2009

Out of stock! Out of business?

The impact of Unilever's delivery performance on final On Shelf Availability

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08-07-2009

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Enschede - The Netherlands
Unilever

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PUBLIC VERSION

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Rotterdam, August 26th, 2009

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Executive Summary

The importance of On Shelf Availability (OSA) for Unilever is currently increasing and senior managerial attention is increasing the focus on this measurement drastically. However, much remained unknown on OSA before this investigation, for example how much turnover is lost annually and what the influence of Unilever delivery performance is.
This research discusses the relation between OSA and Unilever's delivery performance. In this Management Summary, the current (OSA) situation is described, the turnover loss endured by Unilever is calculated, and the causes of Out of Stocks on the shelf, both within and outside Unilever control, are discussed. Based on the insights on OSA, short- and long term improvements projects have been developed.

<u>OSA results and consequences</u>
The officially reported OSA percentage for the Netherlands is %. This is however based on measures less useful for this investigation. Correcting those measurements in order to improve their usefulness, showed Unilever to have an average of availability, which is quite in line with theoretical benchmarks. However, not having 100% availability does result in an annual turnover loss for Unilever of € million Euro, representing of total turnover. This is more than its comparable theoretical benchmarks from existing theory, but these have not taken into account all variables and factors used in this investigation (e.g. marketing costs and long term shopper losses). If Unilever is able to increase its OSA by 3%, turnover would increase by 1.3%.

<u>Variables causing Out of Stocks not under Unilever influence</u>
Variables causing Out of Stocks are mainly in the domain of the retailer (about 85% of all causes are customer related), whereas Unilever is said to be responsible for only 15% of the Out of Stocks on the shelf. Although this research did not investigate the causes directly, several variables were found to determine the OSA. These were (a.o.) the size of the store (bigger stores have a positive effect on OSA) and promotions (promotions have a negative effect on OSA). This investigation found four product variables significant: whether it is a food or non-food product, its research, the sales volatility (sudden changes in customer demand) and which customer (-typology) is involved.

<u>Variables under influence of Unilever</u>
Of the causes within Unilever influence, this investigation focused on Unilever's delivery performance. Statistical analysis shows that Unilever in 2008 causes of all Out of Stock events on the shelf. So % of all missed cases on the shelf are caused by Unilever's delivery performance. This caused the overall Out of Stock level to rise from %. The impact is felt most at high volume products, and for non-food low volatility also indicates high impact. If Unilever were to increase delivery performance to 100%, the resulting increase in OSA would generate an additional € turnover annually combined for the entire Unilever portfolio. The improvement potential for these certain specific products (several margarines and peanut butters, on average €) is much more compared to the average of the other products with improvement potential (€). However, these figures do not take into account the costs involved to increase delivery performance to optimality.
Other variables reducing OSA within the domain of Unilever are (a.o.) long lead times, shelf design and allocation, poor promotional planning and execution, and communicational issues. However, these are outside the scope of this investigation and hence the specific size of their impact remains unknown.

<u>Short and long term solutions</u>
OSA is of high importance. It creates brand value, turnover, and can act as an excellent weapon against private labels. This justifies the perceived importance of OSA by Unilever executives. However, the influence of the delivery performance of the Unilever Supply Chain on OSA is very limited. Some improvements by Customer Service & Logistics (CS&L) are possible through . More promising however are OSA improvement projects carried out in close collaboration with customers. Unilever has quite some experience in

these projects (e.g. in Belgium and the UK) and can fully apply its knowledge base and resources. This report can act as a starting point to identify focus products and customers.

As opposed to Customer Service & Logistics, the department with most influence on OSA is Customer Development. For example by providing incentives to improve the amount of stores that carry Unilever products, Customer Development can increase overall On Shelf Availability. However, most possibilities to increase OSA lie at the retailer. As market power is shifting more and more in the customers' direction, OSA projects in collaboration with these customers can be a way for Unilever to shift some of that shifting back to itself.

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This report will provide the prove of the above mentioned insights in OSA and will clarify many calculations and analysis which are not provided by other investigations. This report by itself can act as a benchmark for other Unilever countries to do a similar investigation. However, further research is needed to be done on the impact of sudden big delivery failures at Unilever, the impact of promotions and the impact of long term delivery failures on (predominantly) non-food items.

Management Samenvatting (Dutch)

Hoge schapbeschikbaarheid (On Shelf Availability of OSA) is van toenemend belang voor Unilever en er wordt steeds meer aandacht aan besteed vanuit het hogere management. Er is echter nog steeds veel onbekend over OSA, bijvoorbeeld hoeveel omzet er gemist wordt door lage OSA en wat de invloed is van de leverbetrouwbaarheid van de leverancier op OSA.
Dit onderzoek focussed op de relatie tussen OSA en Unilever's leverbetrouwbaarheid. In deze management samenvatting worden de huidige situatie, het omzetverlies en de verschillende oorzaken van lage schapbeschikbaarheid (Out of Stocks) beschreven. Op basis van de nieuwe inzichten in OSA zijn korte- en lange termijn oplossingen ontwikkeld.

<u>De huidige stand van zaken</u>
Het officieel gerapporteerde OSA cijfer voor Unilever Nederland is . Dit is echter gebaseerd op metingen die niet direct bruikbaar zijn voor dit onderzoek. Na aanpassingen van deze metingen, heb ik de reële schapbeschikbaarheid van Unilever vastgesteld op . Dit is conform theoretische benchmarks. Het missen van schapbeschikbaarheid leidt jaarlijks tot een omzetverlies van € miljoen, ofwel van de totale omzet van Unilever in Nederland. Dit is verhoudingsgewijs vrij veel vergeleken met theoretische benchmarks, maar die laatste hebben waarschijnlijk niet alle variabelen en kosten meegenomen (bijv. lange termijn verlies en marketing kosten). Wanneer Unilever zijn gemiddelde schapbeschikbaarheid verhoogt met 3%, leidt dat tot een autonome omzetstijging van 1,3% op jaarbasis.

<u>Oorzaken van Out of Stocks buiten de invloed van Unilever</u>
De bekende theorie meldt dat de meeste Out of Stocks worden veroorzaakt door de klant (supermarktketens). Het gaat hier om 85% van alle Out of Stocks. Unilever is slechts verantwoordelijk voor 15% van de Out of Stocks. Hoewel dit onderzoek zich niet direct richtte op de oorzaken, ben ik gestuit op een aantal variabelen die de OSA bepalen. Het betreft hier onder andere de grootte van de winkel (grotere winkels hebben een hogere OSA) en of het product in promotie was ten tijde van de meting (promoties resulteren in lagere OSA). Daarnaast zijn er vier product/klant variabelen gevonden die het OSA gedrag kunnen voorspellen: of het een voedsel of non-voedsel product is, het volume, de volatiliteit van het vraagpatroon van de klanten en tot slot welke klant (-typologie) betrokken is.

<u>De invloed van Unilever</u>
Van alle oorzaken van Out of Stocks die Unilever beïnvloed, heeft dit onderzoek zich gefocussed op de leverbetrouwbaarheid. Statistische analyse gaf aan dat Unilever in 2008 verantwoordelijk was voor % van de lege schappen. Omdat het absolute aantal lege schappen erg laag is (slechts %), is dit overall gezien een kleine invloed Door de suboptimale leverbetrouwbaarheid steeg het gemodelleerde Out of Stock niveau van 6.
%. De meeste invloed bevindt zich in producten met een hoog volume, of –voor non-food producten- een lage volatiliteit.
Wanneer Unilever erin zou slagen zijn leverbetrouwbaarheid te verhogen naar 100%, zou dat leiden tot een omzetstijging vanuit additionele schapbeschikbaarheid van € , voor het hele portfolio van producten en (retail) klanten. Het verbeterpotentieel voor een aantal specifieke producten (gemiddeld € ligt veel hoger dan het gemiddelde van de andere producten met OSA verbeter potentieel (gemiddeld € het betreft hier voornamelijk een aantal.
Tot slot dient te worden opgemerkt, dat dit verbeterpotentieel niet de kosten meeneemt die gemoeid zijn met het verbeteren van de leverbetrouwbaarheid naar 100%.

Andere variabelen binnen de invloed van Unilever die de OSA reduceren, zijn (o.a.) lange leadtimes, schapontwerp en allocatie, matige promotie planning en uitvoering, en algemene communicatie. Dit valt echter buiten dit onderzoek en derhalve zijn deze oorzaken niet verder onderzocht.

Korte- en lange termijn oplossingen

Schapbeschikbaarheid is van groot belang voor producten van consumentengoederen. Het creëert merkwaarde, omzet en is een goed wapen tegen de toenemende macht van de huismerken. Het verklaart de prioriteit die aan OSA wordt gegeven vanuit het hoofdkantoor. Echter, de invloed van de leverbetrouwbaarheid van de Supply Chain van Unilever is zeer beperkt. Verbetering zijn echter wel mogelijk.

Op korte termijn dient hierbij worden gedacht aan

. Meer potentie hebben echter projecten die gezamenlijk met de klant worden uitgevoerd. Unilever heeft hierin al enige ervaring (vanuit België en de UK), en heeft daarnaast de kennis en resources om hierin het initiatief te nemen. Dit onderzoek kan de focus bepalen van deze projecten, om klanten en productgroepen te identificeren met de meeste potentie.

In tegenstelling tot Customer Service & Logistics, heeft de afdeling Customer Development wél invloed op de OSA. Door het vergroten van het aantal winkels dat Unilever producten verkopen, en door naleving van de schappenplannen te controleren, zal de omzet toenemen.

Natuurlijk ligt de meeste potentie bij de klant. Maar met een markt waarbij de macht steeds meer richting de retailer verschuift, zullen gemeenschappelijke OSA projecten mogelijk ertoe leiden dat

Dit onderzoek bewijst de hierboven vermelde inzichten in OSA en zal de lastige berekeningen en analyses die gemaakt zijn, verduidelijken. Dit onderzoek kan ook fungeren als een benchmark, zowel extern als intern binnen Unilever. Andere landen zouden op basis van dit onderzoek een dergelijk onderzoek ook kunnen uitvoeren. Nader onderzoek is verder nodig naar de invloed van plotselinge grootschalige leverproblemen bij Unilever, de invloed van promoties op de OSA en op de invloed van langdurige leverproblemen, voornamelijk bij non-food producten.

Preface

This master thesis, related to the master study Industrial Engineering & Management, describes a study executed for Unilever Benelux in the Netherlands. I'm very grateful that they have provided me this opportunity, to let me have this experience, and for all help and facilities needed (including the afternoon product samples, which are delicious). I've had a wonderful time at Unilever; it's an amazing company.

I especially would like to thank my Unilever supervisors Patrick van Balkom and Tiemen Bloemberg, for their help, support and sharp remarks. One of Patrick's many phrases will always be remembered (besides the 'no panic for peanuts'), which is: 'theory and practice are 100% identical….in theory'.
Besides Patrick and Tiemen, I would like to thank Gökhan Tuncer, Simon Hoogendoorn and Dion van de Gazelle for their help and the wonderful time we've had at our desks. Finally, I would like to show my appreciation to those otherwise involved, especially Jonneke de Koning and Jeroen Dijkema.

In addition to the Unilever support, I would like to thank my three supervisors at Twente University for their help, their sharp eye and positive critique: Leo van der Wegen, Hans Heerkens and Pranab Mandal. Pranab's reaction after my request for help was so sincere and positive, it gave me the positive reaction I needed at that time. It was always easy to contact all three of them and they were always well prepared, which was very helpful in having efficient and productive meetings.

Finally, I would like to thank my parents, sister and girlfriend for having endured my good but also bad moments, including those that involved relentless talking, ADHD and working overtime. And pre-reading this entire 120 page document.

This initial step is taken, the first text is written down, and now I will provide you, the reader, insights in the wonderful world of the Fast Moving Consumer Goods (FMCG) and the difficulties this business segment faces when dealing with Out of Stocks.

Martijn Schneider

Rotterdam, August 26th, 2009

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Glossary

3PLP	3rd Party Logistics Provider
BoS	Back of Store
BU	Business Unit
CLV	Customer Lifetime Value
CS&L	Customer Service & Logistics
DC	Distribution Centre
DF	Delivery Failures
DV	Dependent Variable
ECR	Efficient Customer Response
EDI	Electronic Data Interface
ESM	European Supply Management
FMCG	Fast Moving Consumer Goods
FPE	Full Pallet Equivalent
HC	Home Care
HG	Homogeneous Groups
HPC	Home & Personal Care
IV	Independent Variable
KPI	Key Performance Indicator
LAO	Logistic Account Officer
MCO	Multi Country Organisation
MPSM	Managerial Problem Solving Method
MSO	Marketing & Sales Organisation
NWOM	Negative Word of Mouth
OIP	OSA Improvement Potential
OOS	Out of Stock
OSA	On Shelf Availability
PC	Personal Care
PCA	Principal Component Analysis
PAF	Principal Axis Factoring
POS	Point of Sale [data]
PWOM	Positive Word of Mouth
R&D	Research & Development
SCC	Spreads Cooking Category
SCMT	Supply Chain Management Team
SKU	Stock Keeping Unit
SPSS	Statistical Package for Social Sciences (software)
SU	Sourcing Unit
THT	Tenminste Houdbaar Tot (Shelf life)
TPM	Total Productive Management
USCC	Unilever Supply Chain Company
UT	University of Twente
VMI	Vendor Managed Inventory

Introduction

Suppose you, as a shopper, want to buy a particular brand and size of your favourite peanut butter. In the store you visit, you can't find the product. Where it is located normally, you find an empty place and perhaps an empty shelf-tag holder. The product seems to be missing, whilst you are sure this product normally is available here.
As you are craving for peanut butter, you decide to change your preference to perhaps a private label or competitor's premium label. And finally, you purchase one of these alternatives.

This situation is called an Out of Stock. As can be imagined by the example, frequent occurrences of this might decrease customer loyalty, and result in a reduction of turnover, market share and eventually erode the entire brand.

The importance of Out of Stocks is described very adequately by the following excerpt from ECR (2003):

> The only way [retail and manufacturing] companies can build superior brands and supply consumers in real time is by not letting the consumer down at the moment of truth in front of the shelve – they must reduce stockouts to a minimum.

Much is known from a retailer's perspective, but much less is known from a supplier's perspective. Does a supplier, e.g. Unilever, have an influence on Out of Stock levels? How is this related to Unilever's delivery performance, and how can this influence be expressed? Can this be used for the companies' advantage? How big is this problem? This will all be investigated in this report.

The goal of this investigation is as follows:
Determine which factors influence On Shelf Availability and what the relationship between Unilever's delivery performance and OSA is. Apply these insights to develop an instrument to manipulate the deliveries in such a way as to maximize value through optimal overall OSA of a product at the customers on the short and long term. This will be further discussed in the remainder of the report.

This goal will be achieved by applying the Managerial Problem Solving Method (MPSM, 2008), to provide structure to the problem solving process. The MPSM consists of 7 phases, which all will be discussed in the next chapters. However, not every phase in the MPSM will be located in a separate chapter. The link between the MPSM and the chapters is shown in Figure 1 on the right. The entire report is ended by references and appendices.

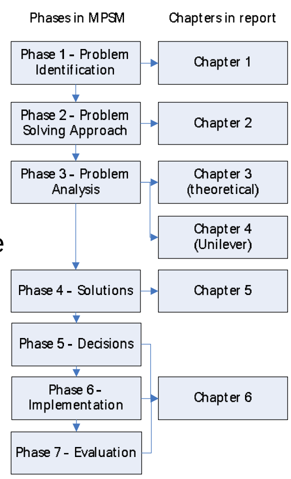

Figure 1 – Build up of report based on MPSM

The report will be started by a company overview in Chapter 1, which identifies the problem and provides background on Unilever.

Chapter 1 - Company background and problem introduction

A description of the company is provided for background purposes. Using a top down approach: Unilever is analyzed from a worldwide level, to the Benelux-level and finally to the department involved in this investigation. Next, the current situation and desired situation are described, where the difference between these two results in the discrepancy.

1.1 Unilever globally

Unilever originated from two different companies; the English soap company of Lever Brothers and the Dutch margarine company of the Margarine Unie (*Margarine Union*), who merged in 1930, thereby creating Unilever. The first 30 years were characterized by product and brand development in their domestic and European markets. From the 1960's, Unilever became increasingly global, leading to one of the largest companies in the world today with annual turnover in excess of € 40 billion[1]. Current strategies are increasingly focused on vitality and sustainability, reflecting the current consumer trends.
The company's original Anglo-Dutch structure is reflected by its structure of two parent companies (Unilever N.V. and Unilever PLC, which are respectively Dutch and English), operating as a single entity.

Unilever's global brand portfolio consists of over 400 brands, of which 12 brands individually account for more than € 1 billion global turnover.

1.2 Unilever Benelux in the Netherlands

Unilever Benelux is a MCO, Multi Country Organization, and part of Unilever Europe. Unilever Benelux employs 1.100 employees to generate an annual turnover of € 1,8 billion and can be considered the biggest producer of premium brands in the Benelux. Unilever Benelux in the Netherlands[2] has 5 distribution centres (DC), 2.500 unique Stock Keeping Units (SKU) and supplies most retailers. Unilever's Corporate Centre in Rotterdam, the 3 Sourcing Units (SUs), the R&D unit in Vlaardingen, and Unilever Foodsolutions (for the professional kitchen) are not part of Unilever Benelux. Unilever only produces premium brands, no private labels.

Unilever is segmented into five clusters, which are;

- Home Care (*e.g. Omo and Cif*)
- Personal Care (*e.g. Dove, Vaseline and Rexona)*
- Savoury and Dressings (*e.g. Knorr, Conimex, Unox and Calvé*)
- Spreads & Cooking Category (*e.g. Becel and Blue Band*)
- Ice Cream and Beverages (*e.g. Ola and Lipton)*

These clusters can be grouped into HPC (Home & Personal Care) and Food (the other three clusters).

The supply chain is driven by both the MCO and the Switzerland based Unilever Supply Chain Company (USCC). The supply chain is visually represented in Figures 2 and 3.

[1] Revenue in 2007 was € 40.178 million, Annual Report 2007
[2] Situation of November 13th, 2008

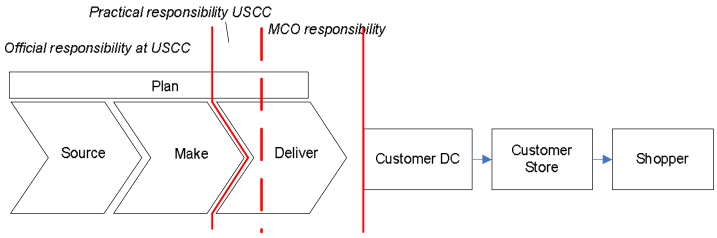

Figure 2 - Visual representation of the Unilever Supply Chain

Even though the official responsibility of the USCC ends at the delivery stage, they remain responsible for the 3rd Party Logistics Providers (3PLP). The MCO responsibility officially ends at the Customer DC, except at Albert Heijn for which Unilever manages the DC's inventory (via VMI).

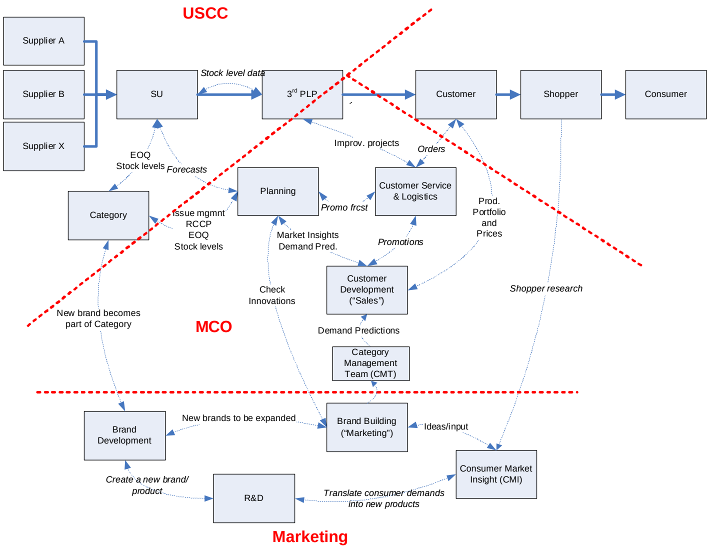

Figure 3 - Visual representation of the Unilever Supply Chain

The Unilever Supply Chain Company (USCC) owns the supply chain from the supplier until the 3rd Party Logistics Providers (external companies responsible for warehousing, transport or other logistics). ESM (European Supply Management) purchases materials on behalf of the Sourcing Units (SU) and is managed by USCC. This allows the USCC to aggregate demand and optimize buying volume. The Sourcing Units rely for their production planning and allocation of resources on forecasts delivered by the MCO and on current stock levels at the Logistical partners.

Part of the MCO is Customer Service & Logistics. This department deals with the logistics concerning the MCO and Customers, and is discussed in the next chapter.

1.3 Customer Service & Logistics at Unilever Benelux

Customer Service & Logistics (CS&L) is responsible for the flow of goods and information to and from the customer. CS&L handles Customer orders, is in charge of the forecasts of promotions and is in direct contact with the 3PLP's and Customer Development (sales).

CS&L and Customer Development are grouped in four (Customer) teams:

- Albert Heijn
- Schuitema/Super de Boer
    - o Drug team (e.g. DA, Kruidvat)
- Superunie (e.g. Plus, Jumbo, Koop Consult)
- Out of Home (e.g. gas stations, Bijenkorf)

CS&L is in direct contact with the four Logistic Providers[3] that manage the Unilever DC's, which handle 100 million cases per annum, representing 130.000 orders and 700.000 pallet equivalents. Orders are received daily per customer per DC, representing hundreds of ship-to-points and orders.

Unilever distinguishes between customers and consumers or shoppers. Customers are retailers, (e.g.) Albert Heijn, Schuitema and Vomar. Consumers or shoppers are ordinary people purchasing Unilever products in any of the stores of the customers. This distinction will also be applied in the remainder of this report.

An overview of the six customers involved in the OSA research and their annual volume (measured from 2008W05 till 2009W04) is shown below in Table1:

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Table 1 - Volume of the customers within the retail channel of Unilever.

Unilever is experiencing a shift in power from manufacturer to retailer. The increasing power of private labels requires Unilever to introduce increasingly more innovations[4] and continuously increase performance. Recent examples of customer boycotts[5] are a sign of the shift in power towards the customer and the resulting conflicts.

1.4 Current situation at Unilever Benelux

Currently, Unilever's delivery performance to the customer is measured through the Casefill. This is the percentage of correctly delivered cases to the customer. These deliveries are made from the Unilever Distribution Centres to the Customer Distribution Centres, as shown in Figure 4.

Figure 4 - Simple representation of the complete supply chain

The supply chain, shown in Figure 4, consists of multiple partners collaborating in a limited way. Many issues can occur on the way from Unilever to the shelf. Errors at Unilever, failures at the customers DC, shipping and storage all can deteriorate final On Shelf Availability (OSA) very much. This reduces turnover both temporarily (not being able to sell an item to a shopper) but

[3] Albeit not relevant for this research, the four Logistics Providers are Kuehne & Nagel (Raamsdonksveer and Veghel), Bakker Logistiek Groep (Zeewolde), Norbert Dentressangle (Tilburg) and Vrumona (Bunnik)
[4] CEO Paul Polman, May 7, 2009
[5] For example: the Xxxxxxxxx – Vrumona conflict of May 2009, the Superunie – Douwe Egberts conflict in May 2009, the temporary ban of Unilever products at Delhaize in Belgium (1st Quarter 2009).

also on the long run (shoppers switching when faced by an Out of Stock (OOS) might not remain loyal customers if the other product is to their liking).

As a FMCG company, Unilever is first and foremost interested in making their product available to the shopper. The availability on the shelf should be as high as possible. Based on studies from Unilever Europe, the USCC and knowledge available within Unilever, senior executives from Unilever globally concluded that OSA should grow in importance for the MCO's (the individual countries). To increase this awareness in the MCO it must be established how big the impact of Unilever is on OSA in the Netherlands and what it can do to improve in this area. Unilever Benelux therefore wants more insight on the OSA and OOS of certain key products at certain key customers, to reduce Out of Stocks at the shelf to an absolute minimum.

Unilever has started measuring OSA for a certain predefined group of products. By measuring 88 Unilever products and 32 competitor's products, Unilever hopes to develop understanding of shelf-performance. This project was initiated in March 2008 and was fully up and running in May 2008. The initial goals for these measurements were to look for planogram- and agreement compliance and to gain understanding. Although this data is created with other goals in mind, it will be used in this research.

After discussing the current situation, the desired situation is discussed next. The difference between the current and desired situation will reveal the discrepancy discussed later.

1.5 Desired situation at Unilever

Although Unilever aims to achieve perfect delivery performance, this is nearly impossible due to difficulties balancing performance with costs, external influences and other factors. In the meanwhile, shelf availability plays an increasingly big role, as this drives turnover and creates brand value. Unilever wants to be aware of the impact of its delivery on the shelf availability and wants to use that knowledge to make informed decisions.

When Unilever is aware what influence its delivery performance has on the final OSA, it can actively steer on its delivery performance for a certain customer. For example, when faced by an (imminent) Out of Stock at Unilever, remaining products often have to be allocated towards customers. This is currently done ad-hoc. This allocation might not be optimal, as it does not take into account the relationship between delivery performance and OSA. Availability to the shopper should be the driver in allocation.

Increased awareness of the impact of Unilever delivery performance on the OSA will also be used for long term projects to improve OSA. These can be internally focussed, but can also be in close collaboration with customers.

1.6 Discrepancy between the current and desired situation

To grow OSA awareness in the MCO, it must be established how big the impact of Unilever is on OSA in the Benelux and what it can do to improve in this area. The most logical link between OSA and Unilever actions (at least in the short term and within the direct control of Unilever) is the Casefill[6] they provide to their customers.

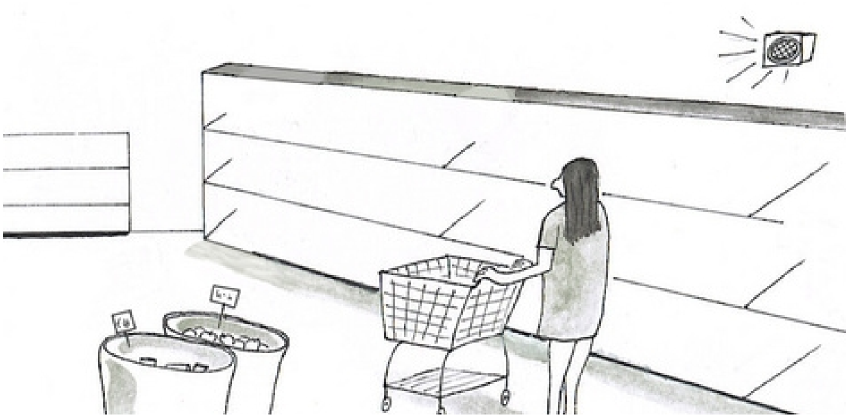
As already mentioned, Unilever is not aware of the exact effect of poor delivery on OSA. It appears as if there is a logical correlation between its deliveries and the OSA, as shown here:

[6] Casefill is the internally used measure for delivery performance

- If deliveries are 100% for a long period, one can assume that the OSA percentage is quite high. All Out of Stocks can then be attributed to customer failures.
- If delivery performance is 0% for a long period (e.g. several months), one can assume OSA is 0% as there are no more stocks.

Based on this example, it is clear to see that there is some correlation between both measures.

Using OSA and delivery failures data, Unilever wants to know per customer and per product, what the delay is between non-delivery and Out of Stocks. With that information, short and long term solutions can be developed and implemented.



"Because Unilever did not deliver your favorite products, you are now faced by an empty shelf!"

Figure 5 – Is there an impact of Unilever's delivery performance on OSA?

