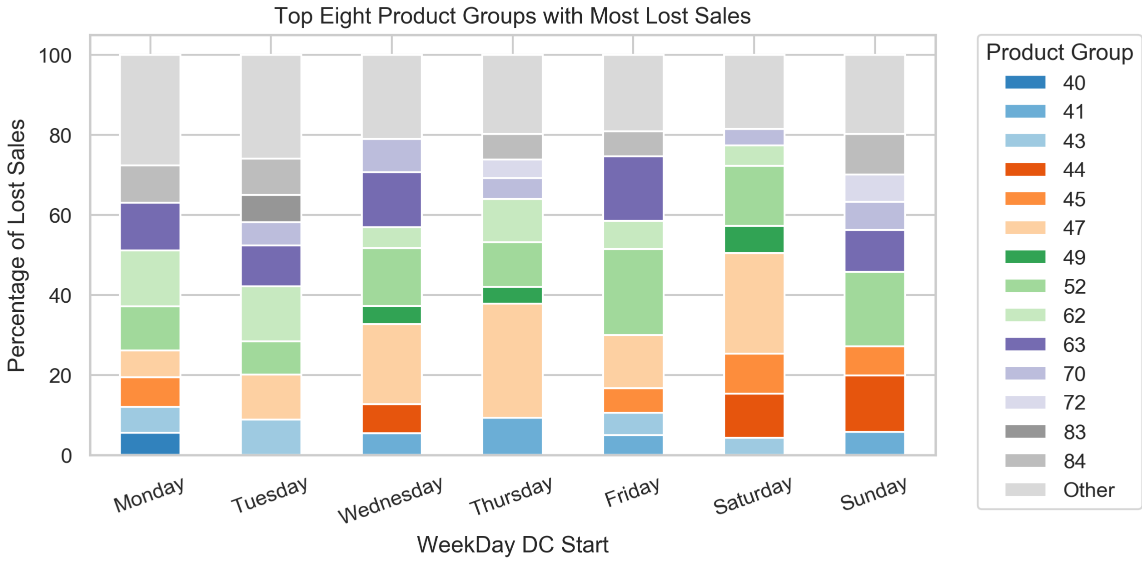


Figure 14.3: Top Eight Product Groups with the Most Lost Sales

14.3 Appendix C: Information Table Dependent Variables

Intentionally left out due to confidentiality

14.4 Appendix D: VIF Values

Df = Degrees of Freedom

Table 14.1: VIF Values DC Duration and Store OOS Rate

Dependent Variable	VIF	Degrees of Freedom	GVIF (1/(2*Df)
Stock on hand	2.671	1	1.634
Brand	1.315	1	1.045
Demand Velocity	1.277	1	1.130
Weekday DC Start	1.042*	6	1.021
Product Group	1.092*	18	1.045
Average	1.48		

*Squared result of GVIF (1/(2*Df)

Table 14.2: VIF Values for the Other Independent Variables

Dependent Variable	VIF	Degrees of Freedom	GVIF (1/(2*Df)
DC Level			
Stock on hand	3.132	1	2.793
Lead-time	3.081	1	2.090
Store Level			
Average Store Revenue	1.421	1	1.196
Sales floor	1.350	1	1.163
Product Characteristics			
Retail Price	1.163	1	1.496
Branded Items	1.081	1	1.250
Case-pack Size	1.195	1	1.187
Ordering Strategy	1.230	1	1.621
Store Dependent Product Characteristics			
MOQ	3.166	1	1.930
Store Space	3.909	1	2.121
Demand Velocity	1.823	1	1.375
Final Supply	1.078	1	1.055
Weekdays			
Weekday DC Start	1.061*	6	1.030
Weekday Store Start	1.036*	6	1.018
Average	1.838		

*Squared result of GVIF (1/(2*Df)

14.5 Appendix E: Linear Formulations MILP

Two constraints, 3 and 5a, defined in the mathematical model are not linear be definition. Due to the help of linear constraint functions in Gurobi, the model is transformed to a linear model. Below the transformations performed by Gurobi are written out.