1.7 Problem Stakeholders

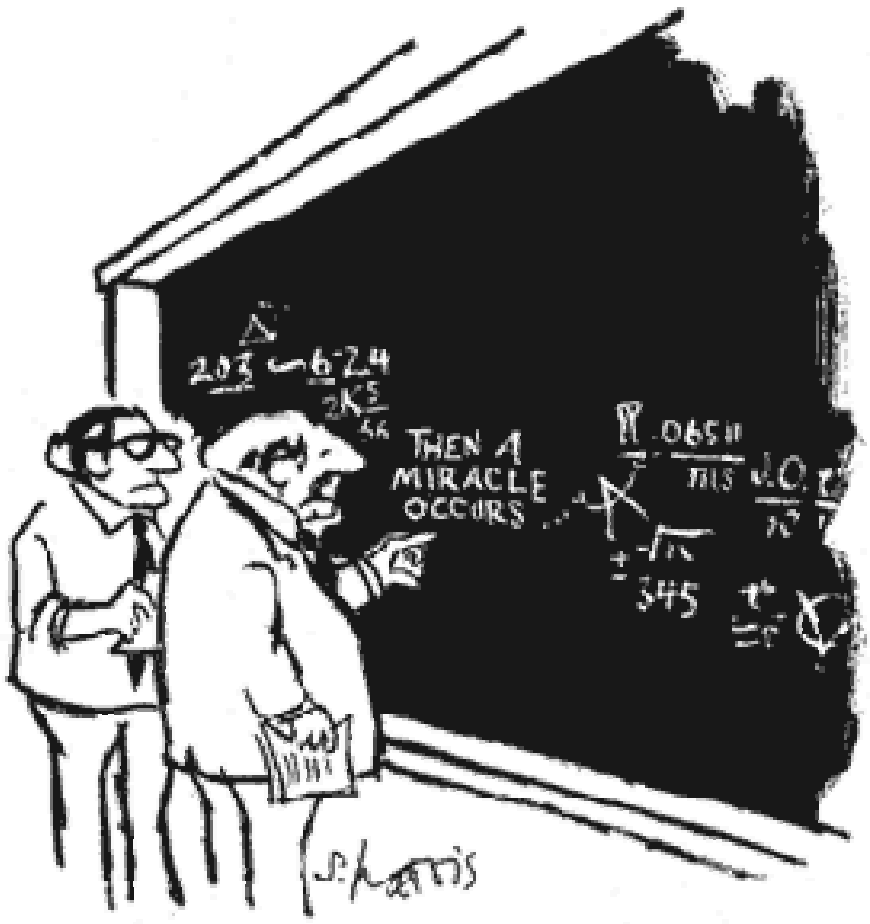
Stakeholders of this problem are both the customers (the retailers) and Unilever. Both lose turnover due to consumer reactions if the product is not available. However, as xxxxxxxxxxeration throughout the supply chain in case of shortages is not common, the major stakeholder under investigation is Unilever. Only the Unilever products measured by the OSA project will be under investigation.
Within Unilever, the MCO is responsible for Sales and Marketing. They are responsible for the sales in their respective countries and have to allocate products in times of scarcity. Hence, they are the major problem stakeholders of this problem and also the main problem owner. As recommendations resulting from this research might affect the USCC and customers, they are also included as stakeholders.

1.8 Conclusion on the Problem Identification

Chapter 1 showed the current situation of Unilever. Unilever currently focuses mostly on Casefill as their Key Performance Indicator (KPI) but has a strong desire to move towards a more shopper-driven metric. This would better capture the availability of the product to the consumer, which is of high importance for a FMCG company as Unilever. Measurements have been initiated to capture the OSA of the products.
In the desired situation, information on the OSA of products and customers is used to steer the processes within the company. This will maximize the OSA and hence the availability to the shopper, to create turnover and build strong brands.

Unilever is currently not fully aware of the impact it has on OSA, and how it can use this impact in its advantage. This will be investigated in this research, and the way how this is done is formulated in Chapter 2.

Chapter 2: Problem Approach



"I THINK YOU SHOULD BE MORE EXPLICIT HERE IN STEP TWO."

Chapter 2 - Problem approach

In Chapter 1, the situation at Unilever was described, including the difference between the current situation and the desired situation. The discrepancy between these two is the lack of insights in the link between Unilever's delivery performance and the OSA. In Chapter 2, the approach to reduce this discrepancy is formulated.

First, the goal of the research is discussed. In order to achieve that goal, main research questions (Chapter 2.2) and sub questions (Chapter 2.3) are formulated and explained. Finally the way data is collected will be discussed in 2.4.

2.1 Goal of the research

In order to reduce the discrepancy discussed in Chapter 1, the goal of the research is formulated as follows:

To develop insights on factors influencing On Shelf Availability and especially on the relationship between delivery failures and On Shelf Availability and based on those insights to develop an instrument to manipulate the Casefill in such a way that value through optimal overall OSA of a product at the customers is maximized in the short and long term.

The goal is twofold. The main focus will be on the knowledge problem expressed in the first part of the goal. Knowledge accumulated here provide insights, which can be used to provide solutions as mentioned in the second part of the goal, the action problem. Only limited focus will be on this type of problem, as many resources are required to solve the first problem.

Several aspects of the goal can be explained in more detail;

- Insight is provided to Unilever on the complete set of influencing factors (both under control and out of control of Unilever).
- The instrument is but can also be used for long term projects (by providing a benchmark or focus points for new products and/or customers, or to act as input for long term projects with customers).
- Manipulation of the Casefill can be done by and improvement projects (long term). This differentiation is discussed in more detail in the last bullet.
- Maximizing value for Unilever is in terms of turnover (sales).
- The level of analysis are the Unilever products and retailers of which the OSA is measured, which will be used to extrapolate the findings to the entire company.

2.2 Main research questions

In order to achieve the goal of the research, main research questions are formulated. The first main research question is formulated as follows:

What are the implications of Unilever's current OSA performance and how does this relate to benchmarks provided by theory?

The knowledge acquired by answering this research question will be applied to answer a second research question:

Which improvement solutions exist within Unilever's influence to improve OSA?

To answer these research questions, several sub questions are formulated in Chapter 2.3.

2.3 Sub questions to answer main research question

To answer the two research questions and achieve the goal, three sub questions are defined, each of which is further detailed. These are mentioned below:

1. What knowledge can be gained from a theoretical analysis?
    a. What knowledge does theory provide on general OSA performance?
    b. What knowledge does theory provide on the costs of Out of Stocks?
    c. What knowledge does theory provide on the influence of the delivery performance of manufacturers on OSA?
2. How does Unilever perform with respect to OSA and how can this be related to the knowledge gained from the theoretical analysis?
    a. What is Unilever's general OSA performance, and is this in line with theory from question 1a?
    b. What are costs for Unilever of Out of Stocks, and is this in line with theory from question 1b?
    c. What is the influence of Unilever's delivery performance on OSA, and is this in line with theory from question 1c? Which customers and products have the biggest influence?
3. What improvement solutions can be derived from the knowledge gained in questions 1c and 2c?
    a. What solutions exist to improve OSA on the short term?
    b. What solutions exist to improve OSA on the long term?

Answering the first two sub questions will result in answering the first main research question, whereas sub question 3 will answer the second research question.

Some further explanation on the steps which need to be taken is provided below, and more detailed information on how specific data is collected is discussed afterwards.

1. To answer sub question 1, literature on OSA is investigated. This starts by defining supply chain management and Key Performance Indicators, to align previous perceptions. Next, theory is discussed on OSA definitions, measurements and findings. After this, theory is discussed on the impact of Out of Stocks in missed turnover, and finally a theoretical analysis is done on the causes of Out of Stocks and the influence of manufacturers.
2. To answer sub question 2, Unilever's findings are analyzed based on the measurement of the 88 products at retailers. This will be done first by comparing Unilever's definitions and ways of measurement with theory. Next, a model is developed to determine the missed turnover of Unilever due to Out of Stocks. Findings from this will be compared to the findings in sub question 1b.
   Finally, a second model is developed to determine the impact of Unilever's delivery performance on OSA, also per product and per customer. These findings will be compared to theory of sub question 1c.
3. Finally, answers from sub questions 1 and 2 will provide input (knowledge) on the action problem discussed in sub question 3. Short and long term solutions are provided.

2.4 How to gather information

Information is gathered through two ways: via theoretical analysis and via data analysis. The theoretical information will be used to answer sub question 1, the data analysis will provide answers to sub question 2. Both ways of information gathering are discussed below.

2.4.1 Theoretical information

In order to develop the theoretical framework to increase insights in OSA, determine the lost turnover and the causes of Out of Stocks, literature available at the University Library of the University of Twente is investigated. Topics include On Shelf Availability, Statistics, Marketing Costs, Costs of Out of Stocks, and other topics. Literature is also investigated at Erasmus University Rotterdam.

2.4.2 Data analysis

When looking for the impact the delivery failures have on OSA, information on both the delivery performance and OSA is gathered. This will be discussed in the next section.

2.4.2.1 Data on delivery performance

Casefill (CCF) is the commonly used measure for delivery failures, and is calculated by this formula:

$$CCF = \left(1 - \frac{TotalFailures}{AdjustedQuantity}\right) * 100\%$$

In this formula, Casefill is expressed as a percentage. Adjusted Quantity is the confirmed and correct order quantity by the customer. Total Failures is the sum of internal and external failures.

Data for this is available on the companies' ERP system. In that system, product characteristics are also available which will be used later to group products having similar significant characteristics. This measure would capture the percentage of customer demand which is actually met. It also incorporates all possible mistakes from the supply chain.

In the remainder of this report, CCF will be referred to by delivery performance. Delivery failures represent the missed CCF (and is hence 1 - CCF).

2.4.2.2 Data on the On Shelf Availability

On Shelf Availability of the products is measured by a 3rd party hired by Unilever. Employees of that 3rd party enter a predefined store with a checklist of 120 products, of which 88 Unilever and 32 competitors' products. They check the shelves for availability of the products on the checklist, and, if not available, may ask store personnel to help them. They measure at different retailers[7], and have a rotation to include any store at least twice per quarter.

Aggregating the results of measurement for a certain product provides OSA percentages (if a product has been measured 5 times, of which 4 times it was available, its availability is 80%).

An overview of the OSA measurements will be provided in Chapter 4.3. A further detailed overview of the build-up of the data, the different options when measuring and the filters applied to ensure data integrity is provided in Appendix A.

[7] Measurement is done at Xxxxxxxxx (119 shops), XXXXXXXXX/Schuitema (121 shops), Xxxxxxxxx (16 shops), Xxxxxxxxx (14 shops), Xxxxxxxxx (67 shops), and Xxxxxxxxx (65 shops)

2.5 Conclusion on the problem approach

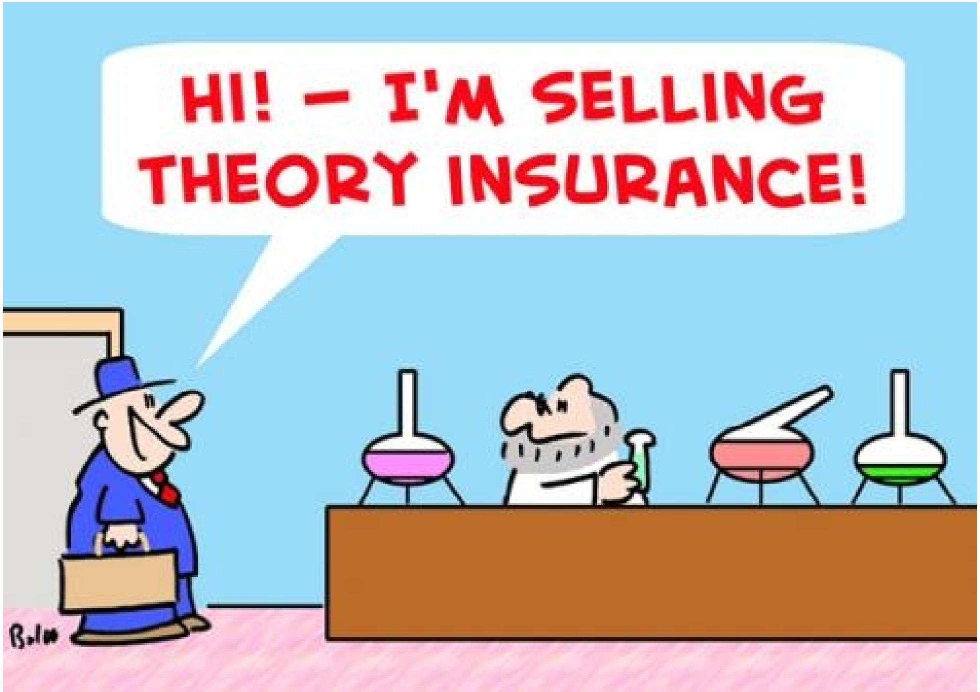
After having formulated in Chapter 1 what the discrepancy is between current and desired practices, an approach is formulated in Chapter 2 to reduce this discrepancy. This approach started by formulating the goal: to develop insights on factors influencing OSA and especially on the relationship between delivery failures and On Shelf Availability. Based on those insights an instrument is developed to manipulate the Casefill in such a way that value through optimal overall OSA of a product at the customers is maximized in the short and long term.

This goal will be achieved when two research questions are answered. These questions are:

1. What are the implications of Unilever's current OSA performance and how does this relate to benchmarks provided by theory?
2. Which improvement solutions exist within Unilever's influence to improve OSA?

The first research question will be answered from a theoretical point of view in Chapter 3 and from the practical Unilever point of view in Chapter 4. The second research question is answered in Chapter 5.

Chapter 3: Theoretical problem analysis



Chapter 3 - Theoretical problem analysis

In Chapter 1, the discrepancy between the current and desired situation is shown. Unilever is not fully aware of its influence on the On Shelf Availability, but wants to be more aware of that and use it for business decisions. In order to reduce the discrepancy, Chapter 2 contains the research questions which will be discussed in this report.

In Chapter 3, the problem will be analyzed from a theoretical point of view, to provide answers to sub question 1. First, an introduction is provided on Supply Chains and Performance Management. In Chapter 3.2, OSA is introduced and its characteristics will be discussed. This will be started by discussing the OSA definitions from theory, then the way of measuring OSA and next theoretical findings. Chapters 3.2 - 3.5 will answer sub question 1a.
Chapter 3.6 discusses the impact of OSA in missed turnover, which will answer sub question 1b.
Chapter 3.7 discusses the causes of missed OSA and the influence of the manufacturer in this, in order to answer sub question 1c.
Finally, Chapter 3.8 is included in this theoretical analysis to combine all theoretical sections, even though it will not answer sub question 1. It will however provide input in answering sub question 3 and the second main research question.

After Chapter 3, Unilever will have much more insight on the influences of all factors on OSA from a theoretical point of view, and answers to sub question 1. This will be compared in Chapter 4 to the actual Unilever findings.

3.1 Background theoretical information

In this section, a general introduction to Supply Chains and to Performance Measures is provided. It will provide background on what a supply chain is, and how performance measures are used to measure the efficiency and effectiveness of these chains. It will clarify which definitions are used in this investigation.

3.1.1 Theory on Supply Chains

A Supply Chain is an organizational structure of distribution channels, which can be viewed as a network of product, services and information flows (Bowersox & Morash, 1989). This has been improved by Christopher (1992) to: "*[A Supply Chain is a] network of organizations that are involved, through upstream and downstream linkages, in the different processes and activities that produce value in the form of products and services in the hands of the final customer*".

The term Supply Chain Management was introduced by Oliver & Webber (1982[8]), and is described as relatively new (Ganuasekaran et al, 2004). After many alterations from (a.o.), Silver et al (1998), Harrison & New (2002) and Ganusekaran et al (2004), the definition from Stadler & Kilger (2008) is used: "[Supply Chain Management is] *the task of integrating organizational units along a supply chain and coordinating material, information and financial flows in order to fulfil (ultimate) consumer demands with the aim of improving competitiveness of a supply chain as a whole".* This definition is chosen as it incorporates not just the direct but also the ultimate consumer as the focus, and because it incorporates the aim of improving competitiveness. Later in this investigation, it will become clear why these definitions are chosen.

Even though an increasing amount of literature is becoming available on supply chains, Fernie et al (2000) and Kotzab & Bjerre (2005) regret the fact that the majority of that focuses on manufacturing companies and that retail supply chains are less under investigation, although Van

[8] http://www.boozallen.com/media/file/133356.pdf, retrieved on January 5th, 2009

Der Vlist (2007) argues that supply chain management is now recognized as a core competence for retailing.

Finally, the retail Supply Chain in practice is highly segmented. Information flows exist, but are complex and often too limited. This poses problems in applying Supply Chain Management, as the exchange of information is crucial. Several initiatives have been taken to improve the supply chain, but most have not been implemented with great success yet (e.g. Van der Vlist, 2007, with the proposed synchronization of the supply chain).

Figure 6 – Shopping in the Netherlands

3.1.2 Theory on Performance Measurements

Fundamental for achieving organizational success is a performance measurement capability (Fawcett & Cooper, 1998). It is frequently quoted as "If you can't measure it, you can't manage it", and represents an "inescapable management reality" (Fawcett & Cooper, 1998). Although performance measures have received little attention in literature (Harrison & New, 2002), several authors like Ganusekaran et al (2004) state that the correct performance measures are those that truly capture the essence of organizational performance. Within the area of Supply Chain Management, Performance Management is used to determine the efficiency and effectiveness of the supply chain (Fleisch & Tellkamp, 2005). The importance of Performance Management can not be overstated because of the effect on the entire company (Harrison & New, 2002), even causing companies not being able to maximize their supply chains potential because of inadequate performance measures (Gunasekaran et al, 2004).

Lee & Billington (1992) and Van Hoek et al (2001) allow us to link the above mentioned definition of Supply Chains (Christopher, 1998) to supply chain metrics, by emphasizing on customer satisfaction when developing performance measures.

3.1.3 Conclusion on the background theory

In Chapter 3.1, the goal was to provide background information on what a Supply Chain really is and how Performance Measures can contribute to organization performance. It showed that a Supply Chain links organizations, to produce value for the final customer. Although the retail supply chain differs on several small things from the general supply chain, the general Supply Chain definition applies to retail well.

In Chapter 3.1.2, the importance of correct Key Performance Indicators is briefly discussed. Choosing the right KPI's is of big importance. Finally, KPI's are linked to the before mentioned Supply Chain definition which is taking into account the final customer: achieving targets measured by KPI's should result in customer satisfaction.

To express the performance of OSA in a KPI results in capturing the essence of organizational performance, thereby fitting Ganusekaran et al (2004) constraint. However, as stated by the same authors, it might be difficult to capture this data. It has to be measured correctly, and Unilever has to have some influence on it. As several companies previously experienced the effect of incorrect performance measurement, it needs to be carefully analyzed. This discussion will be continued in Chapter 4.7 and 5.1.

3.2 Theoretical importance of OSA

OSA and Out of Stocks have been investigated for many decades (e.g. Schary & Christopher, 1979; Peckham, 1963; see Campo et al, 2003). Increased intolerance of shoppers to accept Out of Stocks, increased impact when addressing these problems, and technological developments to address OOS have led to a renewed interest at the end of the 1990's (Gruen et al, 2002). This then triggered improvements in EDI, Category Management and Efficient Customer Response (Campo et al, 2004), increasing knowledge on OSA.
The importance of this topic is also highlighted by ECR Europe (2003), stating that reducing OOS is the third most important shoppers need, after 'shorter queues' and 'more promotions', whereas more recently in the Netherlands Out of Stocks ranked 1st in the 2008 consumer complaint list (EFMI, 2008).

In essence, OSA from a consumer perspective is the availability to purchase all products he/she desires, at that moment, place and in the right quantity. With an OOS percentage of 8.3% (example from Gruen et al, 2002), the likelihood that a shopper with the grocery list in Figure 7 will find all 11 items in place is only 38,5%[9]!

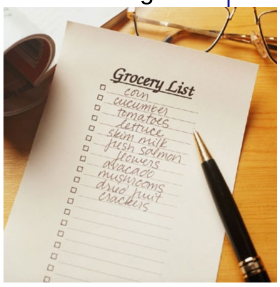


Figure 7 – Grocery list

3.3 On Shelf Availability definition

Due to the high number of researches (see Gruen et al, 2002), many different measures and definitions can be found. Some very common measures are discussed by Gruen & Corsten (2008), starting with a distinction between two different concepts:

1. A single Out of Stock Event; when an item is not available as intended. From a shopper point of view, a product is either available or not available.
2. Out of Stock Attributes; which can be further divided into rates:
   - Item Out of Stock rate; over a given unit of time.
   - Out of Stock Duration rate; Out of Stock rate / available total selling time
   - Shelf Availability rate; 100% – (OOS Duration rate*100%)
   - Out of Stock Losses – either in units or value

The attributes from point 2 can be used to determine the overall OSA performance, which can be defined in two ways (adapted from Gruen & Corsten, 2003[10]):

1. The percentage of SKUs that are on the retail store shelf at a particular point in time[11].
2. The number of times a consumer looks for a SKU and does find it.

In reality and in most researches, the second definition is hardly used (Gruen & Corsten, 2003), and hence will be omitted. The first definition can be further modified by using the definition by ECR (2003), to: an Out of Stock is "a product not found in the desired form, flavour or size, not found in saleable condition, or not shelved in the expected location – from the perspective of the consumer". The OSA definition is obviously the opposite. Again, this links back to the Supply Chain Management definition, which takes into account the final customer.

3.4 Theory on OSA measurements

Gruen & Corsten (2003, 2008) provide two common and adequate ways to measure OSA:

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[9] Likelihood of finding all n products = $(1 - OOS)^n$, so this is $(1{,}0 – 0{,}083)^{11} = 0{,}385$

[10] Although Gruen & Corsten (2003 and 2008) focus on Out of Stocks (OOS) at the retailer and not particularly on Shelf Availability, On Shelf Availability can easily be calculated from the Out of Stocks.

[11] Noteworthy is that this does not take into account the duration of the Out of Stock nor the impact to the retailer. After suggesting this in 2003, in 2008 Gruen & Corsten revise this measure and suggest adding the duration, both in calculation as when using these terms

- Manually by physical audits. This provides very useful benchmarks and is a reasonable estimator of OOS losses. However, it is limited by an arbitrary choice of variables and frequency, does not take into account duration, is expensive and leads to human errors. Finally, and according to Gruen & Corsten crucial, it is very hard to scale these findings up for more SKU's and shops.
- Using direct Point of Sales data (POS data), and comparing this to historical sales patterns. This provides accuracy up to 85% (Gruen & Corsten, 2008), but is severely limited by influences of variables, such as seasonal trends, promotions and other unforeseen variables. More limitations include initial set-up costs, reliance on accurate data and historical patterns (especially for slow moving items), and distrust by store management because of mathematical estimates instead of physical counting.

Using Perpetual Inventory data (more points over time) is also introduced by Gruen & Corsten (2008) as a third way of measuring Out of Stocks. However, the authors immediately dismiss this option as data accuracy is generally below 50%.

Next, distinctions between store-Out of Stock and shelve-Out of Stock (Gruen & Corsten, 2008), or between product and brand OOS (Sloot et al, 2005) are proposed. However, both options are dismissed as they do not provide more insights, the products in the dataset often do not belong to the same brand, and due to data limitations.

3.5 Theoretical benchmarks

Over 50 researches are currently published or distributed. An overview of some of the most important, most recent and best documented researches is shown in Table 2. The star in the last column indicates that the author has combined both the supplier and the retailers DC.

Research	Geographic region	% OOS (range)	% causes manuf.
Coca Cola/Anderson (1996)	U.S.	8.2% (3.9% – 11.1%)	N/A
Gruen et al (2002)	Worldwide	8.3% (4.9%-12.3%)	28% upstream*
Gruen & Corsten (2003, 2008)	Worldwide	8.3% (4.9% - 12.3%)	28% upstream*
ECR Australasia (2001)	N/A	5-10%	20%
ECR (2003)	7 countries (EU)	7.1% (5% - 32%)	15%

Table 2 - Quick overview of different OSA investigations.

Although Mason & Wilkinson (1976) provide some of the earliest figures on Out of Stocks in 1976 (between 6% and 32%), the 1996 Coca-Cola/Andersen Consulting research was one of the first major investigations on OSA and acts as a benchmark for the industry (Gruen & Corsten, 2003). It showed an average OOS percentage of 8.2% over eight categories, and 48% of all products were OOS at least once that month (Coca-Cola Research Council/Andersen Consulting, 1996). Gruen et al (2002) establish and confirm the importance of adequate OSA. They found a global average of 8.3% OOS, in which Europe performed worse with 8.6%.

As all researchers apply a slightly different Out of Stock definition, measurements, methodology, and deal differently with promotions and introductions, comparing these researches to the letter would be hard (Gruen et al, 2002). However, all figures fall in a range of 5-10%, and hence certainly provide insights and benchmarks (*ibid*).

For the remainder of the report, findings by Gruen et al (2002) and ECR (2003) will be applied as they are most often cited and most extensively documented. Based on that, is can be concluded that the average OSA level is between 7,1% and 8,3%. Combined with the theory discussed in Chapter 3.2 – 3.4, this answers sub question 1a on general OSA performance in theory.

3.6 Theory on cost (-estimation)

In the previous chapter, the OSA definitions, measurements and benchmark OSA levels have been discussed from a theoretical perspective. The costs encountered by both the supplier as retailer are discussed next.

Conservatives estimates indicate the entire industry[12] loses a staggering €4 billion per year in turnover due to Out of Stocks (ECR, 2003). This is due to shoppers cancelling their purchase when faced by an Out of Stock, but doesn't include switching or deferring. Neither does it include efficiency losses associated with store employees looking for a product (Gruen & Corsten, 2008). It can easily be assumed that including all customer reactions (which will be discussed in Chapter 3.6.2) would drastically increase these costs.
Gruen & Corsten (2003) argue that Out Of Stocks lead to a value destruction for the entire supply chain of 3.9% globally, and 3.7% for Europe. And although the bulk of research is focused on the retailers, Gruen & Corsten (2008) provide a loss figure for manufacturers: $23 million for every $1 billion in sales (2.3%) if the OSA performance of a company is considered average (91,7%, or 8,3% Out of Stock). Finally, Campo et al. (2000) state that manufacturers can lose up to half of their consumers in case of an Out of Stock.

Unfortunately, there is little evidence of a structured way to determine costs (Zinn & Liu, 2001). Few formulas have been provided or discussed, and if so, they remain subjective (Dion & Banting, 1995), filled with generic assumptions and omitting important variables. Perhaps this lack of clear and unambiguous calculations is because of the difficulty of calculating the costs. The difficulty was confirmed as early as in 1975 by Walter & Grabner, who argue that the financial impact of an Out of Stock is often incorrectly measured (Walter & Grabner, 1975; Zinn & Liu, 2001). Researchers often forget the loss of customer goodwill (ibid), Negative Word of Mouth (Thomas, 2002) and the CLV lost if a consumer is lost. The costs of OOS are often simply calculated by a proportion of demand, and neglect other variables (Dion & Banting, 1995). This results in an underestimation of the loss encountered.

Three specific parts of additional literature will now be discussed, which contain useful input on the calculations next to be applied. These topics are the impact of Customer reactions when faced by an Out of Stock, Word of Mouth (WOM) and Customer Lifetime Value (CLV).

3.6.1 Consumer reactions when faced by an Out of Stock

Gruen et al (2002) provide figures[13] on consumer responses when faced by an Out of Stock, and the implications of those responses for retailers and manufacturers. Although the percentages and the responses can differ per product because of loyalty (Gruen & Corsten, 2003), on average this provides a good insight in consumer responses when faced by an Out of Stock. This is also the case for private labels and for both loyal and impulse shoppers (Campo et al, 2000). They are displayed in Table 3.

Consumer response	%	Loss for manufacturer	Loss for retailer
Delay purchase	15	No, but affects cash flow and increases demand fluctuation	No, but affects cash flow and inventory management
Buy item at other store	31	No	Yes
Substitute other brand	26	Yes	No, only if margin substitute is lower[14].
Substitute same brand	19	No, only if margin substitute is lower	No, only if margin substitute is lower
Do not purchase	9	Yes	Yes

Table 3 - Overview of consumer responses and their impact on manufacturer and retailer

[12] Presumably, 'the entire industry' as focused upon by ECR (2003) is the global retail industry, but they do not disclose their source.
[13] The figures provided by Gruen et al (2002) are a combination of US and European responses. A slight difference exists, as US consumers are more likely to switch stores whereas European consumers are more likely to switch brands (Gruen & Corsten, 2003).
[14] A second note on the findings of Gruen & Corsten (2003), is that 'other brand substitution' for the retailers might not just be a loss, but also might provide an opportunity if the premium brand is substituted for a private label (and only if the retailers margin on that is equal or higher than on the premium brand)

If the item is Out of Stock, most shopper reactions will damage the retailer, manufacturer, or both. In fact, all of the consumer responses above will lead to an inaccurate picture of the supply chain for both the retailer and manufacturer (Gruen & Corsten, 2003) and will result in under- or overestimation of future demand.
These percentages are likely to have been altered as a result of the rise in importance of private labels and the price wars in the Netherlands (e.g EFMI, 2008). These changes however can't be quantified and will therefore be disregarded.

EFMI (2003) argues that the product type and market position are the main determinants of the customer reaction, but provide no suggested reactions or percentages with that. Campo et al (2004) focus on the drivers why consumers react in a certain way. Both findings will not be applied as no percentages are given, neither are the findings directly applicable. They do however shed light on 'why' someone acts in a certain way and are interesting for further reading.

Unfortunately, these percentages shed little light on which replacement will be chosen (Campo et al, 2003), as a consumer very often changes quantity if faced by an Out of Stock. Gruen et al (2002) and Emmelhainz et al (1991) indicate that there is a tendency to select a smaller size (substitution same brand) or a cheaper substitute (substitution other brands).

3.6.2 Word of Mouth (WOM)

Much is written on Word of Mouth (WOM)(e.g. East et al, 2008), providing useful information on the impact of Negative Word of Mouth (NWOM). It is stated that NWOM is more powerful than Positive Word of Mouth (PNOM) (East et al, 2008). According to the Kroloff principle (1988), negative news is about four times as persuasive as positive news. Both East et al (2008) and Kroloff (1988) support the argument that NWOM should be included as a factor in calculating the impact of OOS.

Figure 8 – Word of Mouth

East et al (2008) show that, within the supermarket sector, NWOM affected customers decision making more than PNOM (54% compared to 33%). The NWOM actually shifted the probability to purchase this product down by 16%! However, this shift in purchase probability is equal to PNOM, where a 16% increase is seen for the grocery industry in case of PNOM. Compared to other industries, East et al (2008) showed that supermarket shoppers are more extreme towards the negative side, but less extreme to the positive side. This, again, provides an argument to include NWOM as a factor.

3.6.3 Customer Lifetime Value (CLV)

Another section in literature deals with Customer Lifetime Value (CLV). CLV in essence is the sum of all discounted future cash flows from a customer, minus the discounted costs invested in that customer (Gupta et al, 2006; Pfeifer & Farris, 2004).
Although a vast amount of models exist (e.g. RFM, Pareto/NDB, econometric and probability), the CLV model outperforms all other models (Gupta et al, 2006). Besides providing a value per customer, the duration of loyalty of customer is calculated in estimating the CLV and this will be used for the Unilever calculations.

Finally, CLV excludes fixed costs of the marketing department, and no specific distinction is made between the costs of attracting new customers or maintaining the current customer-set (Berger & Nasr, 1998). However, from Desatnick (1998) it is known that attracting a new consumer costs five times as much as retaining a current consumer.

More information on CLV (-calculations) is provided in Appendix D.

3.6.4 Conclusion

Chapter 3.6 answers sub question 1b, concerning the costs of Out of Stocks from theory. It shows that determining the costs of Out of Stocks is quite difficult and a broad range of values exist. Within this broad range of values, Gruen & Corsten (2008) propose a 2.3% loss in turnover for suppliers in case of an average OSA of 92%, which at first seems plausible. However, they do not disclose their calculations and therefore it is not known which variables they include. This percentage however is the best figure available and hence will be used as the benchmark figure.

In determining the lost turnover at Unilever due to OOS in chapter 4.5, Negative Word of Mouth and Customer Lifetime Value should be taken into account if possible. Word of Mouth increases the short term loss of Out of Stocks and the chance of losing a customer for a long period. It is quite strong, especially for supermarkets, though no exact numbers are available.
CLV increases the cost of losing a customer for a long period of time and provides an estimation of the duration the consumer is lost. The statement by Desatnick, arguing that the costs of attracting a new consumer is 5 times higher than the costs of retaining a current consumer, will also be used in the practical model to determine the costs of marketing.

Besides CLV and NWOM, the different customer reactions as discussed in Chapter 3.6.1 will be applied to determine the short term costs. These different customer reactions play a major role in determining the costs of Out of Stocks for retailers or manufacturers, as not all actions by the shopper result in damaging respectively the retailer or manufacturer.

3.7 Theoretical causes of Out of Stocks

After determining the lost turnover due to Out of Stocks, it is important to determine What and who cause(s) the Out of Stocks? By doing so, solutions can be developed in Chapter 5 to reduce the causes of Out of Stocks and increase OSA. Determining the causes will be done by first discussing the causes suggested by theory. From this, it will show that suppliers are only responsible for a limited amount of the Out of Stocks. The specific impact of Unilever's delivery failures will be analyzed in Chapter 4.

3.7.1 Root causes of Out of Stocks

In all researches, causes of Out of Stocks are identified. Although big individual differences exist between authors, they all conclude that OSA deteriorates most within the last meters. Overall, all prominent authors (Gruen et al, 2002; Gruen & Corsten, 2003 and 2008; ECR Australasia, 2001; ECR, 2003) agree on the following issues:

- Between 60 and 85 percent of the causes are on store level.
- The most occurring causes throughout the entire supply chain are:
    - Shelving procedures - disguising, filling with other product, no timely reaction.
    - Bad Back of Store (BoS) practices – this is mainly caused by too much inventory, bad storage practices causing shrinkage, inventory inaccuracy and other problems.
    - Demand underestimation – too little is ordered.
    - Inadequate shelf allocation – slow movers receive relatively much shelf space, whilst fast movers too little. ECR (2003) provide a case study showing almost 50% of all products had 20 or more days of stock on shelf!
    - Introductions and discontinuations – these could even include slightly new products with only the packaging changed.
    - Lengthy order cycles and low replenishment frequency.
    - Promotions – especially in the first few days (ECR, 2003). The amount of discount is also sometimes correlated with the OOS percentage. The storage of a promotion on two different location (e.g. via a display) should be prevented as much as possible (Gruen & Corsten, 2008).

Besides the root causes mentioned above, several authors provide some additional causes. Those that can be linked or influenced by Unilever are shown below.

- Advertisement and price changes (Gruen et al, 2002) – causing sudden increase or decrease of expected sales.
- Too many SKUs in the assortment (Gruen et al, 2002) – as more SKUs increase complexity, they might increase the number of OOS. According to Broniarczyk et al (1998), the amount of SKU can be reduced without decreasing consumer satisfaction, although a 2009 EFMI report[15] shows that in the Netherlands delisting still causes major customer dissatisfaction.
- Planogram design, implementation and execution (adherence) of the proposed (or obliged) shelf design (Gruen & Corsten, 2003; ECR, 2003). Raman et al (2001) also argue that incorrectly located stocks can be a cause for OOS, and Van Woensel et al (2006) found incompliance ranging from 1.5% up to 24%.
- Data inaccuracy (Gruen & Corsten, 2003; Raman et al, 2001).
- Incorrect ordering (Gruen & Corsten, 2003) – filed incorrectly, too late, or not at all.
- Availability at DC (Gruen & Corsten, 2003) or supplier (Gruen et al, 2002).
- Shelf tag accuracy (Gruen & Corsten, 2008).

Besides these main causes, general remarks are placed at the type and layout of store (hypermarket vs. supermarket, e.g. Gruen & Corsten, 2003; ECR, 2003); speed of movement

[15] Published on http://www.evmi.nl/nieuws/marketing-sales/7565/leeg-schap-super-wekt-ergernis.html, retrieved Sunday June 14th, 2009

(Gruen et al, 2002); supplier reliability (ECR, 2003); and adequate communication (Gruen & Corsten, 2003).

All of these causes differ in importance and impact, and several authors have determined their top 'root causes'. One of the best and most recent lists is provided by Gruen & Corsten (2008). How their seven root causes can be linked to the above list of individual causes is shown in Figure 9, in which the blue boxes are mentioned by all authors previously mentioned. Here, 9 root causes seem to be predicted, but "replenishment" is divided between customer replenishment and store- and shelf replenishment, and "Ordering and Inventory Management" is also divided between customer and manufacturer.

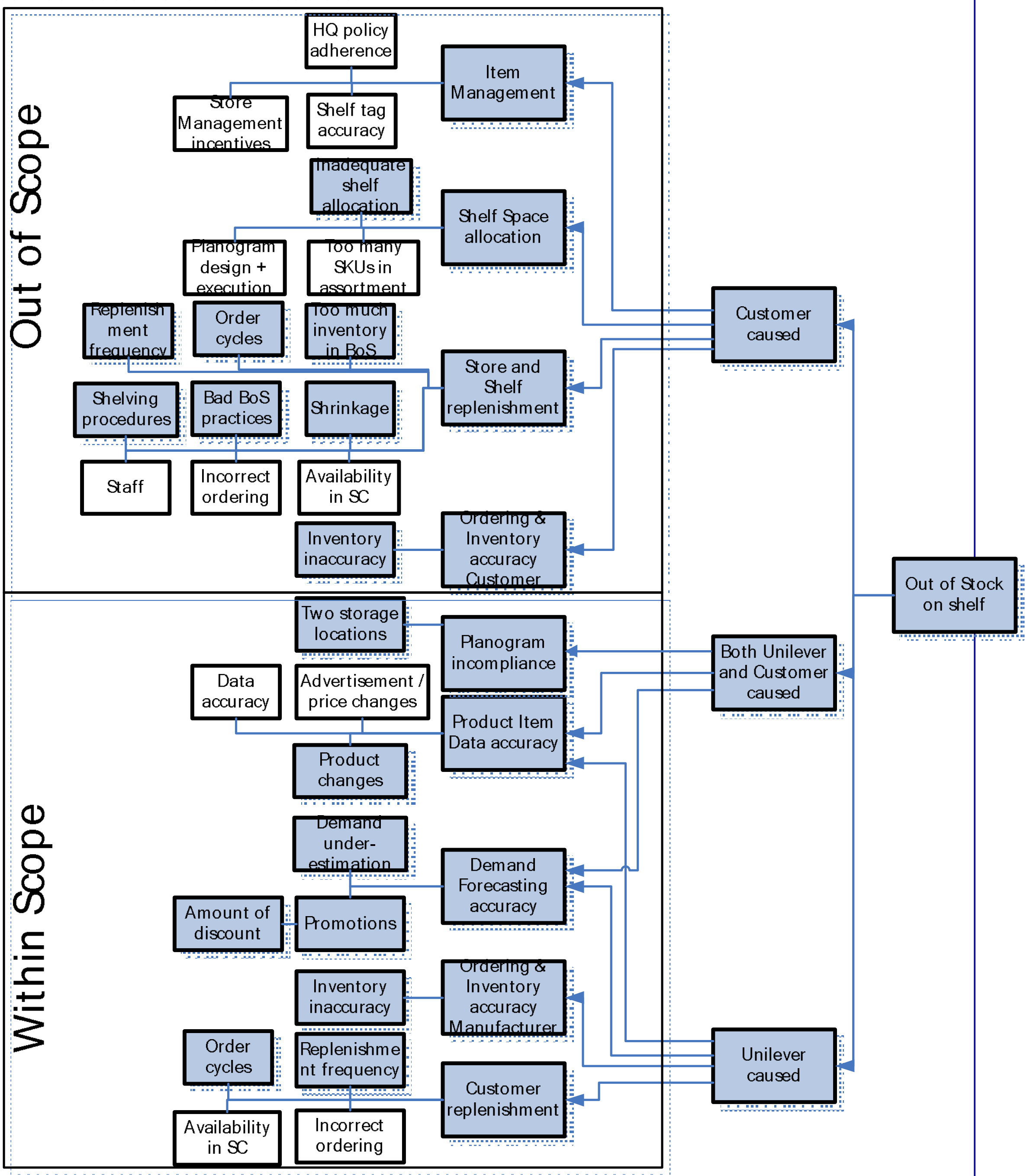

Figure 9 – Overview of all causes of Out of Stocks

3.7.2 Supplier causes are not frequently discussed

In order to directly answer sub question 1c on the impact of the delivery failures on OSA, theory is investigated which discusses this impact. Unfortunately, few studies truly discuss the impact of the supplier, especially when the supplier is incapable of producing enough to satisfy demand of the customers and the Supply Chain (Gruen et al, 2002). They argue that 3-4% of the OOS causes can be directly attributed to insufficient production by the manufacturers. This might vary per category and depends (e.g.) on material supply and capacity (*ibid*).

Another cause in the domain of the manufacturer is poor promotional content (Gruen & Corsten, 2008), which can also include sudden price drops causing unexpected shopper demand (Gruen et al, 2002). Other causes of Out of Stocks caused by the supplier are less specifically mentioned, but encompass (a.o.) delivery lead times, shelf allocation, data synchronization, communication, and general processes.

3.7.3 Conclusion on theoretical causes of OOS

The goal of Chapter 3.7 is to determine the theoretical causes of Out of Stocks. This will answer sub question 1c; the impact of delivery performance on OSA.

From this section, seven root causes of Out of Stocks are shown, of which five (partly) relate to the suppliers performance:

- Demand and Forecasting Accuracy
- Customer replenishment
- Product Item Data Accuracy
- Planogram incompliance
- Ordering and Inventory Accuracy

Several causes are mentioned relating to the supplier's performance, but mostly interesting in line of this research is the delivery performance. The other causes are less directly to measure, are out of scope and require further analysis.

This theoretical analysis also showed that overall 3-4% of the Out of Stocks is caused by the suppliers' unavailability to meet customer demand. This might differ per product and per customer. The correctness of this figure and the product and customer groups which have high influence will be investigated in Chapter 4.6.

3.8 Theoretical best-practices and solutions

Using the seven root causes mentioned by Gruen et al (2002), solutions by Gruen et al (2002), Gruen & Corsten (2003, 2008), ECR Australasia (2001) and ECR (2003) are organized. These are schematically displayed below in Figure 10.

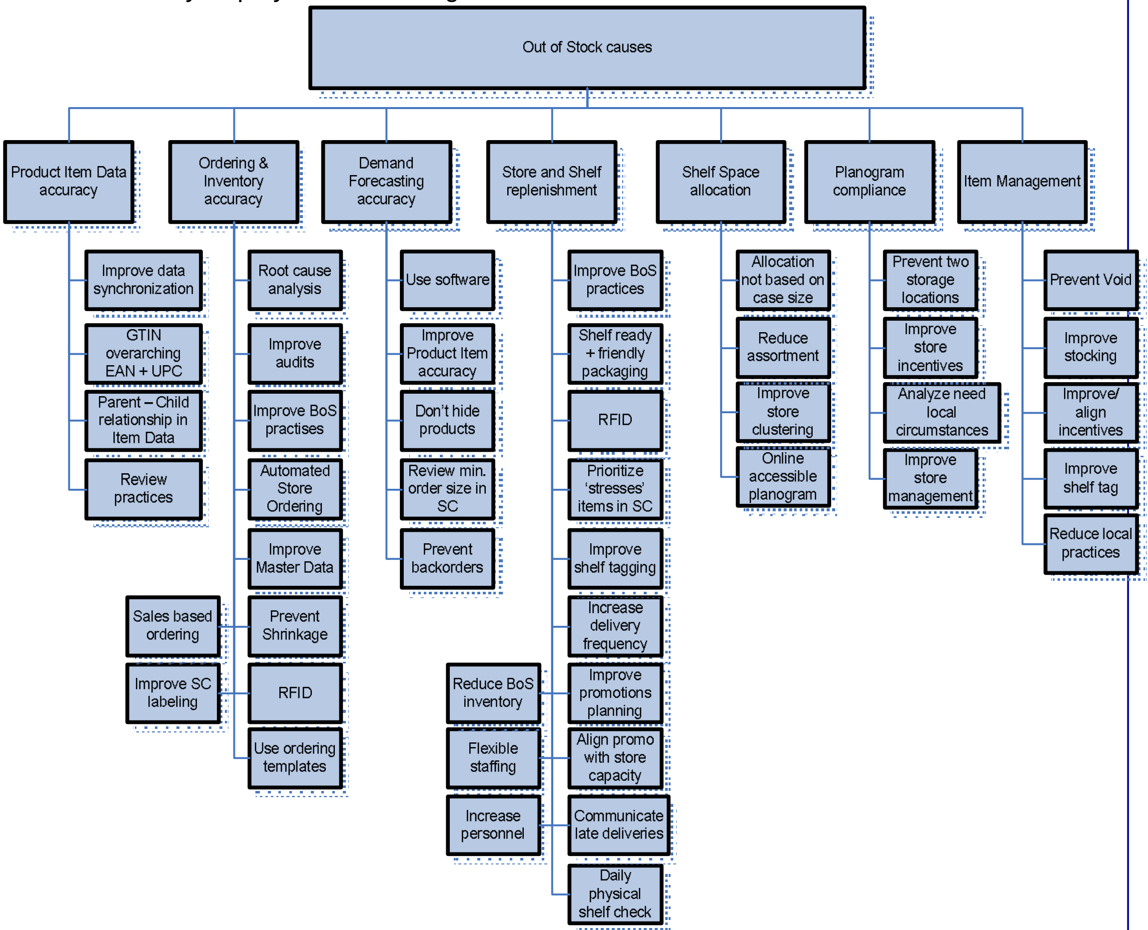

Figure 10 - Graphical representation of the solutions posed by several authors

The most important solutions are to create awareness of the problem amongst management (ECR, 2003), improve forecasting by using computer assisted ordering processes (ECR, 2003; Gruen et al, 2002), and improve Back of Store practices (all authors). The latter is subdivided in reducing stock, improving receiving and storing and cleaning the Back of Store. Finally, shelf space allocation should be based on demand and speed of movement, and not by size of the packaging or other arguments (Gruen et al, 2002).

Given the scope of influence of a supplier, most solutions provided here are of less interest. Of the solutions provided, theoretical solutions directly applicable and useful to Unilever are:

1. Create awareness (both internally as externally with customers).
2. Improve delivery performance.
3. Improve promotions planning – by sharing more information within the chain and not providing just a single number (the quantity ordered).
4. Improve Product Item data accuracy and data synchronization.

These solutions are chosen as their implementation is manageable and within influence of Unilever. Next to these solutions, several projects with customers can be initiated, for example to improve ordering processes, back-of-store practices and planogram adherence.

Chapter 4: Practical insights on OSA

Chapter 4 - Practical insights on OSA

After the theoretical discussion in Chapter 3, the focus is now on answering sub question 2. In order to answer sub questions 2a, 2b and 2c, the practical Unilever perspective will be compared to the theoretical perspective. This will be done respectively in Chapter 4.1 – 4.4 for sub question 2a, in Chapter 4.5 for sub question 2b and in Chapter 4.6 for sub question 2c.

4.1 Unilever's OSA importance

The ultimate moment of truth of an integrated Supply Chain is the availability to the shopper. To maximize this, a good service from Unilever to the Customer is not good enough, as most of the OSA misses are commonly due to retailers. These conclusions are backed by studies from Unilever Europe, the USCC and knowledge available within Unilever. It has therefore been concluded that OSA should grow in importance for the Unilever countries.

Currently projects are being executed in several countries, including Belgium, Mexico, Brazil, United Kingdom and the US. The sheer size of these projects, and involvement from Unilever executives, indicate the importance to Unilever globally. Based on these and other findings, Unilever often applies a rule of thumb to indicate the importance of OSA. This rule, developed by McKinsey consultants, indicates that a 3% rise in OSA would result in a 1% rise in turnover.

Theory and Unilever practice agree that OSA is an important measurement. As shopper satisfaction is heavily influenced by the availability of products, it needs to be optimal. Although interest in OSA is not completely new, it has been renewed recently by measurements showing very figures at Unilever. This caused the importance of OSA to increase drastically.

4.2 OSA definitions at Unilever

By measuring the OSA for certain products at certain retailers, Unilever is able to make decisions based on facts. In order to align all countries involved in measuring OSA, Unilever has implemented a set of global OSA definitions:

- On Shelf Available is defined by the physical presence of an SKU on shelf, in store, that has an item tag and shelf space, and is regularly ordered and stocked by the retailer.
- Out of Stock is when a listed SKU is indeed a regularly stocked item, has shelf space and a price tag, but at the time of the audit, there is no inventory on the shelf.
- Void refers for the circumstances where an SKU is listed by the Retailer, and should be on shelf with a price tag and shelf space, but for some reason (not to be determined or evaluated by the auditor) the item is not on shelf, is not regularly stocked, and has no price tag.

As explained in Chapter 1, Void will be subdivided in temporary- and long lasting void. In this research, only temporary void is taken into account. From a shopper's perspective there is no difference between unavailability due to void or due to Out of Stocks and for this investigation both will be combined.

In Chapter 3.3, a brief overview is provided on the different types of definitions available in theory. The most often used definition concerns the percentage of SKU which are available for purchase at any point in time, which is also applied by Unilever. Unfortunately, the duration of Out of Stocks is not captured by applying this definition. This might result in inaccuracies when trying to predict the turnover lost due to Out of Stocks.
Although the definitions are easy to implement and are objective by nature, they do not capture whether the shelf is 'full enough'. If only a single unit is available on the shelf furthest away from the shopper, it should perhaps be deemed as 'unavailability'. This is especially the case in promotional displays, as these are often custom build in multiple layers on the head of the shelf

and have shelves high up. However, in the current setup of the measurements, this can't be changed without accepting a major increase in subjectivity. Unilever has chosen within its global definitions to reduce the subjectivity and accept the resulting reduction in applicability.

4.3 Unilever's OSA measurements

In order to improve knowledge on OSA, Unilever measures 88 Unilever SKU and 32 competitors SKU, at customers. These products have been identified by Category Management Teams as the most important for Unilever, whether based on volume, growth, or any other reason. The combined volume for these SKU at these customers represented of Unilever's Retail volume in the Netherlands in 2008. These products provide a quite good sample of the Unilever portfolio looking at volume, internal classification and other metrics.

For each of these customers, the most important supermarkets had already been identified before this research, based on volume, location, cooperation and other sales variables. These are mainly big supermarkets. In total, supermarkets were identified to be part of the OSA measurements, and the supermarket owners have agreed to participate in the research. A rotation is developed so each store is visited at least twice per quarter. This currently is enough to show general OSA performance, but in the remainder of the research it will be shown that promotions and sudden Out of Stocks are not captured completely by this infrequent way of measuring. However, given the pilot phase of the project and the limited financial resources, this currently suffices.

Figure 11 – Unilever SKU are measured manually

Measuring is done by manual audits, in which people look for the product and consult (if necessary) store staff. This should resemble actual shopper behavior, as shoppers also do not wait for more than a few minutes before deciding to change the product. Data is uploaded monthly into a web-based application, whilst additional data is sent by e-mail.
A full overview of the active[16] products and of the supermarkets is provided in Appendix B.

4.3.1 How to ensure data integrity?

In order to ensure that the data provided by these measurements truly captures the essence of organizational performance, the integrity of the data needs to be ensured. Measurement errors could severely distort reporting and decision making, in that decisions are taken on incorrect figures. Chapter 3.4 showed that manual measurements are prone for measurement errors, so special attention needs to be on this.

By having 120 products (of which 88 are Unilever products) at so many stores, the measurement agency produces thousands of measurements on a monthly basis. In total, 311.850 measurements are available for analysis after a 10-month collection period. Carefully examining these measurements indicated that the data can't be used directly. Several products were incorrectly measured, there was missing data and data that should not have been measured in the first place. The errors in the data could be attributed to the manual collection of the data, process errors and project leadership errors.

Hence, the data is cleaned in order to ensure data integrity. To do so, four filters are applied, which are described in Appendix A. After filtering, only correct and useful measurements remain. In the remaining dataset, a product is either available to the shopper to purchase, or not available (Out of Stock). These Out of Stocks are caused by supply chain failures (either at Unilever or the customer) and no longer due to sales issues.

[16] The entire dataset is subject to filtering, in order to ensure data integrity. For an overview of this, please see Appendix A. The products and stores in appendix B are those that remain after applying all filters, and are indeed correctly measured.

For the remainder of the report, the focus is on:

- Unilever products,
  which are measured correctly (the obvious incorrect products and incorrect measurements are excluded,

- which had contractual obligations to be sold at the specific store of the measurement.

Of the initial 311.850 lines before cleaning, 217.000 remain after this extensive filtering. Parts of the excluded measurements, those that deal with correctly measured non Unilever SKU (52.468 lines), will be used to provide benchmarks for the Unilever findings.

4.3.2 Conclusion on OSA measurements

In Chapter 4.3.1 the data collection process of Unilever is compared to suggestions on the data collection process from theory. Although in Chapter 3.4, theory suggested the use of point of sales data over manual audits, Unilever's data is collected manually. Advantages at that time were the relative ease of collection, the relative quickness of results (no need to compare and/or find historical data) and the absence of a need to closely work together with customers. With the quantity of measurements, via many stores and many products, Unilever overcomes issues concerning slow movers and statistical significance.

Chapter 3.4 showed that problems might occur in the near future when there is a need to extrapolate these findings to other customers and/or products. Problems might also occur on the part of the data accuracy. Human errors are likely to occur, and measurement definitions need to be perfectly clear for those measuring. Unilever needs to take further action here to ensure data integrity, else decisions will be taken based on incorrect data. Chapter 5.1.2. will discuss this urgency in more detail.

A comment is that manually measuring in this way might not capture the extent of an Out of Stock. Although the arrivals of those that measure can be seen as random, it could happen that they always run into either full or empty shelves (just before or after restocking by store personnel). And sudden short Out of Stocks might not be measured as the store or retailer is not included in that day's measurement schedule.

The consequence of choosing this way of measurement, and the issues concerning data integrity, has implications for the use of OSA as a Key Performance Indicator as discussed in Chapter 3.1. To be useful as KPI, data needs to be correctly measured. Using this type of measurement, Unilever has to be very sure it is correct and no measurement errors exist.
The way OSA is measured however would fit the definitions used by Unilever. As the duration of an Out of Stock is not measured, this way of measuring would suffice.

Findings from these measurements will be discussed in Chapter 4.4.

4.4 On Shelf Availability findings

The goal of discussing the OSA results from the Unilever dataset is twofold: to provide a benchmark and compare general results to other investigations, and to compare specific findings to benchmarks from other investigations. From the latter it will be possible to provide conclusions on the usefulness of the dataset and to provide insights in OSA.

The first chapter will show that Unilever performs better compared to the general benchmarks provided in Chapter 3.6 and its peer in the market, but with room for improvement.
The second part consists of specific research findings on the time and day of the Out of Stock occurrences, the impact of store size and other specific findings. These specific findings are generally aligned with theory, but differ on certain specific topics.

In this analysis only Unilever products will be analyzed, which are corrected for potential incorrect measurements (please refer to Appendix A for more information on the data corrections). This was also discussed in Chapter 4.3.1. The performance of non-Unilever products will be used to acts as benchmarks within the Dutch retail market.

4.4.1 Unilever's overall OSA performance

Unilever shows a high average OSA of % based on the 88 products at 6 retailers. This results in an OOS percentage of %, over the period of May 2008 till and including February 2009. This is shown in Figure 12.

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Figure 12 - The Out of Stock levels at Unilever.

Gruen et al (2002) have wondered whether the often occurring 8% OOS figure would perhaps be 'the natural average'. Although that would still be unacceptable, Unilever is actually performing better (% compared to 8%). Pramatari & Miliotis (2005) suggest that a 2% level of Out of Stock would be acceptable, and ECR Australasia (2001) state that it is not cost-efficient to reduce Out of Stocks when their occurrence is less than 0.5% to 1%, implying an OSA of 99% as the economical optimum.

Comparing Unilever's findings in OSA to the other, non-Unilever SKU in the dataset, shows a somewhat lower OSA for non-Unilever products of %. This can be explained by the fact that this dataset could not be cleaned as extensively as the Unilever dataset (as Unilever is not aware of planogram regulations for other SKU, and neither for temporary boycotts of products). The analysis of non-Unilever SKU shows further that private labels perform slightly better with an OSA of % compared to other premium label products (%).
As the Unilever OSA percentage is in line with theory and its peers, it is possible to conclude that this OSA percentage appears to be correct. No 'strange' figures emerge from both comparisons.

After having established Unilever's performance compared to its benchmarks, the dataset is investigated in more detail on known topics in theory, including the time of the measurement and store- and product characteristics. This will provide insights in OSA, confirm the usefulness of the dataset and partly achieve the main goal stated in Chapter 2.1.

4.4.2 Specific findings of the Unilever dataset

As theory provides several strong findings on OSA with respect to the day of the week, the time of measurement, the volume of a product, store size and promotions, these topics will be further analyzed below.