Constraint 3: The store inventory at (t-1) minus the demand at t equals a new store inventory greater than 1 or is equal to 0.

$$I_{ti} = \max\left(I_{(t-1)i} - D_{ti}, 0\right), \qquad if\ t > 0 \quad \forall\, i \in N, t \in T$$

This constraint can be modelled linearly in the following way:

- $I_{ti} \geq I_{(t-1)i} - D_{ti}$
- $I_{ti} \geq 0$
- $I_{ti} \leq (I_{(t-1)i} - D_{ti}) + M * b$
- $I_{ti} \leq 0 + M * (1 - b)$
- $b \in \{0,1\}$
- $M = large\ number$

Constraint 5a: If the inventory level at a store is equal to 0, it will be labelled as a stock out

$$P_{ti} = \begin{cases} 1, if\ I_{ti} = 0 \\ 0, \qquad else \end{cases}, if\ t > 0\,, \qquad \forall\, i \in N, t \in T$$

Can be modelled linearly in the following way:

- $I_{ti} \leq P_{ti} + M * y - 1$
- $I_{ti} \geq P_{ti} + 2y - 1$
- $P_{ti} + y = 1$
- $y \in \{0,1\}$
- $M = large\ number$

14.6 Appendix F: Fill Rates and OOS Rates per Product Group

Table 14.3: Fill Rate per Product Group

Group	Current (%)	Revenue 1Day (%)	Revenue 2Days (%)	Store OOS Rate 1Day (%)	Store OOS Rate 2Days (%)
40	87.98	96.12	96.38	95.47	95.52
41	86.19	92.38	93.13	91.81	92.81
43	77.52	86.98	85.85	85.90	85.02
44	66.86	71.25	72.27	71.00	72.00
45	77.88	84.14	85.23	83.50	84.28
46	83.43	86.85	87.06	86.82	86.98
47	65.54	82.35	80.51	82.08	80.24
48	88.34	91.25	93.58	91.24	93.50
49	82.26	99.77	99.77	99.72	99.54
51	85.52	91.73	93.06	91.39	92.81
52	51.78	54.18	54.86	54.12	54.76
60	89.78	98.53	98.79	98.38	98.72
62	87.69	94.84	95.35	94.67	95.11
63	85.96	93.40	99.12	92.27	97.27
70	68.48	74.13	74.90	73.74	74.45
71	85.75	92.71	94.30	92.28	93.56
72	76.71	83.19	83.40	82.55	82.64
81	79.52	84.30	85.99	84.10	85.82
83	89.87	96.78	97.19	96.34	97.16
84	80.16	85.04	86.03	84.71	85.36

Table 14.4: Store OOS Rate per Product Group

Group	Current (%)	Revenue 1Day (%)	Revenue 2Days (%)	Store OOS Rate 1Day (%)	Store OOS Rate 2Days (%)
40	11.62	6.76	4.95	5.90	3.90
41	20.89	15.53	15.33	14.85	14.39
43	24.63	16.36	16.40	14.85	14.89
44	33.32	29.21	27.90	28.85	27.43
45	22.88	17.35	16.28	16.06	14.65
46	20.36	14.89	13.76	14.59	13.25
47	35.95	23.88	23.54	22.74	22.38
48	12.73	9.06	6.92	9.00	6.75
49	21.02	0.98	0.98	0.91	0.84
51	19.08	12.74	10.97	11.84	10.41
52	41.25	37.68	36.60	37.53	36.44
60	13.57	4.02	3.13	3.33	2.77
62	13.90	7.00	6.47	6.54	6.01
63	14.63	8.65	3.39	5.52	1.47
70	27.75	21.78	20.41	21.19	19.61
71	14.75	9.14	8.05	8.44	7.03
72	23.28	17.17	16.24	16.34	15.18
81	21.10	17.04	14.60	16.46	14.13
83	14.38	5.22	3.97	4.78	3.95
84	20.52	16.73	15.73	16.41	15.27