4.4.2.1 Day and time of the week

According to Gruen et al (2002) most Out of Stocks occur Sundays or Mondays. This can be explained by the fact that most stores are replenished Mondays and that these replenishments are not directly visible on the shelf. Preparations for the upcoming weekend result in higher OSA for Thursday, Friday and Saturday. However, these findings are dismissed, as the average of the individual days (9,2%) is not equal to the stated overall Out of Stock level of 8,3% by Gruen et al.
ECR (2003) research shows a trend towards lower OSA level on Friday and Saturday, but a more stable trend during the week. This is shown in Figure 13, with the Unilever performance.

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Figure 13 - OSA percentages per day of the week

When analyzing the OSA levels at Unilever, per day of the week as shown in Figure 13, it is clear that these are not completely in line with the general findings from literature.
Unilever shows a rather stable trend throughout the week, resembling the ECR (2003) findings. They show a similar average level, although the Unilever OSA decrease on Thursday is not matched. This Thursday evening increase may be explained partly by the increase of shoppers on Thursday evening (as regular shops are often open to public on Thursday evening), which is also shown in the decreased OSA level of % on Thursday evening compared to the average evening OSA levels of %. Although Friday evening shows better OSA percentages with many measurements, hence implying frequent opening hours of shops, the negative effect of this increased amount of shoppers may be cushioned by improved stocking of shelved just before the weekend. These values are shown in Table 4, in which the OSA percentages and the number of measurements on which they are based, are displayed.

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Table 4 – OSA percentages and measurements per time and day

Analyzing the OSA percentages per time of the day as shown in Figure 14, it is clear to see the (rather intuitive) downward trend occurring from a morning-high to low OSA percentages in the evening. This is confirmed by theoretical researches (e.g. ECR, 2003).

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Figure 14 – On Shelf Availability per time of the day at Unilever

4.4.2.2 The impact of promotions

Promotions are very important to the business as they are 'the' way to increase brand switching by customers. Gupta (1998) found that the increase in sales due to a coffee promotion could be contributed for 84% to new shoppers switching brands. This obviously would decrease if the item is not available, perhaps even resulting in a negative impact on brand value during and after the promotion (Gruen et al, 2002).
Gruen et al (2002) found items in promotions experiencing twice as much Out of Stocks than for non-promoted items. This is even higher if the promotion is an impulsive reaction to competitor behaviour (a competitor's promotion is countered). Finally, ECR (2003) figures for the Netherlands show a 50% increase of Out of Stocks for promoted versus non-promoted items (6.7% to 9.3%), which is even higher (up to 15%) early in the promotion cycle.

For Unilever, there is indeed a somewhat lower OSA for promoted items (as can be seen in Figure 15(1)). In Figure 15(2), it can be seen that the amount of units sold under promo[17] has an unpredictable pattern. However, if all products are sold under promo, then the OSA drops by .

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Figure 15 (1/2/3) - OSA of promoted versus non-promoted products.

Finally, it can be seen in Figure 15(3) that for all customers, promotions result in a decrease of On Shelf Availability compared to non-promotional OSA. This impact is least for . This however needs further statistical investigation to determine whether the difference is statistically significant. This is done in Chapter 4.6.

The theoretical impact, in which promotions double the Out of Stock level, is not reflected in the percentages provided by Unilever's dataset. This questions the theory used as a doubling of Out of Stocks is quite implausible. Reasons for not experiencing the big decrease in OSA as expected, are (a.o.) the importance of promotions to retailers (Unilever's brands are often quite

[17] If a product is promoted, e.g. 10% off or 2-for-1, than all of those items sold are sold under promotion. Besides promotional items, some people still buy the standard item without promo (i.e. perhaps they do not want the second product for 50% if 1 suffices). In that case, the weekly average of promotional items sold is less than 100%.

promotions.

prominent in the promotions) and the improvement of processes in the supply chain since the theoretical researches were published.
Besides that, the definitions of OSA chosen by Unilever might not capture promotional Out of Stocks very well, as having a single product on any shelf would mean it is 'On Shelf Available'. Besides that, the measurement agency is given (a lot of) freedom when it comes to measuring promotions, as it is unsure which shelf they measure. This can be either the normal shelf or the promotional second shelf. With promotions, and the increased sales, these two issues might explain the difference between practice and theory.
Finally, the measurements can also even miss Out of Stocks due to the rotation schedule employed.

Further analysis, shown in Figure 16, shows that the impact of Out of Stocks in terms of units lost, is much higher relatively for promotions compared to non promotions. Based on sales data acquired from the commercial company AC Nielsen, 'promotional' sales represented only % of total units sold during the measurement period, but promotional Out of Stocks accounted for % of the total units not sold. So if an Out of Stock occurs during promotion, this has a high impact on the number of units sold.
This impact is quite clear, even when only applying a rough calculation of which the results are shown in Figure 16[19].

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Figure 16 – Impact of promotional OOS in terms of lost sales

Based on this analysis, it is clear that Unilever's OSA measurements do not capture the impact of promotional Out of Stocks very well. Although general Out of Stock level rises slightly, the impact is felt very much in terms of missed sales, therefore promotions should receive much attention when trying to increase OSA. Currently, the measurements are not suitable for further research on the impact of promotions, so further research is recommended here. This could reveal higher impact of promotions due to the chosen OSA definitions, but also disprove theoretical statements that promotions double the Out of Stock percentages

4.4.2.3 Speed of movement: Fast-movers and slow-movers

Gruen et al (2002) provide lower OSA rates of 50%-80% less OSA for fast moving goods compared to slow movers. This is in line with findings by ECR UK (2007), showing that more profitable (and often fast moving) products have a lower OSA percentage than normal.
Although there is no clear definition of what the annual volume of 'slow mover' is, or what a 'fast mover's' volume should be, it is possible to plot the volume of the Unilever SKU against their OSA percentages, as shown in Figure 17.

[19] Here, the weekly sales is divided by the average OSA to get the 'normally expected' sales. After subtraction of actual sales, an indication of lost sales remains. Of all lost sales, promotional sales accounted for 26%, whereas they only account for % of regular sales

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Figure 17 - Annual volume (cases) of the products against OSA.

The upward trend is clearly visible, visualized by the trend line. These figures are also not in line with the previously mentioned literature. Whereas it is assumed that fast moving products are more frequently Out of Stock, this shows this not to be the case and fast movers have the highest OSA

The difference between theory and practice can't be explained by the number of deliveries from DC to store, as for all 6 customers under investigation, stores are delivered daily. There is also no difference in store delivery between fast- and slow movers as all customers apply cross-docking for their slow moving products (slow movers are first shipped to regional fast moving warehouses before loaded on the trucks heading for the stores).
However, differences can be explained partly by that lower volume products presumably are less often restocked, or too late, or are not ordered at all. They are presumably less important to the retailer, which can explain the tendency towards higher OSA for higher volumes[20].

4.4.2.4 Supermarket size is of influence

ECR (2003) shows an increased performance of supermarkets over hypermarkets. This is mainly due to less complex assortments and a better ratio of employees per SKU. ECR (2003) further argues that this is in line with other researches, but does not specify which ones.

ECR (2003) and other studies often refer to the somewhat ambiguous term 'big' or 'hyper'. The size of a store is often expressed by the amount of products it carries. This ranges from 45.000 in the US (FMI, 2008)[21] to around 15.000 in the Netherlands (Sloot et al, 2005) or even 30.000 products (Van der Vlist, 2002). Unfortunately, due to confidentiality issues, Unilever is not aware of the number of SKU per store. And it is very likely according to Raman et al (2001), that neither do the retailers themselves know this.

Although the difference between normal and big stores is interesting, the supermarkets analyzed in the Unilever investigation are all 'regular' supermarkets. The absence of 'hypermarkets' in the Netherlands (see Fernie et al, 2000, for a discussion on the European supermarket landscape) dismisses the option to compare these types of supermarkets. It is therefore less likely that international theory on OSA is directly applicable.
With the number of SKU per store not available, expressing complexity by the floor surface and the store's weekly turnover shows these results in Figure 18 and 19:

[20] However, there is no clear picture when distinguishing between void and OOS for the products. The measurements do not confirm that low-volume products have more void compared to high volume products, which implies that it can't be confirmed that stores 'choose' not to have low volume SKU.
[21] Retrieved from www.fmi.org on October 21st, 2008

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Figure 18 – On Shelf Availability per supermarket against its weekly volume.

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Figure 19 - On Shelf Availability per supermarket against its store surface.

Figure 18 shows a stable trendline, indicating that the store's weekly turnover is not a major determinant of OSA. Figure 19 however shows store floor surface to be somewhat positively correlated with OSA: more 'complexity' results in higher OSA. This contradicts commonly used literature. Apparently, bigger stores have more sophisticated procedures, have better people employed or are delivered with higher priority from the customers DC. It could also imply that bigger stores have more space on the shelve, so more facings can be placed there and hence the stock level on the shelf increases. This however needs further research to be proven, which will be done in Chapter 4.6.

4.4.3 Conclusion on the OSA findings

The goal of Chapter 4.4 was twofold; compare overall Unilever performance to benchmarks, and compare specific Unilever findings with specific benchmarks. Both will result in additional insights in OSA and will prove the adequacy of this dataset. This will also help answering sub question 2a; determining Unilever's OSA performance and comparing this to theory.

Chapter 4.4.1 shows that Unilever's OSA performance of is quite in line with general benchmarks. This allows using the findings of those theoretical reports in this investigation. Unilever performs quite good compared to theory and to its peers in the OSA measurements, but there is still room for improvement. ECR Australasia (2001) argue a 1% Out of Stock level ought to be the goal, a level Unilever yet has to achieve.

Next, the dataset is analysed on several specific topics mentioned in literature. Comparing Unilever's data to the benchmarks on topics as volume, day and time of Out of Stock and store size, we find them to be mostly in line with theory, but with some contradicting results. Whereas the time and day of Out of Stocks are quite in line with theory, volume and store complexity seems to be correlated the other way around with Out of Stocks. This can be explained by the choice by Unilever to measure at big stores (the selection of as discussed in Chapter 2.4.2.2) and the choice for important Unilever products. It can also be explained by the fact that research findings might not be completely adequate to describe the Dutch market (because of the absence of hypermarkets).

Finally, promotions seem to be much less negatively correlated with Out of Stocks than proposed by theory. This could imply that retailers recently have improved promotional processes, or that the Unilever definitions do not truly capture promotional Out of Stocks.

Overall, the dataset appears useful for further analysis. This chapter provides an overall OSA-percentage and interesting specific findings on product volume, store complexity and the day and time of measurement. However, these findings still need to be statistically proven, as will be done in Chapter 4.6.

4.5 Annual turnover lost due to Out of Stocks

After having established the OSA averages for Unilever, confirmed the validity of the dataset and having gained insights on common OSA topics, the next sub question (2b) discusses the losses endured because of OSA losses. Hence, the next step is to determine the lost turnover due to Out of Stocks. The theory in Chapter 3.6 discussed customer reactions when faced by an Out of Stock, the impact of Negative Word of Mouth, and the Customer Lifetime Value, which are the basic to determine the costs of an Out of Stock.

To determine the annual turnover loss Unilever faces by having a suboptimal OSA is quite difficult, as in practice not much is known on the costs of Out of Stocks. The process to calculate these costs is developed specifically for this research and no directly usable formulas or calculations were found elsewhere.

The process of determining the costs can be graphically represented by Figure 20 and explanation is added below:

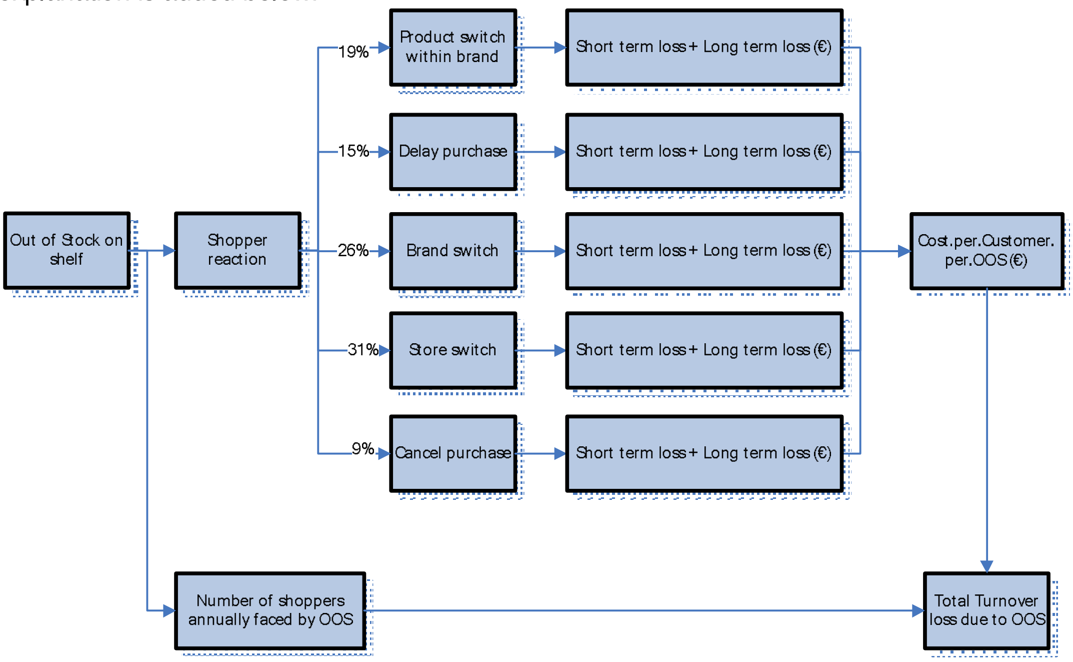

Figure 20 – Graphical representation of determining the lost turnover due to OOS

If an Out of Stock occurs, the impact on turnover is a combination of the costs of the shopper's reactions and the number of shoppers faced. If no consumers were willing to buy the product at time of the Out of Stock, the impact is 0. Or, if all consumers choose an action not damaging Unilever (e.g. store switch), the impact is also 0.
The loss per reaction is based by the short term loss (which is only positive if the reaction damages Unilever) and a long term loss (if the alternative chosen is to the consumers liking).

In Chapter 4.5.1, the formulas which are used to determine the annual turnover loss for Unilever are discussed. The following variables are declared:

- Product i
- Customer j
- Shopper reaction r

The following assumptions are used:

1. Shopper reactions r do not differ between products, except when explicit theory for that product has been published. Neither will there be a distinction between loyal- and

impulse shoppers, due to the absence of shopper reaction percentages differentiating between these two types of shoppers.
2. When a shopper switches within the same brand, there will not be a penalty, even though literature states that the shopper often 'downsizes', perhaps resulting in lower turnover.
3. Seasonality is not taken into account.

Finally, two remarks need to be made:

- Although it is plausible to assume different shopper reactions r for promotions versus 'regular' items, this will not be taken into account. This will result in further research recommendations, which will be discussed in Chapters 5 and 7.
- The substitution effect which occurs because of shoppers switching to Unilever because their product is Out of Stock and Unilever's product is available on shelf, is not taken into account. Low OSA will still result in losing turnover for Unilever, whilst turnover generated because of poor performing competitors can be seen as a bonus. It is too hard to determine a steady state system incorporating all consumer movements, and accurate competitor benchmarks are not available for comparison. It can however be assumed that if one customer or manufacturer is able to increase its OSA, it will not only reduce its lost turnover but also increase volume as it receives shoppers from poor-performing competitors.

4.5.1 Formulas applied to calculate Unilever's lost turnover

In this Chapter, the formulas are provided to calculate the lost turnover for Unilever due to Out of Stocks. A full overview of the formulas is discussed in Appendix C, and a summary is provided here.

Calculating the costs of Out of Stocks depends on the Cost_per_Customer_per_OOS if faced by an Out of Stock, multiplied by the number of shoppers faced by an Out of Stock (Customers_affected), for all products i and customers j:

$$Cost\_of\_OOS_{ij} = Customers\_affected_{ij} * Cost\_per\_Customer\_per\_OOS_{ij}$$

Costs per reaction type consist of both a short term loss and a chance on a long term loss (losing the customer for a long time because (s)he liked the alternative). This chance depends on the customer reaction, and the long term loss also depends on brand loyalty and other variables.

$$Cost\_per\_Customer\_reaction\_type_r = Short\_term\_loss_{ir}(€) + \left(P_{long\_term\_loss_{ij}} * E_{long\_term\_loss_i}(€)\right)$$

Multiplying that with the occurrence of the reaction (e.g. 9% cancels their purchase), and summing that over all 5 Customer Reactions r, an average Cost_per_Customer_per_OOS can be calculated:

$$Cost\_per\_Customer\_per\_OOS_{ij} = \sum_{r=1}^{5} \left(Cost\_per\_Customer\_reaction\_type_r * Occurence_r\right)$$

The short term loss is calculated by the turnover loss encountered by Unilever; normally a customer buys (on average) y units, multiplied by x turnover per unit (sales price of Unilever to retailer). This depends on the reaction r, and a Binary indicating whether this reaction r actually causes turnover for Unilever.

$$Short\_term\_loss_r = \left(\#\_units\_per\_purchase_i * Sales\_price\_Unilever\right) * Binary$$

The long term loss consists of turnover loss on the long term (which included the average units bought per time period, the duration a customer is lost, and marketing costs to get customer back), multiplied by the chance a customer is indeed lost for a long term:

$$E_{long\_term\_loss_i} = (\#\_units\_per\_purchase_i * Sales\_price\_Unilever_i * purchase\_frequency_i * duration\_lost)$$
$$+ marketing\_costs$$

$$P_{long\_term\_loss_{ij}} = \sum_{n=0}^{\infty} \left(P_{n*OOS_{ij}} * Loss\_rate_n \right)$$

The chance a customer is lost for a long time is provided by theory and the marketing costs are calculated by using Unilever data.

Unfortunately, despite the theory provided in Chapter 3.6.2., it proved to be impossible to incorporate the effect of Negative Word of Mouth into the calculations, due to an absence of facts and figures. Determining the quantitative aspect of NWOM is also much more difficult compared to normal CLV calculation (Kumar et al, 2007). As investigations on the effect of NWOM in the retailer industry remain rather qualitative, in this research no explicit assumption can be made on the impact. It however is likely to be significant, but will probably not change the total turnover loss figure upside down.

For a more detailed overview of the formulas applied in this chapter and the other calculations, please see Appendix C. This appendix also includes the sources where information was found on these specific topics.

4.5.2 Calculation results

Using the formulas stated in Chapter 4.5.1, it is possible to calculate the cost of Out of Stocks for all products. As shown in Figure 22, most SKU have an annual turnover loss below € in 2008. Overall, these costs range from € to € [22]. Total Unilever Turnover loss in 2008 over these 85[23] SKU accumulated to € . These 85 SKU represented % of total Retail volume of Unilever in the Netherlands in 2008.

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Figure 21 - Costs of Out of Stocks per product in a single year.

Extrapolating[24] to 100% of Unilever Netherlands volume, results in a turnover loss of € in 2008 as shown in Figure 22.

[22] The 'outlying' dot represents Calve Peanut Butter 600grams; not only a huge product in sales, but with high loyalty and low average On Shelf Availability.
[23] 3 SKU have been excluded from this measurement. Please see Appendix B for the data filtering.
[24] Extrapolation is done via the loss of this volume , extrapolated to the loss over the entire annual volume. If this would be done per volume per cluster (using the clusters introduced in Chapter 1.2), no major changes occur. This is because the products in the dataset are a good representation of the entire Unilever portfolio, so relative volumes in the clusters in the dataset and in reality do no differ very much. Extrapolating using the clusters results in an annual loss of around €30 million. This figure however is not used as it is somewhat weaker in that is has more calculations and much of the cluster volumes can't be allocated optimally to a cluster due to a lack of data in the internal Unilever systems.

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Figure 22 - Extrapolation of Unilever loss of turnover due to Out of Stocks in 2008.

4.5.2.1 Proving the Unilever 3% rule

Unilever applies a rule of thumb to indicate the importance of Out of Stocks for the company, stating that 3% On Shelf Availability improvements results in 1% additional Turnover.

Applying the above mentioned calculations and manually improving the OSA by 3% (whilst obeying a maximum of 100%), results in a turnover increase of € or 1,26%. So the rule used by Unilever to stipulate the importance of OSA is indeed quite correct.

4.5.2.2 Costs for retailers themselves

Using parts of the formulas above, it is possible to approach the turnover loss endured by Customers because of limited OSA. Even disregarding the possibilities to lose a shopper for a long period, the short term lost turnover for this dataset accumulated to € million for retailers, or % more than the Unilever direct short term loss of € million for this dataset[25].
These higher short term costs compared to Unilever losses are mainly due to the occurrences of damaging customer reactions (cancellation and store switch occur somewhat more often compared to manufacturer damaging actions) and because sales prices for retailers are often higher, increasing the turnover loss.

4.5.3 Conclusion on the costs

Investigation on the costs showed Unilever to lose € million per year on Out of Stocks. With turnover approximating € billion, this represents %. In Chapter 3.7, Gruen et al (2002) argued that suppliers loose around 2.3% turnover annually due to Out of Stocks on the shelf. Although this figure is slightly lower compared to the Unilever practice, it is quite accurate. An explanation why it is lower can be found in that Gruen et al (2002) probably have not taken into account the costs of marketing, and neither have they used an assumed 'loyal-shopper-duration' as used in this model. This would have pushed the costs up again.

Small differences in results between reports can be explained by the number of factors and variables taken into account. Unilever has quite strong brands, pushing the losses downwards (EFMI, 2003). Unfortunately, it was not possible to quantify the negative Word of Mouth caused by Out of Stocks. Whilst assumed to be substantial, this cannot be proven. Incorporating this as a factor in the model, would have pushed the losses for Unilever up even higher.

Looking at the commonly applied 3% rule at Unilever, research shows that although the 3% to 1% rule is not completely accurate, calculations show that 3% additional OSA results in % increased turnover. Besides this, the Positive Word of Mouth (PNOM) increases, increasing customer satisfaction and eventually brand value and sales.

[25] It has to be noted, that only deals with the direct losses encountered when a shopper encounters a Out of Stock. Any loss in customer satisfaction or loyalty is not taken into account, as this is not known for the retailers.

Finally, by adding the losses of the retailers (which are likely to be much higher than calculated quickly), a value destruction over the entire supply chain is estimated to be 6%.

Further research can be done on three topics. First, the impact of NWOM needs to be further investigated. Another topic for further research is the impact of promotional Out of Stocks. This is currently not captured very well by the measurements and shopper reactions are not differentiated for promotional circumstances, as these might differ from 'regular' purchase occasions. Finally, further research needs to be executed on the substitution effects of consumers normally buying different products or at different retailers, when faced by an Out of Stock there, and therefore shifting towards Unilever products.

4.6 What is the impact of Unilever's delivery failures on Out of Stocks?

The discrepancy discussed in Chapter 1 concerned the lack of insights Unilever has on OSA and how to apply these insights to improve Unilever's performance. In order to reduce that discrepancy, research- and sub questions are formulated in Chapter 2. In order to answer sub question 2c, and compare that so sub question 1c, this chapter will focus on determining the impact of Unilever's delivery performance on OSA.

In the next 4 chapters, this model which is developed will be introduced, discussed, explained, and executed. Results from this model are then interpreted and conclusions are drawn.

4.6.1 Introduction to this model

In determining the impact of Unilever on OSA, a model is developed. This model is designed to fulfill four goals:

1. Determine the effect of Unilever's delivery failures on OSA of its products at its customers.
2. Use these findings to predict the effect of future delivery failures on the OSA of these products at these customers.
3. Use the findings to predict behavior and impact of other Unilever SKU, which are not investigated in this research.
4. Determine the impact of other variables, even if they are not under the direct influence of Unilever. This will allow for general conclusions and more insights in OSA.

These goals can only be accomplished if:

- The input data is correct ('garbage in is garbage out'). This has already been ensured in Chapter 4.3.1,
- Products and/or customers can be grouped to reduce complexity and increase the number of measurements for statistical significance,
- A focus is on the part of the data where the impact of Unilever is visible. Obviously, if Unilever did not experience delivery failures, no impact of poor performance on OSA will be found (as there is no poor performance). Thus the focus should be at the group of measurements for which there is reason to believe that a significant relationship can be found between delivery failures and OSA.
- A statistical method is applied to determine the impact of a certain variable on the OSA. Most suited for this would be a regression model. In the regression, the impact of known values of variables on the (known) outcome is determined. Based on that, a formula is fitted to describe the influences of these variables on the outcome, and use that for future predictions.

First, a general overview is provided in which the steps taken are provided in Chapter 4.6.2. In Chapter 4.xxx, these steps are further explained, and in Chapter 4.6.4 results from these steps are provided. Finally, the interpretation and conclusion on these results are provided in Chapter 4.6.5.

4.6.2 Steps in the model

To determine the impact of Unilever's delivery failures on the final OSA, three steps need to be taken. Further explanation on these steps is provided in Chapter 4..

1. Create Homogeneous Groups that show the same OSA behavior and find common characteristics. This will allow for benchmarking of OSA figures and for further analysis of the impact of certain variables. This will also allow for increased significance; as similar measurements are grouped, more measurements can be used for the analysis. Finally, this will allow for further extension of these results to products not yet investigated.

2. Determine per product and per customer whether Unilever could have had an impact on OSA. A focus is on the part of the data from which significant results are expected to be found. For example, there is limited interest in looking at products that did not have any delivery failures, as this will only create noise in the model.
3. Create a regression model taking into account influences from the entire Supply Chain and all possible causes of Out of Stocks which Unilever can measure/determine, and run that model on the interesting data found in step 2. This specific model will be referred to as the Supply Chain Model, and will be discussed more extensively later.

4.6.3 Explanation of the steps

4.6.3.1 Step 1 - create Homogeneous Groups

The OSA investigation concerns 88 products (SKU) and 6 retailers, creating (88*6) 528 unique 'Product_customer combinations' (e.g. SKU 1 at 6 retailers, SKU 2 at 6 retailers, and so on). As a certain SKU (e.g. peanut butter) might differ in OSA at or , data should not be aggregated per SKU but per SKU per customer. This prevents missing important customer-related influences.

In the entire dataset, 488 unique product_customer combinations exist after the filtering explained in Appendix A (of the original 528). With this high number of combinations, several issues exist:

- The number of measurements per product_customer combination is limited; perhaps too small to do meaningful statistical analysis.
- There is no objective way to compare product_customer combinations, as there are no 'rules' for grouping or combining them.
- It is not possible for other products to be entered, as it is not possible to assign them to a benchmark group ("Can a peanut butter not yet in this dataset be compared, to a peanut butter already investigated?")

In order to overcome these three issues, product_customer combinations will be grouped into Homogenous Groups. This will allow for proper comparison (e.g. no shampoos with margarine or meat products, unless statistically certain that they can be grouped). Hence, product- and/or customer characteristics need to be found, which allow for a limited number of Homogeneous Groups to be created.
This grouping will allow for stronger statistical results, the possibility to assign new products to existing Homogeneous Groups, and will provide good benchmarks.

In order to create Homogeneous Groups, 3 steps are needed to be taken;

1. Apply a regression model which contains all product- and customer variables, with Out of Stocks as the dependent variable (DV). As this model is not used to actually predict the DV, only the significant variables are interesting but not their coefficients, and neither is the R^2 interesting[26]. As the Dependant Variable is dichotomous (binary), Logistical Regression will be applied. Ordinary Least Squares regression is not possible due to the heteroscedastic nature of the DV and because it is not normally distributed (see Appendix F).
2. If too many variables are significant: reduce the number of significant variables to two or three if possible. The goal of the entire model is to have some variables to group products_customer combinations into Homogeneous Groups. With too many significant variables, too many groups will be created (e.g. with 8 variables, and each of them either "high" or "low", there are already $2^8 = 256$ Homogeneous Groups). The groups need to have enough measurements each, so a limited amount of groups is desired.
3. After determining the useful variables in the previous 2 steps: determine the appropriate ranges or boundaries of those variables. This should result in a limited number of

[26] In this model, I assume to encounter a very limited R^2. Many variables, like store influences and DC influences, are not yet taken into account, and hence OOS will be explained using the outcomes of the model, as the explanatory power is too little.

Homogeneous Groups. For determining these ranges, first the products will be plotted ascending on that variable and a natural cut will be looked for. Based on that, groups will be determined. Next, these groups are investigated and the scales are adjusted (if needed). This is also compared to the entire Unilever portfolio in order to determine future applicability of the scales (if scales are set too high or low, then the other Unilever products might not be assigned appropriately and the model might lose its predicting power).

4.6.3.2 Step 2 - determine whether Unilever could have had an impact

In order to create better results and reduce the influence and noise by non-Unilever variables, the main interest is in looking at a specific part of the dataset. By filtering the dataset on whether Unilever could have had an influence, it is possible to carefully determine the effect of certain Unilever variables. Only in that section Unilever can be responsible for a certain part of the noise and error term. The noise in the other parts of the dataset, on which Unilever has no influence, is sure not to originate from Unilever's variables. Looking at these parts will provide better insights in the impact of certain variables and increase the significance of variables.

The product_customer combinations can be split up into three possible scenarios:

1. There have not been any delivery failures by Unilever for this product_customer combination during the entire measurement period. If Out of Stocks occurred, they are all caused by the customer (e.g. incorrect internal processes, incorrect shelf refilling, incorrect ordering).
   For all Homogeneous Groups in this scenario, their Mean and 95% Confidence Interval will be calculated, as shown in Appendix H.
2. There have been delivery failures in a certain week, but they did not result in a significantly lower OSA compared to its benchmark (the Confidence Interval of the same Homogeneous Group from Scenario 1). Apparently the safety stock at the customer reduced the impact of the Unilever delivery failures.
3. There have been delivery failures in a certain week, and the product_customer combination's average OSA is also significantly lower than its benchmark (Confidence Interval of the same Homogeneous Group from Scenario 1).

The assignment process is graphically depicted below in Figure 23:

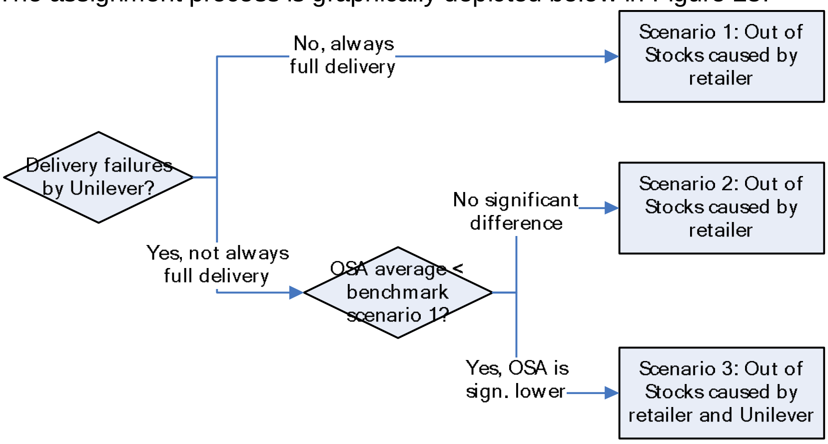

Figure 23 - Visual representation of the Scenario's

Besides applying this rather 'rough' selection, all product_customer combinations will be manually checked whether they are correctly assigned to their Scenario. This is done by comparing the correlation between temporary spikes in delivery failures to spikes in OOS. If they coincide, or could coincide, this product_customer combination should be left (or placed) in Scenario 3. If they do not coincide, or it is very plausible they do not relate, it should be left (or placed) in Scenario 2. The full procedure and final results are discussed in the next chapter and can also be found in Appendix I.

After this selection, each product_customer combination (and all its measurements) is assigned to only one of the three scenarios. Presumably all Homogeneous Groups are represented in all scenarios. Final results are shown in Appendix I, and show that indeed most Homogenous Groups are well represented throughout all Scenarios.

4.6.3.3 Step 3 - create a regression model to determine the influences of all variables

Looking at the retail Supply Chain shown in Figure 4, three echelons exist that can each cause an Out of Stock on the shelf:

- Unilever.
- Customer DC.
- Customer store.

Variables from these echelons are all represented in the following model. This model is referred to as the 'Supply Chain Model' and will be used to determine which variables are significant and what their coefficients are. The full equation is:

$OutofStock = \alpha_1 * StoreFloorSurface + \alpha_2 * StoreTurnover + \alpha_3 * Margin + \alpha_4 * ShelfAllocation + \alpha_5 * Promo + \beta_1 * DC + \beta_2 * Customer + \beta_3 * DeliveriesULtoDC + \gamma_1 * DeliveryFailures_i + (\gamma_2 * DeliveryFailures_{i-1}) + (\gamma_3 * DeliveryFailures_{i-2})$.

In this equation, the variables with α-coefficients represent Store Influences, variables with β-coefficients represent DC influence and values with γ-coefficients represent Unilever Influences. The variables are defined in Appendix J.

The reason why $DeliveryFailures_{i-1}$ and $DeliveryFailures_{i-2}$ are between brackets is that they are only incorporated if there are respectively two or three weeks of consecutive delivery failures. This increases quality and ease of interpretation of the results. For more information, please see Appendix K.

Referring to the Scenario's used in Step 2, it can be seen that each Scenario is linked to the supply chain:

- Scenario 1: all OOS are caused by the store or by the DC, Unilever Influences are 0.
- Scenario 2: all OOS are caused by the store or by the DC, but this also tells something about the Safety Stock level of the DC, which was enough to smooth the impact of Unilever's delivery failures. Delivery Failures-variables will be expected to be not significant.
- Scenario 3: all OOS are caused by the store, by the DC, or by Unilever.

After running the model above on all 3 Scenarios, the following figures are expected:

1. Scenario 1 will act as a benchmark in this study; if Unilever were to perform optimally, this would be the average OSA. It will also provide results on the variables outside of Unilever's influence (like store complexity).
2. Scenario 2 will act as a control group for checking whether the distinction between Scenario 2 and 3 was indeed correct: Delivery Failure variables should be not-significant, as they should not have an influence on the Out of Stock levels.
3. The impact of Unilever's delivery failures can be calculated from Scenario 3, as this Scenario presumably contains data which might show this influence. These coefficients represent the additional impact on OOS due to Unilever's delivery failures, and can be added to the benchmark OOS level (when there are no delivery failures). Given a certain

delivery failure, the predicted On Shelf Availability can be calculated. Please see Appendix K for the precise calculation.

4.6.4 Execution of the model

4.6.4.1 Step 1 - create Homogenous Groups

Step 1a - logistical analysis

Based on theory, several product and customer variables are investigated. They are mentioned below, including their unit of measurement (in brackets) and their 'name' in SPSS:

- Product changes in last year (number) - Intros
- Responsiveness of Unilever factories for product (days) - Responsiveness
- Sourcing Unit distance to Unilever DC (km) - Su_dist_adj
- Shelf life (days, but grouped) - Group_THT
- Volume (cases per year) - Volume_adj
- Stock Levels at Unilever (weeks on hand) - Stocks
- Demand fluctuations at Unilever (%) - Sales.Volat
- Forecast Error (%) - FE

And for the customer variables;

Typology (name) - categorical (

For a more elaborate overview of variables, their definitions and decisions why some were included please see Appendix E.

Applying Logistical Regression, all variables are significant at p=0.05 (please see Appendix F for more details). This is shown below, where one is missing (with the other two binary variables it is possible to express all three customer types):

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Table 5 - Overview of SPSS output on the Logistical Regression

With 8 product variables and 1 customer variable (expressed by three dummy variables) significant, there are (too) many variables significant for easy handling. Creating groups based on 9 variables could become quite difficult and could create too many unique groups with too little measurements. The customer variables are already reduced to only 1 variable ("typology"), so there is no need for any further analysis on this. To reduce the number of product variables, Factor Analysis would be the best and most commonly used option (McNabb, 2004). This is discussed next.

Step 1b - apply Factor Analysis

Factor Analysis is usually used to group variables together on underlying scales and thereby reduce the number of variables without losing too much information. For this though, one needs to check for appropriateness of the data.

This dataset is indeed appropriate for Factor Analysis (Correlation determinant p=0,269; KMO value is 0,713; Bartlet's test is significant and all communalities are well above 0,25). After using the Principal Axis Factoring extraction method and applying a Varimax rotation for ease of interpretation, two underlying factors are found. For more details on Factor Analysis see Appendix G.

Rotated Factor Matrix[a]

	Factor	
	1	2
Group_THT	,724	
Volume_adj	-,634	
Su_dist_adj	,613	
Responsiveness	,609	
Stocks		,856
Sales.Volat		,592

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Table 6 - Overview of SPSS output on Factor Analysis outcomes

That all variables belong to only one of the two factors and with very high loading values indicates a clear split. Factor 1 contains variables indicating volume and speed, whilst Factor 2 contains variables indicating volatility. As this is used for explorative purposes, it suffices to select a single variable per factor, to represent all variables on that factor.

- To represent Factor 1, volume is chosen. Although this does not have the highest loading factor, it is applied for simplicity of calculation and because Group_THT is more subjective (the ranges to fit a product in a certain THT-group were chosen subjectively).
- To represent Factor 2, Sales Volatility is chosen. Although this also does not have the highest loading factor, it is chosen as this represents volatility in the supply chain most directly. Stock levels (the other variable) are merely a consequence of high volatility, and therefore less direct.

Combining the results from the Factor Analysis with the previous findings from the Logistical Regression, the following 4 factors are significant:

1. Volume of the Supply Chain – measured in annual volume in cases (Factor 1 from the Factor Analysis).
2. Volatility of the Supply Chain – measured as the Standard Deviation / Mean of the Unilever sales to the customers (Factor 2 of the Factor Analysis).
3. The customer typology – either ‘ (originated from the Logistical Regression).
4. HPC or Food – a further distinction between these two different types of product (Foods and HPC – Home and Personal Care), because of their differences in product characteristics and On Shelf Availability.

For a more detailed overview on Factor Analysis, please see Appendix E.

<u>Step 1c - determine boundaries/scales for the Homogeneous Groups</u>

Using these four factors, homogenous groups can be created. Borders for this have either been implied by the nature of the variable ("Customer" and "HPC or Food" are categorical), or was investigated using an iterative process.

- First, the products are plotted ascending on this variable and natural break points were looked for.
- Based on these break points, groups were formed and results were examined
- To determine whether these groups were logical, the results were checked using business- and common sense. Based on that, the borders were adapted.

The final result is shown below in Figure 24.

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Figure 24 - Overview of the somewhat natural breakpoints for the variables.

The results are shown in Table 7, where volume is expressed by annual cases for the customers:

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Table 7 - Overview of the borders of the Homogeneous Groups

All 488 product_customer combinations will be assigned to only one of the (2*3*2*3) 36 Homogeneous Groups resulting from these variables.

4.6.4.2 Step 2 - determine whether Unilever could have had an impact

As already discussed in Chapter 4.xxx.3, three scenarios exist:

1. No delivery failures
2. Delivery failures but no apparent impact on the OSA
3. Delivery failures and an apparent impact on the OSA

If a product_customer combination has had no delivery failures, it is assigned to Scenario 1. All others are assigned to Scenario2+3, waiting for the further split between 2 and 3.
Of all Homogeneous Groups represented in Scenario 1, the Mean and 95% Confidence Interval are calculated. So, with 97.5% confidence (only one side of the 95% Confidence Interval), the On Shelf Availability of the Homogeneous Group is within that Confidence Interval, if no delivery failures occur.

Next the average OSA of all product_customer combinations in Scenario2+3 is compared with the Confidence Interval of their corresponding Homogeneous Group in Scenario 1. If the average OSA < Lower Bound of the Confidence Interval, this product_customer combination is assigned to Scenario 3 (apparently the delivery failure has impacted the OSA).
If the average OSA is within or above the Confidence Interval of the Homogeneous Group, it is assigned to Scenario 2 (apparently the delivery failure hasn't impacted the OSA).

Given this procedure, there is a 2,5% chance that combinations are located in the incorrect scenario. However, to reduce this chance and check this analysis, all product_customer combinations are double-checked manually. If Unilever delivery failures coincided with abnormal rises in Out of Stocks, this product_customer combination was placed (or left) in Scenario 3. If delivery failures could not have been the cause of Out of Stocks (too little failures, no correlation between spikes), it was placed (or left) in Scenario 2. 28 product_customers (8% of the total in Scenario2+3) were swapped. The outcome is shown below in Table 8:

	Initial:	After swap:
Scenario 1	155 (32%)	155 (32%)
Scenario 2	196 (40%)	210 (43%)
Scenario 3	137 (28%)	123 (25%)
Total	488	488

Table 8 - Results of Scenario assignment

Most products are located in both Scenario 2 and 3, for example a certain product which has had an influence at customer A (so Scenario 3) but not at customer B (so Scenario 2). Twenty two products have not had an influence at all for any of the customers, whilst for six products there has been an influence at all customers. For information is shown in Appendix I.

The check whether this assignment was done correctly is done at the end of Chapter 4.6.4.3. Please see Appendix I for a full overview of all product_customer combinations assigned to their Homogeneous Groups and the scenario they are assigned to.

4.6.4.3 Step 3 - apply Supply Chain model on Scenario 3 to determine Unilever's impact on OOS

Finally, the Supply Chain Model as previously explained is applied to all Homogenous Groups in Scenario 3, in order to determine the impact of Unilever's delivery failures.

The default Supply Chain Model will be executed;

- On the Homogeneous Groups in Scenario 3 (so 36 Homogeneous Groups, based on the customer typology [ ])
- With three different time spans for the delivery failures;
    - o Including as variable the delivery failures in same week of OSA measurement.
    - o Including as variable the delivery failures in same and preceding week.
    - o Including as variable the delivery failures in same and two preceding weeks.

Besides this, the Supply Chain Model will also be executed (Supply Chain Model Adapted):

- On the Homogeneous Groups in Scenario 3, but with all customers treated separately (so 72 groups instead of 36), in other words all customers are entered into the model separately [
- With the same three time spans as the default Supply Chain Model.

Applying these models, each with three time spans, will result 6 different outcomes:

- The distinction between the customers (Homogeneous Group per Customer Typology or per Customer) is made because results per customer provide more accurate results (it can distinguish between , even though both are in the same Homogeneous Group). However, if no measurements per customer are available, results from the Homogeneous Group (with Customer Typology) will be applied.
  If measurements do exist but show no significant relationship, they would remain 0.
- The reason for applying three different time spans is that the impact of a sudden delivery failure should be felt directly, and should not be felt after two weeks of resumed normal deliveries (delivery failures two weeks ago but since then 100% performance will not result in OOS this week). However, if Unilever experiences two consecutive weeks of

OOS, the time span of looking for an impact should be two weeks, and the same goes for three weeks.

Applying the FSTEP(LR) method in Logistic Regression in SPSS, the following significant results for the Delivery Failures (p= 0,05) are found for Supply Chain Model and Supply Chain Model Adapted. The combination of these two models is shown in Table 8.
In this table, per Group (so the Homogeneous Groups split up per customer), the coefficients of delivery failures (DF) can be seen, expressed by 'logit'. If delivery failures would increase by 1 (100%), then the logit of that Group would increase by this value (1 * coefficient).

The maximum of the coefficients is set at 4, as this value represents a 1:1 relationship between delivery failures and Out of Stocks (10% increase of delivery failures results in 10% additional Out of Stocks). The impact of delivery failures can never be above that (not delivering 10% can't result in Out of Stocks above 10%), and hence Logit coefficients are cut off at 4.

As shown in Table 8, a positive coefficient indicates that more delivery failures would result in more OOS, and bigger coefficients result in bigger impact.
The logit can then be used for calculations, and can be used to predict the OSA. How this is done is shown in Table 9 and in Appendix K.

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Table 9 - Overview of the delivery failures coefficients for the groups

Interpretation
In order to explain how Table 8 needs to be interpreted, the following example is provided using a high volume, low volatility, HPC product at :

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Figure 25 - Excerpt from overall results to explain interpretation

If there is a delivery failure in week i, the first week of a delivery failure, the logit increases by (Delivery Failure * 1,301). So a 10% delivery failure results in an increased logit of 0.1301.
Suppose the normal Out of Stock level for this group is xxx%, which can be transformed in a 'Base_logit' of xx. Adding the logit increase due to the delivery failure to the 'base_logit' results in a 'new' logit of xx.

From Logistical Regression, it is known that:

$$OOS = \left(\frac{e^{Logit}}{1+e^{Logit}}\right) = \left(\frac{e^{-2.57}}{1+e^{-2.57}}\right)$$

So, new Out of Stock level is xx%, or xx% above 'normal' Out of Stock level of xxx%.

In case of 2 consecutive weeks of delivery failures, the impact of the first week of delivery failures is felt most. Two weeks of delivery failures (both 10%) would result in an additional logit of 0.34, resulting is a 'new' logit of -xx and thus an OOS level of xx%

In case of 3 consecutive weeks of deliveries failures (all 10%), the additional logit is xxx, so the 'new' logit is xxx and new OOS level is xx%.

Confirmation on the Scenario's
In order to confirm that the product_customer combinations have been assigned correctly to their Scenarios in Step 3, the Supply Chain Model is also run on the Homogeneous Groups in Scenario 2. When doing so a statistical link between delivery failures and OSA was occasionally found. Next, the delivery performance was plotted against the OSA, and checked for abnormalities. An example on how this is done is shown in Appendix I. Carefully examining the data for those significant groups revealed that the link is coincidence or a measurement error. These coincidences can therefore be omitted and it is safe to say that Scenario 2 and Scenario 3 are clearly distinct.

Besides that the Scenario's are clearly distinct, further analysis displayed in Table 10 also shows some insights in the adequacy of current service levels. The 4th column in Table 10 shows the allowable average duration of Unilever's delivery failures to increase when volume increases. For high volume products, an average delivery failure of 1,2 week can be managed whilst low volume product can handle only 1,5 week on average. So customers are able to deal with increasingly longer periods of delivery failures if the volume of the SKU decreases.
The 3rd column in Table 10 showed the average allowable maximum delivery failure also increases when volume decreases, both for HPC and Food products. It increases for high volume SKU from 30% (food) or 45% (HPC) to around 60% for low volume products (both HPC as Food).

This not only (again) confirms that Scenario 2 is significantly different from Scenario 3, it also provides insights in the allowable delivery failures: to which extent Unilever is able to not-deliver whilst not affecting OSA.

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Table 10 – maximum allowable increase and duration before OSA is affected

Due to the data and the unavailability of long lasting consecutive delivery failures, no further exact statistical analysis can be done on the allowable duration and extent of delivery failures.

4.6.5 Interpretation of the statistical results

After running the model, the findings can be interpreted. A distinction is made between two types of findings. In the analysis of Scenario 3, the impact Unilever has on OSA via its delivery performance has been investigated. In the analysis of Scenario 1, results were found on the other variables which influence OSA, but are outside the direct influence of Unilever. Both will be presented here, starting with the general variables of influence, then the impact of Unilever's delivery performance on OSA, and finally a short investigation on the internal causes of poor delivery performance.
Results will, if possible, be compared with the 'simplistic' findings provided in Chapter 4.4, where the impact of a single variable is plotted.

4.6.5.1 What is the impact of general variables on OSA?

The results from the Benchmark group, Scenario 1, are analyzed first. A full overview is provided in Appendix J, and a summary is provided here:

1. The number of deliveries from Unilever to the customer's DC is negatively correlated with Out of Stocks: more deliveries decrease the OOS percentage (and hence increase OSA).
2. Promotions show to be not very significant; only at promotions are less properly executed, resulting in an increased Out of Stocks level for promotions.
   This is partly reflected by the simple analysis done in Chapter 4.4.2.2, where OSA levels are differentiated between promotion and non-promotion. It is however interesting to see that has no significant promotional result, even though OSA decreases much in case of promotions. As promotions at correlate with margin (Pearson correlation of 0.045, p=0.000), it is therefore excluded as a predictor on its own.
3. Mixed results exist for Store surface and Store turnover:
   - Bigger stores (based on turnover) from perform better in OSA, whilst bigger stores from perform worse.
   - Bigger stores (based on floor surface) from perform better in OSA, but perform worse for .

   Chapter 4.4.2.4 showed overage store size to be positively correlated with OSA: higher stores have higher OSA. This is not completely reflected by looking at these specific, significant, variables. This can be explained by the fact that for some customers, store size correlates statistically with other variables[27], or that they are just not significant in predicting OSA.
4. Finally, margin does play a significant influence at all retailers. Higher margin correlates positively with increased OOS. This is counter intuitive, as one would think OOS should decrease for higher margin products. Apparently there is no such driver of store employees or management to perform better on products with higher margin (at least not visible in this dataset with these products).

Although it is difficult to determine the true causes of Out of Stocks at the customer, the size of the above described variables is now discussed. As the statistical method employed does not provide linear results (if the variable increases by 1, the outcome does not increase by the coefficient * 1), examples are provided to show the impact. In Table 10, examples per customer are displayed showing the increased Out of Stocks if either margin increases by 10%, Store size increases by a factor 2, Store turnover doubles, too little shelf space is allocated or if there is a promotion, but all other variables stay the same. Empty cells indicate no statistically significant relationship.

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Table 11 – Examples on the impact of general variables on the Out of Stock levels

4.6.5.2 What is the impact of Unilever's delivery performance on OSA?

Several conclusions can be made from the analysis on Scenario 3:

1. Unilever does have an overall impact on the OSA when delivery failures occur, based on the statistical coefficients of the variables. The weekly impact ranges from 0% to very high per product per customer. For example, when Unilever is faced by only a 10% Delivery Failure, the Out of Stock percentages of several product groups increases by 3 to 8%. Examples on the impact are shown in Figure 26:

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   Figure 26 - Graphical representation of the impact of a certain delivery performance

2. However, applying these coefficients on last year's delivery performance shows that total impact Unilever actually had is very limited. The unweighted average OSA over all 88 products in case of no delivery failures is (so this is all caused by the retailers). Unilever's impact of current delivery performance has resulted in an increase of OOS from . Hence, Unilever is responsible for % of all Out of Stock events on the shelf, or a % increase of OOS level compared to the situation in which there had not been any delivery failures.
   The % increase of Out of Stock events also emerged when applying the findings of this research on the entire Unilever product portfolio in the Netherlands. This proofs the applicability to, and usefulness of the findings for the entire product portfolio.
3. The Unilever impact can best be analyzed per time span chosen:
   a. The impact of 1 week of delivery failures – Food is affected most severe, especially on high volume and low volatility and low volume, high volatility. Several customers have too little safety stock even for a single week of delivery failures. For HPC, the biggest impact is on high volume SKU.
   b. The impact of 2 consecutive weeks of delivery failures – for HPC there is a strong influence on high volume, low volatility products, whilst Food has a high influence on all high volume SKU. Several customers have too little safety stock.
   c. The impact of 3 consecutive weeks of delivery failures – quite a strong influence on high volume Food products and low volatile HPC products.

4. It appears as if there is an overall bigger impact on foods than on HPC. This can be explained by an increased safety stock level at the retailer for HPC due to smaller absolute volumes and ease of stocking piling (e.g. no shelf life), but also due to a lack of measurements for certain HPC groups.

Overall these conclusions show only a limited influence of Unilever's delivery performance on OSA, but this differs from product group to product group. According to these figures, it might even be suggested to lower delivery performance for those products on which we have little or no influence (lower performance hence does not result in Out of Stocks). This however can't be proven, and would require further research.

4.6.5.3 What are the other causes of OOS under control of Unilever?

Based on the theory provided in Chapter 3, the manufacturer is said to cause around 15% of the Out of Stocks. According to Chapter 3.7.2, this can be divided between delivery performance causing 3-4% and the other variables causing 11%.
Chapter 4.6.5 showed Unilever's delivery performance to be responsible for % of the Out of Stocks. As the delivery failures-measured in this investigation captures many of the causes of OOS (incorrect ordering, data integrity and others), the remaining 11% (assuming Gruen et al (2002)'s figure is correct) is said to be caused by events like long lead times, shelf allocation, promotional content and other variables:

- Long lead times can cause Out of Stocks. If the retailer orders a product but the manufacturer delivers only after a few days, meanwhile the product could have run Out of Stock. Several Unilever countries have multiple days of lead time. France for example has, in some cases, a lead time up to 5 days. Delivering after that many days still results in correct delivery, but the store shelves could have run Out of Stock in the meantime.
- The definition of delivery performance does not capture sudden rises in shopper demand in case of a (big) promotion. As Unilever does not control the price, officially the retailer is responsible for any price changes. However, Unilever is often aware and can use this awareness to improve demand predictions.
- Shelf allocation is another cause of Out of Stocks, which can be partly attributed to Unilever. Unilever proposes objective shelf layouts to customers, which they can incorporate. Unilever also bases the content of the cases (how many units are placed in a case) on demand by customers, which themselves base this demand on shelf size.

Based on the definitions and practice, it is very unlikely that Unilever is totally responsible for 15% of all Out of Stocks (delivery performance and other variables). Based on the definitions, delivery performance is one of the biggest manufacturer-controlled influences of Out of Stocks. With that being only 4%, it is highly implausible that total Unilever influence is 15%.

4.6.5.4 What are the causes of poor delivery performance by Unilever?

Delivery failures can be further subdivided into three main areas on which the missed cases are accounted. They can be caused by data integrity issues (incorrect ordering codes, data inaccuracy), by incorrect forecasting (both baseline as promotions), or by inadequate customer replenishment. The latter can be the result of incorrect order and replenishment cycles, or unavailability in the supply chain.

Given the delivery performance over the same period as the OSA measurements, the size of the different causes can be investigated. Their occurrence is visualized by adapting Figure 9 to include only those causes under direct influence by Unilever. In Figure 27, the occurrence of these causes is shown, resulting in increased delivery failures and perhaps OOS on the shelf. Data for this model is taken from the internal ERP system at Unilever.

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Figure 27 - Graphical representation of OOS-causes under Unilever influence.

From this brief analysis it is not possible to analyze which cause of delivery failures results in most Out of Stock level. However, it can be seen that

are the main causes of delivery failures. Hence they are likely also to be the main causes of Out of Stocks caused by delivery failures.

However, it needs further research to determine which factors cause poor delivery performance. Further research can also be done on whether the cause of Unilever's delivery failures differ per product(group) and per customer. This was out of scope in this research, as all supply chain failures are captured by the 'delivery performance' measure. In order to analysis the causes of low delivery performance, a whole new internally focused investigation has to be initiate. This would shed light on which specific internal Unilever causes should be improved to improve delivery performance and hence OSA, but not on the one-on-one relationship between certain causes of low delivery performance and OSA.

4.7 Conclusion on the Problem Analysis

This chapter will provide a summary of the extensive analysis of current Out of Stock issues. It will discuss: the general findings on Unilever's OSA performance, the financial impact of Out of Stocks and the impact Unilever's delivery performance has on OSA levels. This is compared to the theoretical answers in Chapter 3 to provide answers to sub question 2. Finally, the OSA Improvement Potential is introduced.

4.7.1 General Unilever OSA performance

In order to answer sub question 2a, the general OSA performance and OSA findings are discussed. The conclusion of this is provided in Chapter 4.7.1.

With an average OSA, although adjusted for Sales-related non-availability, of %, Unilever performs quite in line with the general benchmarks. However, as a FMCG company, Unilever should aim for minimization of Out of Stocks to increase competitiveness and do not 'let consumers down at the moment of truth' (ECR, 2003).

Unilever performance is also in line with expectations when comparing the OSA per timeslot and per day. Although mixed figures emerge from theory (e.g. Gruen et al, 2002 and ECR, 2003), the findings from ECR (2003) are quite close to Unilever's products. Differences can be explained by the product portfolio; Unilever's products are perhaps a little less perishable and hence can be kept on storage a little longer. Unexpected spikes in Out of Stocks on a certain moment can also be explained by different shopper behavior: (e.g.) the Thursday evening late opening hours of regular stores generate more traffic to grocery stores.

Contradicting commonly applied literature are Unilever findings on the store complexity and size. Whereas most authors argue that Out of Stock levels increase with store size and store complexity, Unilever findings show the opposite. In this dataset, bigger stores (based on weekly turnover and selling surface) have less Out of Stocks compared to smaller stores. This was statistically investigated, showing mixed results when distinguishing between retailers:

Likewise contradicting are Unilever findings which show declining Out of Stock levels with increasing volume (annual cases). This trend is quite strong, even when removing the most extreme values (several high volume margarines). Whereas literature argues that high volume results in higher Out of Stock levels, this is not applicable for these products. This could be explained by either incorrect theory or by differences in the dataset for the theoretical analysis (if they have included more extremely slow-moving and fast-moving articles).

Finally, statistical analysis showed that the number of deliveries to the customer's DC is negatively correlated with Out of Stocks; more deliveries decrease the Out of Stock percentage (and hence increase On Shelf Availability). This is quite logical intuitively but it also proved to be significant. Statistical analysis, shown in Table 9, also showed promotions are not very significant; only at promotions are less properly executed and Out of Stocks increase in case of promotion. This counters commonly believed ideas in theory.

Overall, it can be concluded that Unilever performance is in line with findings from theory and the benchmark figure provided by Gruen et al (2002) and ECR (2003). Not only is overall OSA level around %, specific findings overall prove that this dataset is correct. There are small differences with theory, but either they are explained or they need to be investigated further using statistics.

Unfortunately, given this type of analysis, not the root causes but variables are investigated. The size of a store is not the root cause, but could imply that processes are better/worse. In that sense, bad processes are the root cause. However, due to limited time and resources, further research needs to be done on this.

4.7.2 Financial impact of Out of Stocks

In order to answer sub question 2b, the financial impact of Out of Stocks is analyzed and compared to practice. The conclusion of this is provided here.

In theory, several figures are mentioned to express the costs of Out of Stocks. They largely depend on the customer reaction, the average on shelf availability and normal volume. These figures range apart quite rigorous, from € 8.5 million (EFMI, 2003) to € 28 million (Gruen & Corsten, 2008) when converted to fit Unilever in the Netherlands. However, these researches respectively apply very generic and broad calculations, or do not disclose their calculations. Hence, it is difficult to compare figures, and to adjust the variables to fit Unilever's product and customer portfolio.

Determining the turnover lost for Unilever revealed the sheer amount of different variables which come into play. The costs do not just depend on average OSA levels, the amount of shoppers and the customer reactions, but also depend on loyalty towards a product, turnover generated per product, units per purchase and per year, and expected duration of loyalty.
After determining all variables, calculations indicated Unilever loses around € million in turnover per year due to the current Out of Stock level. This represents around % of Unilever's annual turnover in the Netherlands, indicating that the estimate made by Gruen & Corsten (2008) was actually pretty close, and the EFMI (2003) estimate was much too low.

4.7.3 How does Unilever's delivery performance influence OSA?

In order to answer sub question 2c, Unilever's impact on OSA has to be determined. Based on the statistical analysis, two types of answers are provided. First, the product and customer characteristics which predict OSA are discussed, and next the link between Unilever's delivery performance and OSA is provided.

The product and customer characteristics which predict OSA figures are:

- Whether it is a HPC or a Foods product,
- Whether the annual Volume is high, average or low,
- Whether the average Sales Volatility is high or low,
- Which customer typology we are dealing with.

For each product, it is possible to determine these characteristics and thereby predicting the average OSA of that product and the influence of certain variables, like Unilever's delivery performance.

After using these characteristics to create Homogenous Groups, it is possible to statistically determine the influence of Unilever's delivery performance on the OSA. It is shown that:

- The impact of delivery failures on Food is more extensive and quicker felt compared to HPC. This is likely to be caused by less safety stock in the supply chain due to higher absolute volumes of Food products compared to HPC products.

- The major determinant for the impact on Foods is volume; high volume indicates a stronger impact of delivery failures (this increases the likelihood of the conclusion drawn in the previous bullet).
- The major determinant for the impact on HPC is both volume and volatility; besides high volume, low volatility increases the impact of delivery failures on Out of Stocks. This can be explained by the safety stock level at the customer; low volatility decreases the need for high levels of safety stock. If something does happen, it quickly results in Out of Stocks.
- Most customers can only (partly) handle delivery failures less than 1 week. Delivery failures in excess of a single week often result in increased Out of Stock levels on the shelf, as has been stated in Chapter 4.6.4.3.

- If no significant result is found for long-lasting delivery failures, this is predominantly caused by either a lack of measurements, or because no delivery failures of that duration occurred during the measurement period. It is likely to assume a quite big impact.

Given this statistical analysis, it is possible to determine the product groups on which Unilever has the biggest influence. These are high volume, and (mainly for HPC) low volatility products. Differences exist between customers and also depend on the number of consecutive weeks of Out of Stocks. These findings will later be used in Chapter 5 and 6 to develop an allocation tool for short term improvements. This tool will be used if customer demand can't be met due to limited availability of products in the supply chain.

The findings from the statistical analysis can be used for two things. The first application is to determine last year's impact on OSA. Given a situation where no delivery failures occurred, and adding to that the delivery performance of last year, would result in an increase of Out of Stocks. This increase is caused by Unilever.
The second application is to determine the internal OSA Improvement Potential. This is explained in Chapter 4.7.5.

Overall impact of Unilever's last year's delivery performance
After determining the impact in case of delivery failures, the next step is to compare that to the 'normal' delivery performance. Last year's[28] delivery performance will act as input and will be used to examine the values of the variables found. Results show:
- An unweighted average of xxx% Out of Stock (unweighted average of the Group's base' Out of Stock level if no delivery failures occur).
- A % increase of all Out of Stock events due to the experienced delivery failures to an overall Out of Stock level of if no delivery failures would occur). So OSA would increase by (on average) if there would be no delivery failures.
- Impact per product_customer per week ranging from additional Out of Stock level. Thus Unilever has never caused a customer to go completely Out of Stock because of poor delivery performance. Incorrect allocation of the scarce products (scarce because customer demand is not met) by the customer to the stores therefore caused Out of Stocks, which is the responsibility of the retailer.
- Impact per product per customer differs quite substantially, ranging from 0% additional Out of Stocks due to delivery failures for most products to additional Out of Stocks for Knorr Vegetable Soup at . The increased impact on this soup is likely to be caused by extensive delivery failures on this product (Unilever was not able to deliver anything for 5 weeks in total during the measurement period).

Hence, the overall impact of Unilever's delivery performance is in line with findings from theory, both stating around of the Out of Stocks are caused by delivery failures at the supplier. This differs per product and therefore product-specific impact might be higher.

[28] Period May 2008 till February 2009, the same period on which the results have been based

Although delivery performance of the OSA SKU was much better than average delivery performance on the entire portfolio, as shown in Figure 28, it appears as if the impact is identical. Applying the statistical findings to the entire portfolio revealed a similar impact. However, the impact of missing statistical findings (for Homogenous Groups for which no measurements were available in Scenario 2), has a bigger impact.

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Figure 28 – Delivery performance of OSA-SKU compared to non-OSA SKU.

Besides this, some data was missing so several product groups could not be measured, and for most products a three week consecutive period of delivery failures did not occur. Hence, no data could be collected to determine this impact.

The difference in delivery performance of the SKU will also influence the OSA Improvement Potential discussed in Chapter 4.7.4.

4.7.4 What is Unilever's internal Improvement Potential?

This chapter will summarize the results when linking the found relationship between delivery performance and OSA to the financial impact of Out of Stocks. First, the OSA Improvement Potential will be defined.

As discussed in Chapter 2, the OSA Improvement Potential (OIP) is defined as:

$OIP_{ij} = Unilever\_influence_{ij} * Total\_Losses\_due\_to\_OOS_{ij}$
where
i = product i
j = customer j

Imagine Unilever has a 10% influence on a product, which is experiencing a € 10.000 annual loss due to all Out of Stocks. If Unilever were to improve delivery to 100% delivery performance, then 10% of €10.000 more turnover would be realized, so €1.000 more turnover would be generated. This is the internal improvement potential.

Analyzing the impact of the current delivery performance on the OSA, and multiplying that with the previously defined Costs of OOS per product_customer, shows:

- Total OSA Improvement Potential for Unilever for this dataset containing 85 products after filtering is € .
- As these products represent of Unilever's 2008 volume, linearly extrapolating this for the entire company represents additional turnover per year if there would be no delivery failures.
  However, the delivery performance of the SKU in this dataset was much better (%) than the Unilever average (%), as shown in Figure 29. Hence the other products, to which we now extrapolate, have performed worse. This implies that total Unilever OSA Improvement Potential is higher than proposed. Extrapolating that linearly based on

volume ánd on delivery performance, would result in an Improvement Potential of € of annual additional turnover.

- Looking at the specific products, it is recommended to focus (from an OSA-point of view) on the delivery performance of Product 1 and product 2. Improving these 3 SKU will yield €51.706 only for these 6 retailers. Besides that, it is assumable that improvements in these products also result in improving delivery performance and hence OSA for other products. This results in increased turnover for both Unilever and the customer.

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Figure 29 - The Improvement Potential per customer

Finally, the internally focused improvement potential can be compared to the total loss endured by a customer on Unilever products because of low OSA. This is the sum of the losses caused by both the retailer as Unilever. This is shown below in Figure 30.

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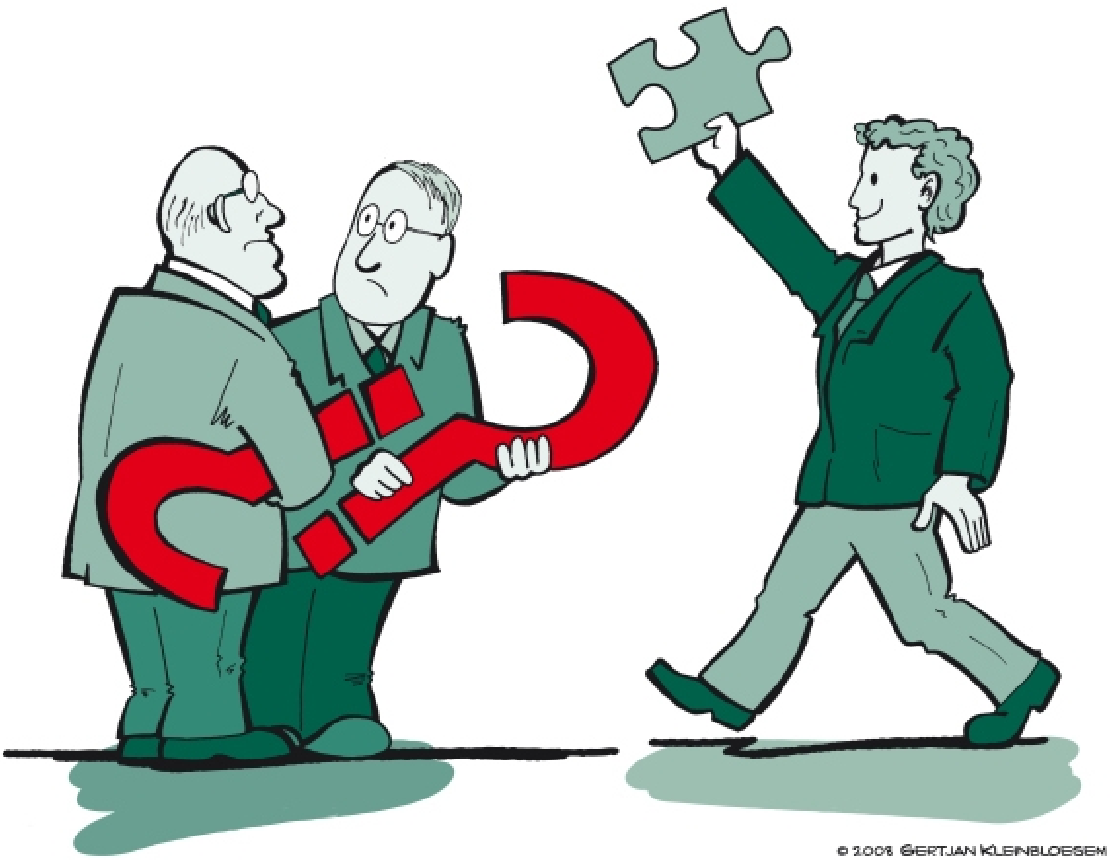
Figure 30 – Total Unilever loss due to low OSA, per customer

In this figure, it can be seen that of the total annual turnover loss of Unilever because of low OSA (€ million), the majority originates at

Chapter 5: Possible solutions



Chapter 5 - Possible solutions

Chapter 1 showed that Unilever faces a discrepancy between the current and desired situation: increasing insights on OSA and the impact of their delivery performance on OSA. They wanted to use that for decision purposes. Chapter 2 provided several research questions to decrease that discrepancy, dealing (a.o.) with the question 'what short and long term improvement possibilities exist?'.
In Chapter 4, the problem was analyzed from Unilever perspective. With an overall OSA of %, the annual turnover loss by Unilever is € million. Of all causes of these OSA loses, Unilever's impact is quite low overall. However, for several product- and customer groups, this impact is bigger.
In Chapter 5, an analysis of the possible solutions is provided. This chapter contains short term internal solutions (5.1) and long term external solutions (5.2), which will be linked to the four theoretical solutions discussed in Chapter 3.8. This Chapter will answer sub question 3.

5.1 Short term internal improvement projects

It is possible to distinguish two internal improvement areas. These are active allocation of scarce products and data improvements. These topics are discussed next.

5.1.1 Active allocation

Applying the knowledge gained, it is possible to allocate scarce products to customers based on the impact on Out of Stocks. Allocation is done by the Delivery Specialists within the MCO. Improving the allocation will result in an improved delivery performance, which is in line with the 2nd theoretical solution recommended in Chapter 3.8.

5.1.1.1 Process

The Allocation tool will provide the optimal allocation of products, if demand from multiple customers can't be fully met. It consists of several steps:

1. Initialization of the tool (all fields are blank)
2. User opens pop-up to enter product code (MRDR), and check all customers which have ordered the product. Checking the customer opens fields to enter the amount of historical delivery performance (up to three weeks ago).
   Finally, the user enters the amount available for allocation and confirms and closes the form.
3. The user clicks on the button to run the algorithm. The algorithm is discussed in more detail in the next chapter. After the algorithm is run, the results are shown in the tool.

Given these proposed results, the user can determine how many cases (s)he sends to a customer, taking into account the effect on OSA.

5.1.1.2 Optimization algorithm

By using the Excel solver method, it is possible to optimize the overall OSA. The exact formulas applied are shown in Appendix L.

5.1.1.3 Usefulness

However, in order to have this model fully operational, more research needs to be done on longer lasting delivery failures, on more products (especially HPC), and a mindset change needs to occur within the MCO to not always have the 'normal' customer segmentation as discussed in Chapter 1 to be prevailing.
Results from this tool however might be very limited as we are dealing with a very limited amount of cases which need to be assigned using this tool. Besides that, only a limited amount of customers is included, resulting in limited applicability when extrapolating this for the entire Unilever customer portfolio.

A simplified application of the tool is created by using a tabular sheet indicating the biggest impacts of poor delivery performance on OSA. By using colour indications, the user can identify the customer with the most priority and allocate according to this. Although this is not as sophisticated as the tool, and does not incorporate the weekly sales as an objective, it is simpler and quicker to use. Examples of these tables are shown in Appendix L.

The flowchart describing the steps op the model, the formulas of the optimization algorithm and several screenshots are discussed in Appendix L.

5.1.2 Data improvements

The data used for both the official reports and conclusions is often not fully correct. This is shown for the dataset in the Netherlands, and there is no reason to believe otherwise for other countries.

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Some of these solutions have already been discussed with the measurement team and are implemented. During this investigation, the awareness on the importance of correct measures has increased, store specific lists were developed (1), the third party was met to discuss quality purposes and process improvements (2 and 3), and pictures of products are provided (4). The other implementations have to be spearheaded by the manager

The issue on the correctness of the data should also be discussed in other measuring countries. To achieve this, it should be discussed first with the Unilever executives responsible for OSA. This will not be achieved in this investigation, but these results will be provided to those responsible and follow-up will be given by the MCO supply chain development managers.

It appears as if this solution refers to the 4th theoretical recommendation from Chapter 3.8. However, the theoretical recommendation on data integrity deals with the communication between Unilever and the customer, whereas this solution is internally focussed. The theoretical solution will be linked with practical solutions in Chapter 5.2.

5.1.3 Further internal decisions

After having established the benchmark data and a first start is made in understanding the impact of delivery failures on Out of Stocks, the investigations can be further specified. Two things are suggested for further analysis:

- Increase flexibility of the 3rd party measurement agency to be able to quickly change the products measured. If this would be possible, it would be possible to measure ad-hoc situations if they occur. If Unilever experiences major delivery failures on a certain product, the 3rd party should be instructed to introduce this product in their measurements and increase measurement frequency. By doing so, it becomes clear what the impact of the delivery failures was on the shelf and when exactly the Customer runs out of stock.
- Increase measurements on promotions. Certain promotions almost certainly increased Out of Stocks. From business experience, Unilever knows the impact is big. This impact is now not fully captured, as shown in the limited significance of promotions as a predictor for OSA. This could be caused by a rather low measurement frequency, thereby missing some of the Out of Stocks on promotions. Another cause could be the measurement definitions, and ambiguity on which storage location to measure in case of dual locations.
  This increased focus could also prove, or disprove, the correctness of the statement by ECR (2003) that predominantly in the beginning of the promotion OOS occurs. Finally, it could be an argument for further improvements on promotional planning and alignment, as stated by the 3rd solution suggested by theory in Chapter 3.8

Referring back to the Performance Measurement section in Chapter 3.1, it is clear that although OSA is relatively easy to measure, it is quite difficult to manage. OSA does capture the performance of the entire Retail Supply Chain, but does not capture Unilever's organizational performance. Unilever can perform optimally but still OSA does not need to be optimal. Therefore, incorporating OSA in the current form in the MCO's current set of KPI's would not be recommended.

5.2 Long term external improvement projects

The results from this investigation can be used for long term external improvement projects which involves collaboration with customers. This is in line with the 1st and 4th theoretical solution from Chapter 3.8, in which awareness of OSA is increased (internally and externally) and issues like data synchronization are dealt with (through these projects).

Chapter 4.7.3 discussed the four significant product variables that determine the OSA, which are HPC/Food, the volume, volatility of customer demand and which customer is involved. These variables can be used to predict both the normal OSA level in case of no delivery failures, and the impact of certain delivery failures on the OSA. This can be used for:

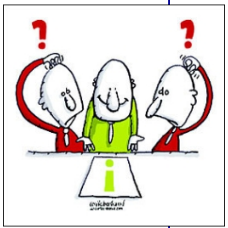
- To create awareness at the customer and at Unilever.
- Contract negotiations with customers, to discuss the target OSA beforehand. This can be done per product, per range and on an overall level, but should only be done after achieving the increased awareness.
- To determine the focus point of project in cooperation with the customer. Based on these characteristics, it is possible to determine which group should be investigated first.

By using the results found per product group, it is possible to determine the group with the highest potential. This can then be used to start the project. Based on the results in this investigation, several ideas are formulated for these joint improvement projects:

These solutions have to be implemented in close cooperation with the customers, as they both benefit from it as both face a part of the costs. Especially increasing safety stock is costly, but this will be compensated by improved Shelf Availability and could also be compensated by commercial deals with Unilever. This trade off between OSA and safety stock (costs) however will not be made during this investigation as it is out of scope. Further research could be done on this topic.

Implementing these solutions would also increase total Supply Chain Management as discussed in Chapter 3.1. Here, it was stated that Supply Chain Management links all partners in the supply chain by sharing information and aligning product and financial flows. By collaborating with the Customer, improved Supply Chain Management will be achieved.

In initiating these projects, Unilever should take the lead as they have better knowledge and more resources available (more financial resources, more people available to be part of this project). How this is implemented further is suggested in Chapter 6.



5.3 Conclusion on the solutions proposed

OSA is an issue for Unilever, where an average of OSA results in an annual turnover loss of € million. Although predominantly caused at the customer, Unilever is responsible for some of the Out of Stocks. Overall, this investigation showed that Unilever's delivery performance is responsible for % of all Out of Stock events. However, this differs per product(group) and per customer, and hence specific findings can be used for improvements. Discussing these improvements will result in answering sub question 3 on the short and long term improvement solutions.

Theoretically, solutions for suppliers are predominantly to create awareness, increase data accuracy with customers, improve promotional planning and, of course, improve delivery performance. This however remains quite general.

There are three specific solution areas for Unilever:

- Active allocation .
- Internal improvement projects, with or without customers. These include (a.o.):
    - Data optimization:
        - Equip measurement agency with measurement lists adapted per store (no generic list)
        - Refresh definitions of On Shelf, Void and Out of Stock
        - Provide up-to-date clear examples of the products
        - Keep track of all changes made in the past years, do not discard information.
        - Include a performance clause in the contract with measurement agency, so payment of the contract fee depends on the data quality.
    - Increased focus on promotions as these play a major role, as shown in Chapter 4.4.2.2.
    - Increased focus on the effect of temporary but major delivery failures, as discussed in 5.1.1.3.
    - Increased awareness amongst logistics and sales.
- External improvement projects, in collaboration with customers.

If demand from multiple customers can't be fully met, decisions need to be taken to allocate cases to a certain customer. This is currently done ad-hoc, certainly without taking the effect on the shelf into account. By using this tool, it is possible to assign cases to the customer that most needs these; else their stores will run Out of Stock. This tool is discussed in detail in Appendix L.

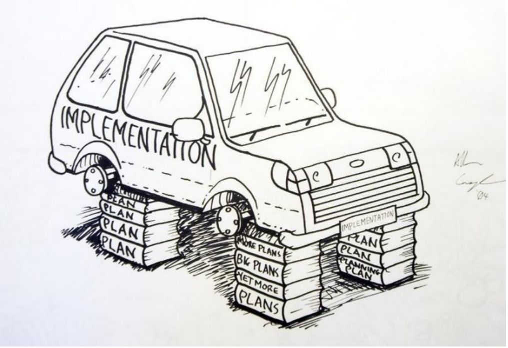
By running internal improvement projects, such as renegotiating with the 3rd party measurement agency and redefining data quality in collaboration with that same 3rd party, Unilever will be able to resolve the data integrity issues (thereby providing a much more accurate view of its performance), and it will align internal urgency with actual influence. The latter will result in a lower urgency for Logistics as they have little influence.

Finally, most improvement potential for Logistics is likely to exist in external improvement projects with customers. The results from this investigation will provide the focus areas of these projects and do provide a theoretical analysis of the likely causes of Out of Stocks.

As these overlap, it is recommended to start with one of these customers, of which all three are already positive when looking at OSA. As for the products; the major Unilever influence is on fast movers already via other programs (e.g. the Pareto program), so it is recommended to focus on these fast moving SKU. This is in line with the findings on the internal impact Unilever already has on these SKU, as shown in Chapter 4.7.4.
External improvement projects based on these findings can also influence contract negotiations, as Unilever now has much better insights in OSA and thus a better bargaining position.

How the decisions on the solutions proposed in this Chapter have to be taken and how these solutions need to be implemented is discussed next in Chapter 6.

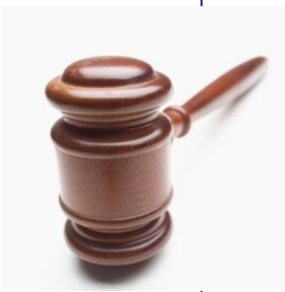
Chapter 6: How to decide and implement?



Chapter 6 - How to decide and implement

In this Chapter, the decisions and implementation plans for the internal solutions proposed in Chapter 5.1, and the external solutions proposed in Chapter 5.2, are discussed.

6.1 Decisions



This investigation is executed on behalf of the department of Customer Service & Logistics. As previously discussed in Chapter 1.3, it is responsible for the contacts with their logistic counterparts at the customers and is responsible for meeting customer demand.
Given this responsibility, their main interest is whether poor delivery performance results in additional Out of Stock levels on the shelf and how much influence this has. In Chapter 5 several short- and long term solutions were developed to influence OSA by Unilever's delivery performance. Any decision to implement the findings in this report will be made by the Director of CS&L, in coordination with her team leaders and Supply Chain Development Managers. These decisions include:

- The application of the findings in the form of an allocation tool to be used by Delivery Specialists? Decisions on this have to be made by the Delivery Specialists themselves in cooperation with the team leaders and Logistic Account Officers.
- How will these results be transferred to the Executives responsible for OSA? This will very likely be done by discussing the results from this analysis at the Supply Chain Management Team meeting and via teleconferencing with those responsible for OSA from the USCC in Switzerland and England. Both the SCMT and the teleconference meetings have to be initiated by the Director Supply Chain Benelux, and have to be scheduled during her attendance.
- How will these results be rolled out within the MCO, to introduce this to (e.g.) the sales department? For this several presentations will be prepared to be given during Sales MT meetings. They however need to be carefully prepared to prevent confusion and misinterpretation.
- Will the proposed options to improve measuring be implemented? For this, these findings have to be discussed with the managers within Customer Development who are responsible for the OSA measurements. This also includes discussing these findings with the 3rd party measurement agency, and perhaps re-discussing or renegotiating performance measures and data quality definitions.

The main decision which needs to be taken is to start collaborating with customers to introduce OSA projects. This is a decision to be jointly made by Customer Development and CS&L, and will require top level support (not only for the implementation as discussed in Chapter 6.3 but also for the decision itself). Arguments for this are, amongst others, willingness of the customer to cooperate and the priority of Unilever (which is indicated by the OSA Improvement Potential and other variables).

Given the findings presented in this report, not many difficult decisions on internal solutions need to be taken. The decisions above have all either been taken, or are in the process of being taken.

6.2 Implementation of internal solutions

Several solutions were provided in Chapter 5, which most senior managers probably will approve. These decisions have been discussed in Chapter 6.1. They do require some implementation, which is described in Chapter 6.2 for the short term internal solutions and in Chapter 6.3 for the long term external solutions. The short term solutions proposed here are a short term Allocation Model and improvements in data integrity.

6.2.1 Short term Allocation Model

In cooperation with the final users (Deliver Specialists), a tool is be developed for the allocation of scarce products. This tool can be used if two constraints are met:

- Multiple customers have ordered that product.
- Total customer demand for that product can't be met, but there is a certain amount of cases available of that product.

This tool will include an allocation algorithm developed to minimize the effect of non-delivery on the On Shelf Availability.

In order to endorse this tool, several meetings will be joined and held with those involved to increase awareness of OSA and the usefulness of the tool. By developing this tool in cooperation with the users, the implementation will be aided.
The tool will also be placed on an accessible section of the shared drive, so all people responsible for the allocation can access and use it.

6.2.2 Improvements in data integrity

In order to improve data integrity and ensure the current quality after my departure, several steps need to be taken. These include:

- Arrange a meeting with the project leader and project manager of the Unilever OSA-measurement team. In this meeting, the results from the investigation will be discussed and their role in that. Several of the recommendations made in Chapter 5 are executed already, and some still need to be discussed and/or executed.
- Develop a document carefully describing the steps in the data and in SPSS which have been taken. This will allow others to re-run the tests and to keep them up to date.

Improvements in this area will require more effort, as those responsible have a slightly different focus on OSA. They are more focused on increasing sales by reducing the number of stores not carrying Unilever products.
Given the big efforts required to exclude incorrect measures in the past, it is unlikely that the historical data will be cleaned to improve results. However, several solutions do influence and improve their results, which are therefore easier to suggest (e.g. better communication with the 3rd party, carefully examine whether a store should carry this product).

6.2.3 Increase awareness of the findings of this report

In order to achieve increased knowledge of the findings from this report, the awareness within the organization needs to be increased and needs to be founded on true facts. In order to achieve that increased awareness, several steps need to be taken:

- Findings from this research have to be shared with sales representatives in order to introduce OSA and create awareness. To do so, meetings will be attended and a presentation will be provided. Special focus in that will be the costs endured by Unilever and by the customers, and the impact areas. Some example slides for this presentation are added in Appendix M.
- To create awareness within the MCO, the results have been summarized in a three-page document and delivered to Supply Chain executives and those that participated in this research. This has allowed for a quick spread of the most important results throughout the MCO.

In order to increase and maintain awareness, the results from the investigation need to be repeated and often discussed. To achieve this, good communications with the sales managers and logistical employees is required. This will be achieved by top management support from both the Vice President Supply Chain as the Vice President Sales, which will be attending the Supply Chain MT meeting.

6.2.4 Conclusion on implementing internal solutions

With only a limited internal influence on OSA via Unilever's logistical performance, the solutions posed will not require major changes in process and will require extensive discussion and increase awareness during the implementation phase. Much needs to be discussed and many meetings have to be attended in order to create the awareness necessary.
The Allocation tool is most tangible, whereas increased awareness and changes required to ensure data integrity are more intangible.

6.3 Implementation of external solutions

Not only are the external solutions proposed in Chapter 5 more difficult to implement, they also require more seniority in Unilever and in the customers management. If Unilever were to engage in an endeavor in close cooperation with one of its customer, the following steps need to be applied:

1. Strategic alignment between Senior Executives from both Unilever and the Customer. From Unilever, this needs to be executed by the VP Supply Chain and VP Customer Development.
2. Agreement on definitions in order that both parties agree on the results and draw conclusions from those. Chapter 3.3 showed that definitions are the most important part of such a project. Unilever has already formulated an appropriate set of definitions (please see Chapter 4.5 for these) which can be quickly used.
3. Establish a loss tree to visualize the biggest losses causes of Out of Stocks in the store.
4. Root cause analysis to understand 'why'. Why has this caused an Out of Stock?
5. Implement solutions based on the previous steps.

This is graphically depicted as the Unilever 5-step Approach, as shown in Figure 31.

Figure 31 – Unilever's 5 step approach

Several lessons-learned exist to smoothen the process and prevent previously made mistakes to occur again. They mainly originate from case studies in the UK at Coop, Asda and Tesco. The most useful and applicable are listed below:

- Unilever has to initiate the process and move first, as it has more knowledge and resources and can apply these to create momentum
- Total Productive Management (TPM) as a philosophy has to be implemented to improve processes, but this has to start small to reduce the risk of complexity overload

- Either start on the DC level (with advantages of clear visibility, limited stakeholders, automation, top down), or on the store level with TPM coaches (with advantages of intense collaboration, less resources needed, high visibility and impact). The latter is often mentioned as preferred by Unilever executives in the Netherlands.
- Do not add OSA as yet another KPI but apply it separately.
- Use cross functional teams for bigger commitment and participation, and use specially trained TPM/OSA coaches from production facilities. They know the processes, speak the language, work in the same operational environment and are familiar with continuous improvement processes.
- Preferable project period is 3 to 6 months.
- Set a reduction target of x% instead of an end-target (like 98% availability). Doing the first takes the starting point in account, and has proven successful in the UK.

Although these projects are the most difficult to initiate and require major resources, they might results in the best improvements. Most Out of Stocks are caused on the store level, and by focusing there, perhaps much improvement can be made. This was shown by previous case studies in which these projects improved OSA drastically.

6.4 Evaluation / feedback

After the implementation described in Chapter 6.2 and 6.3 of the solutions provided in Chapter 5, OSA measurements need to be continued to measure the effectiveness of the solution and the implementation.

The effectiveness of implementing the findings discussed in this report can be measured in several ways:

- Increase of well-measured average OSA.
- Decrease of the impact when a product has delivery failures (of less than an average of 100% over all customers, only then the allocation tool can be applied).
- Improvements in Ways of Working when dealing with, and interpretation of, these measurements.
- Increased awareness of OSA within the MCO.
- Increased awareness on the limited impact of Unilever on OSA within the USCC and other MCO's.
- The increased Unilever influence on OSA via other endeavours, such as close cooperation with other customers.

Measuring the effectiveness on the points discussed above will be rather difficult due to their ambiguity. The first two options are more concrete but rely heavily on other events (e.g. sales-driven events, customer performance in reducing Out of Stocks). In order to be fully aware of the effects of this report, to expand findings to products not yet investigated and to cover all questions left unanswered, further research needs to be done.

Chapter 7 - Conclusions and recommendations

This chapter contains the conclusion on the research questions. During this investigation, several points for further research are identified, which will be discussed in Chapter 7.2. Afterwards, a brief analysis on the limitations of this research is provided in Chapter 7.3.

7.1 Conclusions

This research started with discussing the discrepancy between the current situation and the desired situation at Unilever in Chapter 1. Unilever had limited insights in its OSA performance, and the link between their delivery performance and OSA. Increasing that knowledge was desired, as this can be used for decision making purposes.

The goal of the research was formulated in Chapter 2.1 as:

To develop insights on factors influencing OSA and especially on the relationship between delivery failures and OSA and based on those insights to develop an instrument to manipulate the Casefill in such a way that value through optimal overall OSA of a product at the customers is maximized in the short and long term.

Two research questions were formulated in Chapter 2.2 to achieve this goal:

1. What are the implications of Unilever's current OSA performance and how does this relate to benchmarks provided by theory?
2. Which improvement solutions exist within Unilever's influence to improve OSA?

Theoretical benchmarks in Chapter 3.2 to 3.5 showed an average OSA of around 92%, slightly increasing during the week and somewhat lower for bigger stores and faster moving products. Theory in Chapter 3.6 showed a value destruction of 2,3% of turnover annually for manufacturers, because OSA is not 100%. Although the majority of causes for low OSA lies on the store floor and on the customer DC, it truly has a major impact on the manufacturers. However, only 3% - 4% of all Out of Stocks are caused by the manufacturer's unavailability to deliver, as discussed in Chapter 3.7. A further 11% is caused by 'general' manufacturers mistakes (including long lead times and promotional planning) and the remaining 85% is caused by the retailer.

In reality, Unilever is performing quite good with respect to OSA, with an average OSA of %, as shown in Chapter 4.4. Although overall the detailed picture is in line with theory (e.g. on OSA per day), unexpected results emerge when combining OSA and store size and product volume. This can be explained by the nature of this data set (big products, big stores), but theory is also likely to not be completely compliant with Dutch retail reality.
The implication of not having 100% OSA is an annual turnover loss for Unilever of € million in the Netherlands, or % of annual volume. This has been calculated in Chapter 3.5. The increase compared to the theoretical benchmark can be explained as the % figure incorporates much more variables and costs, which are likely to be excluded in the theoretical figure. Total value destruction in the supply chain is likely to accumulate to x% because of OSA failures.
Finally, Chapter 3.6 showed Unilever indeed to have only limited impact on OSA via its delivery performance. Overall, if Unilever were to increase delivery performance to 100%, OSA would increase from . Hence, Unilever is responsible for % of all Out of Stocks events. Distinction in this can be made as high volume SKU have a bigger impact. If Unilever were to increase delivery performance to 100%, an additional annual turnover of € million would be generated because of higher OSA.

Improvement solutions are proposed in Chapter 5. They are either short term internal solutions or long term external solutions. The short term internal solutions are to allocate products based on

OSA in case of low stock management (e.g. give the cases to the customer which needs it the most before it results in empty shelves), improvements in data gathering to ensure the correct figures are used for analysis, and to do further research on promotional Out of Stocks and sudden major delivery failures.
The long(er) term external solutions have most potential, where in collaboration with the customer, OSA is improved. Unilever has the knowledge and resources to initiate this collaboration, which increases Unilever's direct impact on the OSA and directly deals with the part of the supply chain that is responsible for most OSA failures.

7.2 Limitations

Several limitations are identified based on this report:

- The main limitation is the number of customers included. With only the 6-biggest customers, it poses some problems to extrapolate these findings to the entire customer portfolio. This becomes apparent in Chapter 4.6 where doubts have been discussed on the upscaling. It also results in difficulties to apply the allocation model to the entire Unilever customer portfolio, as discussed in Chapter 5.1.1.
- The remaining Unilever causes are not identified using this approach (in which the focus is on the delivery performance), although they are mentioned shortly in Chapter 4.6.5.3. Further research should identify the impact of the other causes of Out of Stocks which can be attributed to the manufacturer, e.g. lead times and promotional content.
- Unfortunately for this research, there have not been many major delivery failures from Unilever's side. Although very positive for the business itself, it poses some difficulties to determine some of the findings and impact.
- Research indicated in Chapter 3.4 that upscaling might be problematic for manually measured figures. This has been used in this investigation. Further research should provide insights in whether the upscaling applied here was done correctly.

A potential limitation of whether the dataset applied was a random sample of the products within the Unilever portfolio, is explicitly not mentioned here. As it scored well on all measures to indicate whether it represented all Unilever products, and extrapolation of these findings showed similar results for the entire Unilever portfolio, it is likely that these measures truly capture this 'randomness'.

7.3 Further research

Further research needs to be executed on:

- The impact of big delivery failures at Unilever. Special measurement teams need to be instructed to measure only products which experience a big delivery failure, but far more extensively, in case something occurs at Unilever. In this way, the speed of the supply chain can be truly examined. This is especially the case of certain HPC products.
- The impact of promotions. Both theory (Gruen et al, 2002) and business practice show that promotions are difficult to forecast, implement and execute and often are a major cause of Out of Stocks. Special measurements teams should be instructed to monitor this. The impact of Out of Stocks during promotions is very big, as shown in 4.4.2.2. This is a major incentive to improve OSA during promotions and conduct further research on this topic.
- The impact of other Unilever-controlled variables on OSA, not captured by delivery performance
- How to incorporate Negative Word of Mouth as a factor in the estimation of the costs. Most research on Word of Mouth (WOM) is qualitative, proving it impossible to find quantitative data on the impact of WOM.
- Different shopper reactions when faced by Out of Stocks are not taken into account. The general percentages will (presumably) differ per product and likely even per store. In this investigation, the value of brand loyalty for that product was applied to adjust the different

customer reactions slightly. For example, as margarine has major brand loyalty, the chance of shoppers switching to another brand was somewhat lowered. However, it is likely to assume that this procedure does not capture the differences in shopper reactions to their full extent, and further research is required.

Finally, further research can be done to determine how much Unilever would be able to lower its delivery performance before this has a negative effect on the OSA. However, this is not recommended as this investigation will be difficult to execute due to a lack of empirical evidence, and findings will be nearly impossible to implement as it will not be accepted by the customer. Besides, this would reduce the efficiency of the supply chain overall, as (e.g.) downstream partners in the supply chain will adjust to lower delivery performance by keeping higher safety stocks, and partners are no longer striving for optimality in their actions.

Closure

As stated in the preface of this report, I hope I have guided you through the wonderful world of OSA and the difficulties Unilever faces in that. As can be seen from Chapter 7, much remains unknown and needs further research, but much has also been investigated thoroughly, providing answers which at first were unknown.

I hope you have enjoyed reading this as much as I have enjoyed writing it.

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Appendix A - Data analysis

Within the OSA measurements, a product can be measured in one of three states:

- On Shelf Available
- Not available to shoppers, but with a shelf tag: Out of Stock
- Not available to shoppers, and without a Shelf Tag: Void

Officially, On Shelf is defined by the physical presence of an SKU on shelf, in store, that has an item tag and shelf space, and is regularly ordered and stocked by the Retailer. Not available without a shelf tag, or "Void", refers to the circumstances where an SKU is listed by the Retailer, and should be on shelf with a price tag and shelf space, but for some reason (not to be determined or evaluated by the auditor) the item is not on shelf, is not regularly stocked, and has no price tag. Out of Stock is if the product is not on shelf, but has a shelf position and shelf tag.

This research will be focussing on reducing Out of Stocks caused by Unilever. Although "void" implies unavailability to the shopper, a distinction should be provided between 'temporary void' and 'long-lasting void', as not all void is caused by a poor performing Supply Chain:

1) Temporary void created by failures in the supply chain (e.g. incorrect or insufficient deliveries), on which the store management reacted by removing the shelf tag. These out of stocks are often temporary and could be the result of poor performance by Unilever. Temporary void is often characterized by a single void measure in the midst of 'regular' measurements. If there are not more than 2 consecutive void measurements, it is deemed as temporary void.
2) Long-lasting void created by product unavailability due to (e.g.) planogram[29] incompliance or incorrect measurement. Reasons for this are for example that the store is too small, or Store Management has decided not to carry the product due to low margins or low sales, thereby overruling the planogram. Reducing this long-lasting void is the primary responsibility of a part of Customer Development. As these Void measurements are not caused by a poor performing Supply Chain, they will be excluded from the analysis. Long lasting void is often characterized by long consecutive void measurements (more than 3).

The final object of analysis is schematically displayed below in Figure 32 where the red line indicates what will be measured.

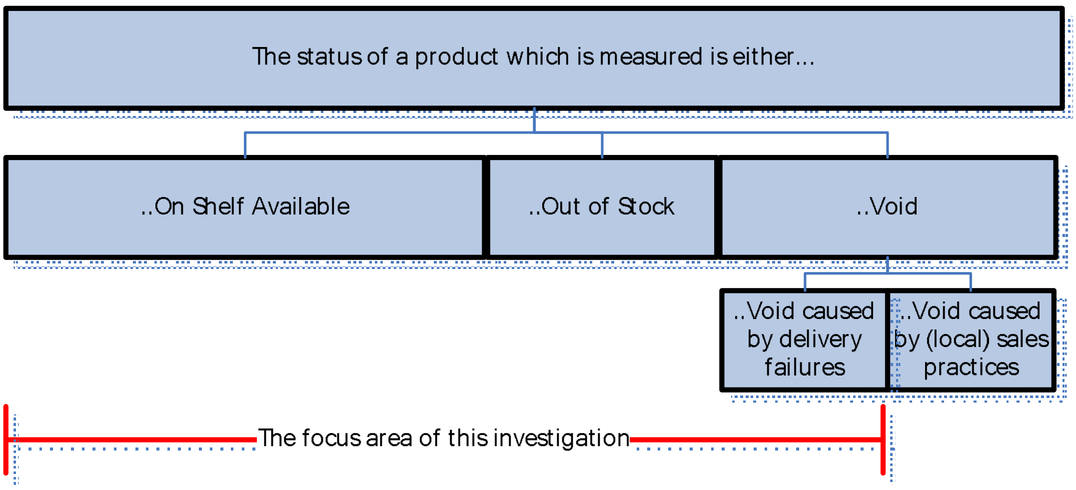

Figure 32 - Graphical representation of the data on how it is measured

[29] The planogram is a graphical representation of the optimal shelf design, taking into account volume, rotation, brand recognition and other variables. It is often created in xxxxxxxxxeration with suppliers and retailers, as suppliers often are more knowledgeable on this topic. These plans are objective by agreement, so Unilever will not give its own products a more prominent place compared to what they deserve.

Because of data inaccuracy (mainly due to the 3rd party measuring agency) the OSA measurements are not directly usable. Four filters were employed to ensure data integrity.

1. The first filter was to exclude all non-Unilever products from the analysis, as they are measured even more poorly, no data is known on them and they are not part of this analysis.
2. The second filter was to discard all measurements of products at stores which did not have contractual obligations to carry the product (i.e. due to a limited shelf size). If a store did carry the product, but was not obliged to by contracts, these measurements were also excluded as this might lead to incorrect measures (for example imagine a store carrying ice cream only during summer. Measurements during summer then would show a much higher OSA percentage than during winter, when it would be zero).
3. The third filter was to exclude long-lasting void-measurements, as these can never be the effect of supply chain disruptions, but are (as explained previously) mainly due to contractual issues and sales issues. It was deemed long-lasting void, if
   - The product_store combination were measured as 'void' at least from the last quarter of 2008 (hence at least 4 consecutive void measurements); or,
   - If there had never been a order for that product by the Customer (e.g. Bona margarine is not in any of one customer, and hence were never ordered); or,
   - According to Nielsen purchasing data (information bought by Unilever from A.C. Nielsen containing sales data over all customers), there has not been any sales of that product at that customer.
4. The fourth and final filter was to exclude products_customer combinations on a case-by-case basis. Reasons for excluding these cases were, for example;
   - Temporary political bans on products - several important SKU had been banned by Schuitema in the period of week 21 to week 30 of 2008, hence measurements in that time period had to be excluded; or,
   - Known incorrect measurements by the 3rd party – one product (Sun Tabs all-in-1 30pc) had been relaunched during measurement period into Sun Tabs all-in-1 30+50%pc. However, this had not been properly communicated to the 3rd party, resulting in incorrectly high levels of Void and Out of Stock.
   - Similar products interchanged by measurement agency. For example, some customers have the Dove Soap Tablet 2*100grams (not having the 4*100 grams), whilst some have it the other way around. This was sometimes measured to the letter (as two different products), but also sometimes the measurement agency measured it as if were the same product. As this showed a mixed picture, customers that have never ordered the 2*100 grams at Unilever were excluded.
   - All frozen products for one customer are excluded. Frozen products are delivered to a DC shared with other customers. Unilever only knows its delivery performance to that DC, but not which customer is affected. Hence it is excluded.

Data integrity for other data is ensured by using internal Unilever systems, and did not need filtering as extensively as the OSA measurements.

Finally, this resulted in exclusion of 24 product_customer combinations (4,5% of the entire dataset).

Appendix B - Products and Stores

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Appendix C - Cost calculation model

In this Appendix, it will be explained how the lost turnover due to Out of Stocks is calculated.

1) Cost_per_customer_per_OOS for Product i at Customer j
The tree in Figure 32 represents the lost sales if a shopper is confronted by an Out of Stock of the product (s)he wants to purchase.

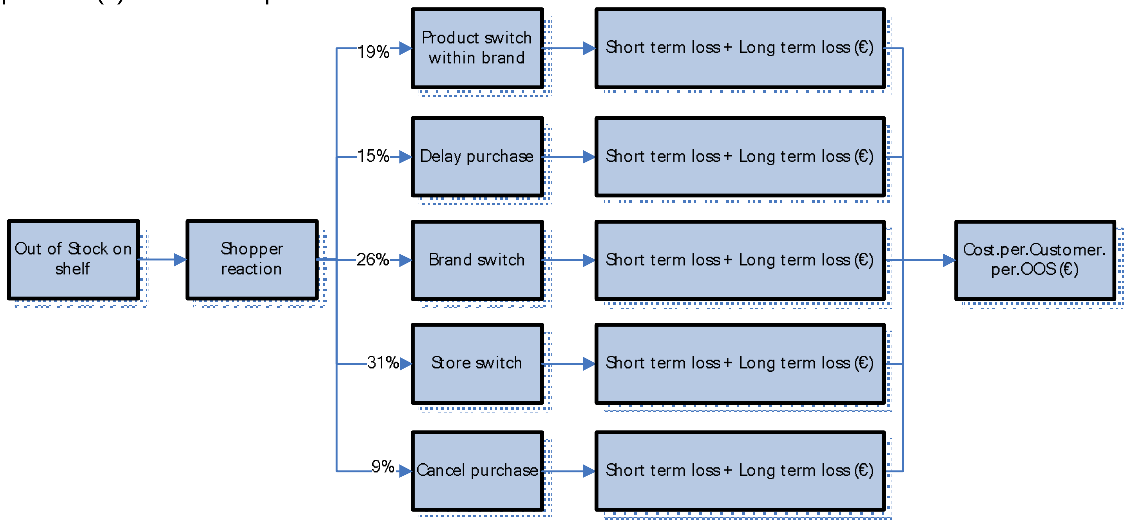

Figure 33 - Graphical representation of how customer reactions relate to costs of OOS

Given that an Out of Stock occurs, a shopper willing to purchase that product has to make a decision. The shopper can have five different reactions, who's percentages have also been provided by Gruen et al (2002). They are displayed in Figure 32 for explanatory reasons.

First, the financial impact per reaction r per customer faced by an OOS is calculated by determining the Cost_per_Customer_Reaction_type$_r$:

$$Cost\_per\_Customer\_reaction\_type_r = Short\_term\_loss_{ir}(€) + \left(P_{long\_term\_loss_{ij}} * E_{long\_term\_loss_i}(€)\right)$$

with

$$Short\_term\_loss_r = \left(\#\_units\_per\_purchase_i * Sales\_price\_Unilever\right) * Binary$$

Here the Binary indicates whether this reaction does actually result in lost turnover for Unilever.

$$E_{long\_term\_loss_i} = \left(\#\_units\_per\_purchase_i * Sales\_price\_Unilever_i * purchase\_frequency_i * duration\_lost\right)$$
$$+ marketing\_costs$$

$$P_{long\_term\_loss\,ij} = \sum_{n=0}^{\infty} \left(P_{n*OOS_{ij}} * Loss\_rate_n\right)$$

and,

$$P_{n*OOS} = OOS.percentage_{ij}{}^{n}$$

The chance of losing the customer for a long time is dependent on the number of consecutive times the customer is faced by an Out of Stock, multiplied by the reaction by the customer.

ECR (2003) has provided figures on shopper reactions when repetitively faced by an Out of Stock; in which shoppers tend to cancel or not buy a product if it is more Out of Stock. This is shown in Figure 33.

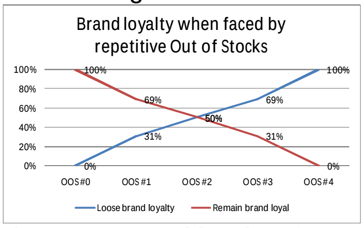

Figure 34 - Brand loyalty of customers when faced by repetitive Out of Stocks.

These values can be multiplied by the chance these P_{n*OOS} values occur (for that $Product\_customer_{ij}$) to determine the $P_{long\_term\_loss_{ij}}$. This is in line with recommendations from Verbeke et al (1995), who state that long term brand loyalty may decline when faced more frequently by Out of Stocks.

The duration_lost is calculated by applying and adapting the formula provided by Pfeifer & Farris (2004), as shown below. The formula is adapted by subtracting 1 from the duration, resulting for β=0 (no loyalty) to 0 years of duration.

$$Duration = \frac{1}{1-\beta r} - 1$$

where

r = constant retention rate (which has been shown above to be equal to the loyalty figure)

β = per period discount ratio (which, in essence, is $\beta = \frac{1}{1+d}$

For β figures are provided on a SKU-group level by Gfk on the loyalty for that product group (hence for Becel Pro.Active, but not per se for the 500 grams or the 250 grams unit). However, these are assumed not to differ significantly.

Applying this formula results in Table 12, with r=10%

β (loyalty, %)	Duration (yr)
0%	-
10%	0,10
20%	0,22
30%	0,38
40%	0,57
50%	0,83
60%	1,20
70%	1,75
80%	2,67
90%	4,50
100%	10,00

Table 12 - Duration as result of brand loyalty

Applying the formula by Pfeifer & Farris overcomes the problem of the subjective choice of duration. Applying this formula also prevents overestimating duration, an often made mistake (Gupta & Lehrman, 2005).

The marketing costs are calculated by using the 5-1 ratio proposed by Desatnick (1998), where it is 5 times more expensive to get a new loyal customer then to retain a current loyal customer. Hence, the market budget per product can be determined per product, hence per purchasing household. Together with the existing loyalty and this ratio will result in the costs per shopper if marketing is required to get him/her bac.

Although it is clear that Out of Stocks also might result in decreased customer satisfaction (Dion & Banting, 1995) and negative Word-of-Mouth (East et al, 2008), this is not taken into account. If it were to be, the $E_{longtermloss_i}$ would be even higher.

By using these formulas, the Product_customer loss for all shopper reactions (r=5) can be calculated. By summing these losses per customer choice, the average loss of an Out of Stock for a Product_customer combination is calculated:

$$Cost\_per\_Customer\_per\_OOS_{ij} = \sum_{r=1}^{5} \left(Cost\_per\_Customer\_reaction\_type_r * Occurence_r \right)$$

2) Cost.of.OOS for Product i at Customer j

The total cost of Out Of Stocks for product i per week can easily be calculated by multiplying the cost per customer with the number of customers faced by an OOS. This is shown below in these formulas:

$$Cost\_of\_OOS_{ij} = Customers\_affected_{ij} * Cost\_per\_Customer\_per\_OOS_{ij}$$

In which;

$$Customers\_affected_{ij} = \sum_{k=1}^{18} OOS\_percentage_{ijk} * Percentage\_of\_Sales\_in\_Timeslot_{ik} * Expected\_Customers\_per\_week_{ij}$$

where k is the timeslot, of which 18 exist per week (morning, afternoon and evening for 6 days), and the Cost_per_Customer_per_OOS is already calculated.

For the Customers_affected, the time and day on which the Out of Stock is measured, is taken into account. Using sales data defined per timeslot and day, it is possible to see the average sales of a product in a certain time slot (e.g. on Monday morning). As the day and time of the measurement is known, these can be linked. Furthermore, it is assumed that if the OSA in that timeslot is 93% (and hence the product was not available in 7% of the measurements), the product is not available for 7% of the time in that timeslot.

3) Cost of OOS for Product i

By summing the $Cost\_of\_OOS_{ij}$ for all customers j, it possible to get the total $Cost\_of\_OOS_i$ for all customers. The following formula is used:

$$Cost\_of\_OOS_i = \sum_{j=1}^{6} Cost\_of\_OOS_{ij}$$

Appendix D - CLV theory

In the cost calculation model, two variables are adapted from theory on Customer Lifetime Value. These variables are;

- Duration - the number of years a customer remains loyal to a brand
- Customer Lifetime Value – the turnover generated by a customer

Within the CLV models, it needs to be noted that two types of underlying assumptions exist; a customer can be lost for good or might return. Examples for this are respectively mobile phone operators and car dealers versus grocery and retail chains, clothing, and others. Although the 'return' option, also referred to as 'customer-migration' or 'always-a-share' might seem more appropriate for the grocery market industry (Berger & Nasr, 1998), several authors (e.g. Dreze & Bonfrer, 2005; Thomas et al, 2004) have stated that both can actually be applied when customers are renewed (Gupta et al, 2006).
Following the set of quantitative frameworks provided by Pfeifer & Farris (2004), first it needs to be pointed out that the term retention is equal to loyalty (Pfeifer & Farris, 2004). Although this paper investigates CLV from a lost-for-good perspective, above it is concluded that both types can be applied to this problem.

Slightly adapting the formulas provided by Pfeifer & Farris (2004), CLV ánd duration can be expressed using;

$$CLV = (M - R^{PV}) * \left(\frac{\beta r}{1 - \beta r}\right)$$

$$Duration = \frac{1}{1 - \beta r}$$

where

M = margin received per period by that customer
R^{pv} = present value at the beginning
r = constant retention rate (which has been shown above to be equal to the loyalty figure)
β = per period discount ratio (which, in essence, is $\beta = \frac{1}{1 + d}$

Applying the slightly more advanced formula by Kumar et al (2007), CLV is calculated as;

$$CLV_i = \sum_{y=1}^{T_i} \frac{CM_{i,y}}{(1 + r)^{\frac{y}{freq_i}}} - \sum_{l=1}^{n} \frac{\sum_m C_{i,m,l} * X_{i,m,l}}{(1 + r)^i}$$

where

CLV_i = Lifetime Value of Customer i
$CM_{i,v}$ = Contribution of customer i in purchase occasion y
r = discount rate
$C_{i,m,l}$ = marketing costs for customer i in channel m in year l
$X_{i,m,l}$ = contacts with customer i via channel m in year l
$Freq_i$ = purchase frequency customer i
n = duration (or number of years to forecast)
T_i = predicted number of purchases by customer i until end of planning period

Appendix E - product and customer variables

In order to determine, which product and/or customer variables are significant in predicting the OSA, statistical analysis is done by applying a regression model. The model consisted of the following variables:

Product variables		**Hypothesized effect on OSA**
P1	Amount of product changes resulting in new product codes (either EAN or internal codes) in the period wk10 2008 to wk08 2009 (number)	-
P2	Unilever production responsiveness – time between urgent production request by MCO planners until delivery at MCO DC (days)	-
P3	Sourcing Unit distance to the corresponding Unilever Distribution Center	-
P4	Shelf life – external shelf life plays a role in OSA according to Van Woensel et al (2007) (days)	+
P5	Volume – absolute volume per product, as stated by Gruen & Corsten (2008), and (ECR UK, 2007) (cases)	-
P6	Stock levels at Unilever (weeks on hand)	+
P7	Demand fluctuations at Unilever (ECR, 2003) (standard deviation of the demand per week, for wk10 2008 to wk08 2009, as percentage of the mean volume)	-
P8	Forecast Error – incorrect forecasting of the demand should decrease On Shelf Availability (ECR, 2003)[30]. This can be expressed as the average over all weeks k, of the Forecast Error or product i, at customer j, in week k: $$ForecastError_{ijk} = ABS\left(\frac{ActualSales_{ijk} - SalesForecast_{ijk}}{SalesForecast_{ijk}}\right)$$	-
Customer variables		**Hypothesized effect on OSA**
C1	Customer (categorical	-
C2	Customer identification. Typology of the customer (e.g. discounter, value customer) (categorical;	-

As there is a clear distinction between food and non-food items (both at Unilever, as in retailer practice, as in many other occasions), an additional split will later be included on whether it is a HPC product or a Food product.

[30] As ECR (2003) does not distinguish between over- and under forecasting, it can be assumed that predominantly under forecast might result in Out of Stocks. This distinction is not taken into account here due to time constraints.

Appendix F - Logistical Regression

In this Appendix, it will be shown that Logistic Regression needs to be applied instead of 'normal' Least Squares Regression. Next, the product- and customer variables will be found, of which we are statistically certain that they predict the On Shelf Availability.

On Shelf Availability is measured as a dichotomous or binary variable;
$$On\ Shelf\ Availability = [available; not\ available] = [1,0]$$

For regular Dependent Variables (DV's), most straightforward would be to apply Linear Regression, using Ordinary Least Squares (OLS)(Cohen et al, 2003). However, in order to apply this, the measurements have to be normally distributed (with N(μ,σ)) and exhibit homoscedasticity[31] (ibid). When the DV is binary (as in this case), it is clearly not normally distributed. Furthermore, it is also heteroscedastic in nature.

To see this, recall that for a binomial distribution with probability of success p,
$$mean(Y) = P$$
$$var(Y) = P(1-P)$$
The latter results in a maximum var(Y) of var(P=0,5) = 0.25. This example clearly shows the dependence of the variance on the mean (it is dependent on the mean), and hence the heteroscedasticity. OLS can thus not be applied. In order to overcome this problem, it is possible to apply a method from the family of Generalized Linear Models (GLM); namely Logistic Regression.

Although Hellevik (2007) argues that OLS can also be applied to dichotomous variables, he stands alone. His argument is mainly that the increased risk of finding 'weird' outcomes by using linear regression is less than the measurement error included by those who are measuring. Although this could be true, it is clear that one has to assume that the initial measurements are correct. Nevertheless, he correctly points to the fact that linear regression might be less correct for small sample sizes (Hellevik, 2007). Besides that, Hellevik does have a valid point with the ambiguity and counter-intuitive nature of the results from logistic regression, as it is less straightforward to interpret.

<u>Theory on Logistic Regression</u>
Logistic regression is often applied in medicine and epidemiology (case versus non-case), quantitative marketing (bought versus non-bought) and risk assessment.

Applying Logistic regression model results in the following regression, in which $\hat{p}_i$ is the probability of belonging to the group with value = 1.
$$\hat{p}_i = \frac{1}{1+e^{-(\beta X)}} = \frac{e^{(\beta X)}}{1+e^{(\beta X)}}$$
Where βX is the regression equation or logit, which is linear, ranging from (-∞ ; ∞)

In order to test the appropriateness of the model, several measurements can be applied. These include (a.o.) the R^2 (Nagelkerke), which has the advantage over other R^2 measures that is it can reach 1 (maximum fit), whereas others can't.

<u>Applying Logistic Regression</u>
In order to determine the significance of all variables mentioned in Appendix E, logistic regression was applied using SPSS v16. In that model, the Dependant Variable (DV) is the Out of Stock

[31] Homoscedasticity means that the variance does not depend on mean x, and hence is rather constant. However, heteroscedasticity means the opposite in which the variance depends on x.

occurrence (dichotomous), and the before mentioned variables are the Independent Variables (IV).

The initial SPSS output is shown in Table 13:

Case Processing Summary

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	217914	100,0
	Missing Cases	0	,0
	Total	217914	100,0
	Unselected Cases	0	,0
	Total	217914	100,0

a. If weight is in effect, see classification table for the total number of cases.

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	92357,455[a]	,014	,039

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001.

Table 13 - Output generated by SPSS on the variables

It can be seen in Table 11, that there are many measurements still in the dataset (n=217.914), much more than the proposed 20:1 ratio per variable (TU Delft, 2008). However, there is a low R^2. The low R^2 can be explained by the fact that this is a submodel, which is created to find underlying factors and variables. Many variables (e.g. all Supply Chain variables, like store influences and DC influences) have not yet been incorporated in this model.

After running the regression, the following variables are found to be significant (p<0,05):

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Table 14 - Output generated by SPSS on the significance of the variables

Appendix G - Factor Analysis

Factor Analysis is a specific technique to reduce data complexity. This is done by analyzing variables to find whether there are underlying scales. In that way, variables can be grouped without losing too much information.

One initial assumption is made that two scales can be found in the initial dataset; a product scale and customer scale. As the customer scale is dichotomous, Factor Analysis is not appropriate (Jöreskog & Moustaki, 2001). We already found variable "Customer Typology" in the Logistical Regression in Chapter 4.6.4.1 and in Appendix F significant in predicting the OSA. This is a strong indication of which customer scale needs to be applied, but this will be discussed later.

Factor analysis – Iteration 1

Factor analysis is applied on the product-related variables. First, the data is tested whether it is appropriate for Factor Analysis by running 3 tests; Correlation Matrix determinant, KMO Measure and Bartlets test.

In this dataset, the determinant of the Correlation Matrix is well above p=0,001 with p=0,207. Next to that, the KMO measure is above 0,6 (to be at least mediocre (Kaiser, 1974)) and Bartlett is significant with p=0,000 (Dziuban, & Shirkey, 1974). Hence it is likely to conclude, that this dataset is appropriate to be used in Factor Analysis (Dziurban & Shirkey, 1974). Finally, there are many correlations above 0.3 in absolute value. All these findings suggest the possibility of finding good results using Factor Analysis (TU Delft, 2008).

For the Factor Analysis, TU Delft (2008) suggests to apply Principal Axis Factoring. Although the SPSS default value of Principal Component Analysis (PCA) at first sight provides stronger results, this type of analysis is not useful. This can be explained by assuming that in all variables variance occurs. This variance is a combination of unique variance of the variable, and shared variance between that variable and other variables. In Factor Analysis, only the shared variance is the variance of interest.
PCA treats all variance as if it is shared variance, thus combining unique and shared variance. By doing so, it can provide stronger and more exact values, but its results are by definition incorrect.
Although the findings from PAF are somewhat weaker, PAF only explains the shared variance and hence provides a better answer. Hence, PAF will be applied for this analysis.

Next, the communalities provided by the SPSS output are analyzed.

Communalities

	Initial
Responsiveness	,315
Stocks	,335
Sales.Volat	,371
FE	,161
Intros	,085
Group_THT	,380
Volume_adj	,381
Su_dist_adj	,282

Extraction Method: Principal Axis Factoring.

Table 15 - Output generated by SPSS on the communalities before Factor Analysis

A commonly applied 'rule of thumb' indicates that the communalities of the variables should be well above 0,25 before and after extraction. However, 'Intros' and 'FE' are not fully passing this test, therefore restricting SPSS in extracting the factors. Hence they need to be sequentially removed, starting with 'Intros' as the lowest variable.

Iteration 2

Excluding 'Intros' results in a Correlation determinant of 0.226 and a KMO value of 0.692. Both are somewhat higher compared to Iteration 1. Although SPSS is now able to extract factors, FE remains to have a communality of 0.113 after extraction, and is removed subsequently.

Iteration 3

The Correlation determinant further increases to 0.269, whereas the KMO increases to 0,713, well above another rule of thumb stating that KMO should be around 0,7 to be at least middling (Kaiser, 1974). All communalities now pass the test, as shown in Table 16.

Communalities

	Initial	Extraction
Responsiveness	,303	,390
Stocks	,292	,735
Sales.Volat	,302	,378
Group_THT	,371	,537
Volume_adj	,344	,464
Su_dist_adj	,272	,377

Extraction Method: Principal Axis Factoring.

Table 16 - Output generated by SPSS on the communalities after Factor Analysis

By choosing the SPSS default selection on Eigenvalues > 1 to determine the number of factors ("Latent Root Criterion", by Hair et al, 1992), two Factors are found in the dataset, explaining 48% of total variance.

Total Variance Explained

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2,486	41,441	41,441	1,957	32,611	32,611	1,701	28,355	28,355
2	1,358	22,633	64,073	,923	15,385	47,996	1,178	19,641	47,996
3	,688	11,465	75,538						
4	,523	8,714	84,252						
5	,512	8,539	92,791						
6	,433	7,209	100,000						

Extraction Method: Principal Axis Factoring.

Table 17 - Output generated by SPSS on the Factors and Eigenvalues

Next, the solution is rotated. Rotation increases the readability of the model and increases the likelihood of a 'simple structure' (Hair et al, 1992). Rotation is done orthogonal. Assuming not much correlation between the two scales, there is no need for the more difficult and weaker oblique rotation. Besides, this will be used for further statistical analysis and hence the better developed orthogonal rotation suffices (Hair et al, 1992).
Varimax rotation is a special case of orthogonal rotation developed by Kaiser (1961). The goal is to have simplicity per column, and should result in 'factorial invariance' (Hair et al, 1992).
High loadings of a variable on a factor indicate that this variable is 'linked' to this factor. As a target, a value of 0,5 or more is considered quite good (Hair et al, 1992), and values above 0,8 are already considered quite rare (TU Delft, 2008).

After applying the PAF with Varimax rotation, and filtering out values below 0,4 (below 0,4 is considered not very strong by Hair et al, 1992), results show:

Rotated Factor Matrix[a]

	Factor	
	1	2
Group_THT	,724	
Volume_adj	-,634	
Su_dist_adj	,613	
Responsiveness	,609	
Stocks		,856
Sales.Volat		,592

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Table 18 - Output generated by SPSS on the Rotated Factor Matrix

Two factors are found with very high loadings of each variable on each of the factors. Furthermore, the reproduced Correlation matrix only shows 1 non-redundant residual (6,0%) with an absolute value greater than 0,05, which is an excellent result.

As these findings are used for explorative purposes, it suffices to select a single variable per factor, to represent all variables on that factor.

- To represent Factor 1, we choose volume. Although this does not have the highest loading factor, it is applied for simplicity of calculation and because Group_THT is more subjective (the ranges to fit a product in a certain group were chosen subjectively).
- To represent Factor 2, we choose Sales Volatility. Although this also does not have the highest loading factor, it is chosen as this represents volatility in the supply chain most direct. Stock levels (the other variable) are merely a consequence of high volatility, and therefore less direct.

<u>Third variable; customer</u>
Please recall that Customers are not taken into account due to their dichotomous character. As Factor Analysis is not possible here (Correlation determinant = 0,000 because there is no correlation due to the dichotomous character of the variables), no underlying scales will be investigated. It is clear that the customer typology (which turned out to be fully significant for all three binary variables) can be applied directly:

<u>Fourth variable; Food versus HPC</u>
Being aware of the difference between food and non-food, not only in product characteristics but also in assumed process differences, a further variable is significant to add. Unfortunately, adding a dummy variable "HPC" to the regression did not result in a significant variable. However, filtering the data on that same dummy variable and re-running the above executed statistical tests on both the HPC- and Food datasets, resulted in identical solutions.

<u>Interpretation of the factors</u>
The four factors are indeed quite distinct and can be interpreted as:

1. HPC or Food?
2. Speed of Supply Chain (Factor 1 of the Factor Analysis) – represented by Volume.
3. Volatility of Supply Chain (Factor 2 of the Factor Analysis) – represented by sales_volatility.
4. Customer – expressed as

Appendix H - Confidence Interval per Homogeneous Group

For all Homogeneous Groups in Scenario 1, the 95% Confidence Interval is calculated in SPSS and shown in Table 19 below:

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Table 19 - 95% confidence interval of the mean of HG's in Scenario 1

The same can be done for the Homogeneous Groups split up per customer.

Appendix I - Distribution of Product_customers

In this Appendix, background is provided on how product_customer combinations were assigned to one of the three Scenario's based on their delivery performance and average OSA levels.

Assigning the product_customers with delivery failures to Scenario 2 or 3 is done in two steps;

1. If the average OSA of that Product_Customer combination is smaller than the 95% Confidence Interval of its Homogeneous Group in Scenario 1 (see Appendix F), it was deemed to be negatively impacted by the delivery failure. Hence it was assigned to Scenario 3.
   If it was not smaller, then it was deemed not to be significantly impacted and hence it was assigned to Scenario 2.
2. After this, all product_customers were manually checked for consistency. Using business insights, it was investigated whether delivery failures indeed corresponded to abnormalities in the weekly OSA figures. Two examples are given in Figure 35.

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Figure 35 – Examples of manual changes

<u>From Scenario 2 to Scenario 3; Dove Deodorant Original at</u>

This product_customer combination (Dove Deodorant Original at) was initially assigned to Scenario 2. However, carefully looking at the graph indicated that delivery failures could indeed have caused a temporarily spike in Out of Stocks (especially the delivery failures in week 27 of 2008, and the spike in Out of Stocks the week later). Hence it was reassigned to Scenario 3.

<u>From Scenario 3 to Scenario 2; Adez Mango/Apricot at</u>

This product_customer combination (Adez Mango/Apricot at) was initially assigned to Scenario 3. However, carefully looking at the graph, indicated that delivery failures could not have caused a temporarily spike in Out of Stocks (especially the delivery failures in week 08 of 2009, which is áfter a temporary spike in OOS in week 5/6 of 2009). Hence it was reassigned to Scenario 2.

After both steps, the following distribution was found of Product_Customer combinations across all three scenarios:

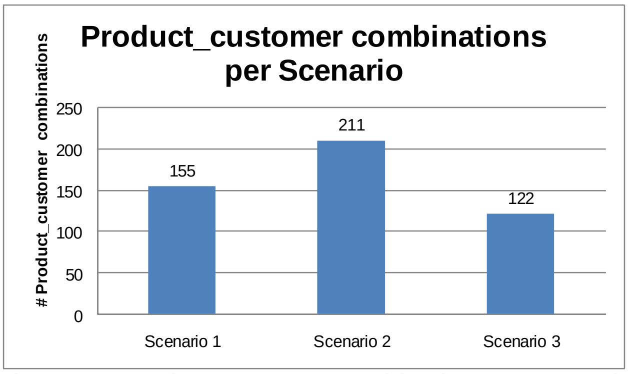

Figure 36 - Product_customer combinations per scenario

Looking at the distribution of product_customer combinations per customer over the Scenario's, it is shown that relatively many product_customer combinations are located in Scenario 3 for Relatively few products for are located in Scenario 3. This is shown in Figure 36 below:

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Figure 37 – distribution of product_customer combinations over the Scenario's per customer.

And the following distribution was found for Product_Customer combinations across the Homogeneous Groups as defined in Step 1:

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Table 20 – Distribution of the product_customers across Scenario's and HG's

Appendix J - Outcome Scenario 1

In the Supply Chain Model, several variables were identified and tested. These are:

- Store floor surface – the selling floor surface of a store (m2)
- Store turnover – the weekly turnover by the store (Euro)
- Margin – the additional selling price of a retailer compared to the Unilever selling price: (additional price / UL price) * 100%
- Shelf Allocation – the chance current shelf capacity is inadequate given the demand per day (and hence demand per leadtime).
- Promo – whether this product was on promotion at this customer during the measurement week
- DC – the distribution centre that supplies the store
- Customer – the retail chain
- Deliveries UL to DC – the number of deliveries from Unilever DC's to the customer's DC.

After applying the Supply Chain Model on all measurements in Scenario 1, several variables are found significant (p=0,05). Their coefficients are shown below, including a table which indicates the range of the variables:

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Table 21 - Overview of the variable ranges

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Table 22 - Significant variables Scenario 1 on all data

This clearly shows that DC's have a strong influence in interpreting these variables, so the analysis should be done per Homogenous Group. Results do show that;

- Store Turnover is negatively correlated to Out of Stocks. This is countering commonly believed ideas in theory (where it is believed that larger stores face more Out of Stocks). This can mean two things;
  - This might be caused as the stores in the Unilever dataset were quite large to start with (and hence the dataset is somewhat biased)
  - This can also mean that the theory is less applicable for the Dutch market (where there is no distinction between super- and hypermarkets).
- Although theory argues that a lack of Shelf Space is a major driver of Out of Stocks, this data proves otherwise. Intuitively one can argue that theory is correct here, and hence this variable might be ill-defined. However, this needs to be further analyzed.

Next, the Supply Chain Model is applied on the data in Scenario 1 *without the customer separation.* Results are shown below:

Variable	(Homogenous) Group grouped over all customers											
	1110	1120	1210	1220	1310	1320	2110	2120	2210	2220	2310	2320
Store VVO (00m2)	-0,16	-0,05				-0,05				-0,16		
Margin		10,95	2,01	-8,11	-10,78	-5,15	14,50	9,14			4,09	-6,05
Promo (binary)			0,67									
Shelf Allocation (binary)							0,94	0,92				
Store Turnover (0000 EUR)									-0,02	-0,02		-0,03

Table 23 - Significant variables Scenario 1 on Homogeneous Groups without customer separation.

Looking at these groups, we find some remarkable findings;

- When Store Surface or Store Turnover is significant, they negatively influence Out of Stocks. As both are an indicator of the size of a store, it is likely to conclude that the size of the store negatively correlates with Out of Stocks; countering theory
- Promotions seem not to play a very big role except for average volume, low volatility HPC products (1210). This is countering much theory
- Finally, Margin is very volatile and should be investigated further.

Next, the Supply Chain Model is applied on all Homogeneous Groups as defined in step1:

Variable	Homogeneous Group HPC																	
	1111	1112	1113	1121	1122	1123	1211	1212	1213	1221	1222	1223	1311	1312	1313	1321	1322	1323
Margin	-5,198	-16,998	-6,680	-19,674	17,346					8,854						-3,400	-2,498	-6,645
# DC deliveries			-0,340			-0,692	-0,695		-0,727	-1,515		-0,696		-1,297		0,267		
Promo			0,892						1,281	0,733								
Store Turnover	0,003				-0,008								-0,026					-0,004
Store Surface							0,000			0,001				0,001			0,000	
Shelf Allocation																		

Variable	Homogeneous Group Food																	
	2111	2112	2113	2121	2122	2123	2211	2212	2213	2221	2222	2223	2311	2312	2313	2321	2322	2323
Margin	11,890	9,088	11,962	10,824	8,407	8,452	3,144	3,195	-2,865	7,110		-13,010	4,558		-16,482	-25,695	-8,321	
# DC deliveries			-1,041			-0,863			-0,379				0,810			3,704		-0,239
Promo						-0,441				0,450							1,246	
Store Turnover								-0,003	-0,002			-0,004			-0,006	-0,003		-0,004
Store Surface		1,764		-1,042										-0,001	0,001			
Shelf Allocation						1,179												

Table 24 - Significant variables of Homogeneous Groups

Two variables are of interest in the above displayed regression outcomes;

1. The number of deliveries to the customer's DC is indeed negatively correlated with Out of Stocks; more deliveries decrease the OOS percentage.
2. Margin remains to be a rather volatile variable. It appears as if margin is somewhat more leading for . It also appears as if lower margin items (both at HPC and Foods) negatively correlate with Out of Stocks (more margin results in less Out of Stocks).

Running the model on the Customers (hence grouping all measurements just on 1 variable; the customer), reveals the following significant (at p=0,05) results:

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Table 25 - Significant variables per customer

It can be seen that:

1. Promotions remain to be not very significant; promotions are less properly executed and increase OOS levels in case of promotion.
2. Mixed results exist for Store surface and Store turnover:
3. Mixed results exist for Shelf Allocation (the chance a product has enough space on shelf compared to its volume). Apparently this does have an intuitively correct influence for too little shelf space seems to improve the OSA. This can be explained perhaps by improved shelving processes for these customers, in which they tend to check and restock shelves more regularly. However, results are not fully correct as shelf plans for many categories are not known at Unilever (and hence by default Shelf Allocation is 0 for those categories).
4. Finally, margin does play a significant influence at all retailers. The higher the margin found, correlates positively with increased Out of Stocks. This is counter intuitive, as one would think OOS should decrease for higher margin products. Apparently there is no driver of store employees or management to perform better on products with higher margin (at least not visible in this dataset with these products). One can finally conclude that .

Appendix K - Logit calculation

In this Appendix, the Supply Chain Model will be applied to determine the impact of Unilever's delivery failures.

The default Supply Chain Model will be executed;

- On the Homogeneous Groups in Scenario 3 (so 36 Homogeneous Groups, in which the customer distinction is on customer typology [ ]).
- With three different time spans for the delivery failures:
  - Including as variable the Delivery Failures in same week of OSA measurement.
  - Including as variable the Delivery Failures in same and preceding week of OSA measurement.
  - Including as variable the Delivery Failures in same and two preceding weeks of OSA measurement.

Besides this, the Supply Chain Model will also be executed (Supply Chain Model Adapted):

- On the Homogeneous Groups in Scenario 3, but with all customers separately (so 72 groups instead of 36), in which the customer distinction is
- With the same three time spans as the default Supply Chain Model.

Hence, applying these models, each with three time spans, will result 6 different outcomes.

The distinction between the customers (Homogeneous Group per type or per customer) is made because results per customer provide more accurate results (it can distinguish between even though they are in the same Homogeneous Group). However, if no results per customer are available, results from the Homogeneous Group (with customer typology) will be applied.
If no measurements exist within a Homogeneous Group for a specific customer, then the values of its Homogeneous Group will be applied. If measurements do exist but show no significant relationship, they would remain 0.

The reason for applying three different time spans is that the impact of a sudden delivery failure should be felt directly, and should not be felt after two weeks of normal deliveries (delivery failures two weeks ago but since then 100% performance will not result in OOS this week). However, if Unilever experiences two consecutive weeks of OOS, the time span of looking for an impact should be two weeks, and the same goes for three weeks.

'Base Logit' is the Logit value of the average OOS level of the corresponding (Homogeneous) Group in Scenario 1. A logit is linear and not bound by asymptotes and is calculated by:

$$Logit = -\ln\left(\frac{1 - OOS\%}{OOS\%}\right)$$

Finally, results are somewhat modified to fit business experience;

- The sum of all Logit values per Group should be positive. If the Logit value for delivery failures in week i is negative, this will be changed to 0. A loss in delivery performance will never result in improved OSA in that same week.
- The Logit is maximized at 4. Values generated by SPSS above 4 are by default incorrect; if Unilever fails to deliver 10% of the quantity, this will never result in more than 10% increase of OOS on the shelf. The maximum value of four is chosen as this represents a 1:1 relationship (if Logit is 4, than 10% delivery failures result in 10% increased OOS levels).

Table 26 – Explanation of the Logit calculations

Below, a tabular example of the logit calculations is shown, and explanation is added. The example is based on by assuming Homogeneous Groups and a 3 week consecutive Unilever delivery failure of 50%.

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For ease of explanation, the columns are given an index letter;

A) We have only focused on measurements in Scenario 3; delivery failures possibly resulting in reduced On Shelf Availability
B) There are (2*3*2*3=) 36 Homogeneous Groups, however group 1313 is missing as it is not represented in Scenario 1 and not in Scenario 3. Each of these Groups has a corresponding Homogeneous Group in Scenario 1, of which the means will be used in step G.
C) Columns C – F explain the characteristics of the group on the four variables
G) The corresponding Homogeneous Group in Scenario 1 has a mean, which is shown here. This is the expected OSA if there would have been no delivery failures
H) The OOS-value is calculated as 1-OSA, hence 1-column G
I) The OOS-value of column H can be converted to a logit value using the formula;

$$Logit = -\ln\left(\frac{1-OOS}{OOS}\right)$$

J) Columns J-L are logit values of when in that week (week i, i-1 and i-2), 50% delivery failures would have occurred.
M) Total Logit = Base Logit (column I) + DeliveryFailure Logit ((SUM over columns J-L)*50%), so this is the logit of the Homogeneous Group if there would have been 3 weeks of delivery failures (of 50%).
N) Expected OOS is now calculated by;

$$OOS = \left(\frac{e^{Total\_Logit}}{1+e^{Total\_Logit}}\right)$$

O) So 50% delivery failures for three weeks would result in this increase of the OOS levels in stores for this Homogeneous Group.

It can clearly be seen that OOS levels rise drastically. If they do not rise drastically, this means one of three things;

- There is no significant relationship found in the data
- No data is present for this group
- In the data present for this group, there has never been a long-lasting delivery failure by Unilever.

Especially for HPC (non-food) products, the last two options are quite plausible due to a lack of data. This could be corrected by a further investigation.

Appendix L - Allocation model

Algorithm

The algorithm applied uses Linear Programming, in which the objective function z is minimized. This objective function z represents the missed sales due to the additional Out of Stocks at customer j. Other variables are the week (i) and number of successive weeks of Delivery Failures (k). The k-variable is used as the coefficients of the impact of delivery performance on OSA differ for the number of weeks in which delivery failures occurred.

$$\min z = \sum_{j=1}^{n} Extra.OOS_j * SalesLastYear_{ij}$$

Function z is further detailed by the function below, where the additional Out of Stock level is calculated by the current Out of Stock level minus the normal Out of Stock level (when no delivery failures occur);

$$z = \sum_{j=1}^{n} \left(\left(\frac{e^{Logit_j}}{\left(1 + e^{Logit_j}\right)} - BaseOOS\%_j \right) * SalesLastYear_{ij} \right)$$

with

$$Logit_j = \sum_{k=1}^{3} \left(\left(Value_{k1j} * \frac{Niet.lev_{1j}}{AdjQ_{1j}} \right) + \left(Value_{k2j} * DF_2 \right) + \left(Value_{k3j} * DF_3 \right) + Base.Logit_j \right)$$

Above, the Logit function is explained. This Logit is used to determine the Out of Stock percentage, and is determined by the previous delivery failures and that impact, and the impact of current delivery performance. The historical figures are known and the Adjusted Quantity is received as input from the user. Based on these two figures, the algorithm determines the optimal amount of non-delivery (expressed by 'niet.lev') for each customer, in order to minimize the lost sales.

The formulas above as subjected to three constraints. These are:

s.t.

$$Niet.lev_{1j} \geq 0 \quad \forall j$$

The amount of non-delivery should be non-negative for each customer. This excludes the possibility to have a delivery performance above 100%

$$Niet.lev_{1j} \leq \left(1 - Pnodig_{1j}\right) * AdjQ_{1j} \quad \forall j$$

For each customer, the amount of non-delivery should not be more that the maximum of the initial order that can be discarded. If a customer requires at least 25% of its 400 case-order to be delivered, up to 300 cases can be discarded. If 'Niet.lev' is above 300, this constraint is not met.

$$\sum_{j=1}^{n} Niet.lev_{1j} = \sum_{j=1}^{n} \left(AdjQ_{1j}\right) - Beschikbaar_i$$

The total amount of non-delivery should be equal to the total amount that has to discarded

In advance of applying this algorithm, the following values are already known from other sources:

- DF_{2j} and DF_{3j} for all j
- $Value_{k1j}$ and $Value_{k2j}$ and $Value_{k3j}$ for all k and all j (these are the coefficients of the logistical regression executed in the models as explained in Appendices J and K.
- $SalesLastYear_{ij}$ for all i and j
- $BaseOOS_{j}$ for all j

After the initialization of the tool, the user will specify;

- The amount available and which is destined to stay after this week
- $AdjQ_{1j}$
- $Pnodig_{1j}$
- #wekenDF to determine k (as the coefficients of the impact on OSA differ if the delivery failure is in its first, second, or third week).

Flowchart model

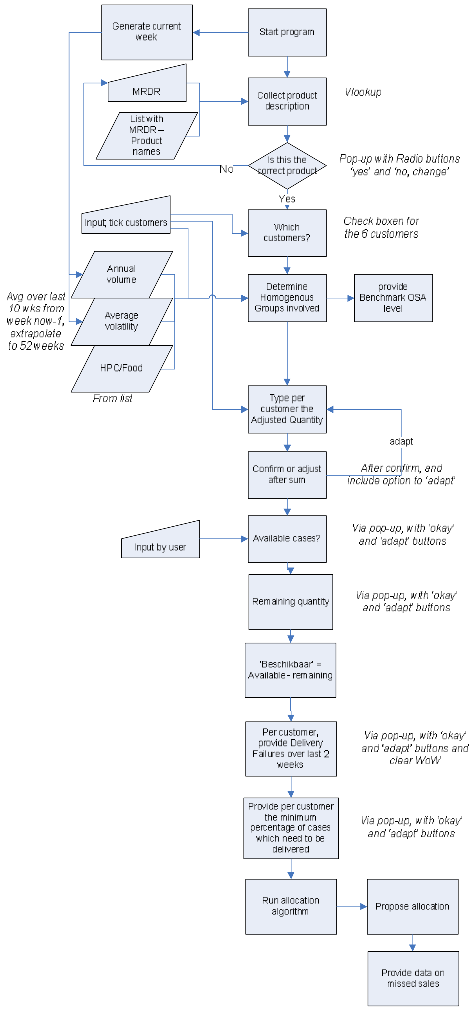

Figure 38 – Flowchart of the Allocation model

Model Interface

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Figure 39 – Screenshot of Allocation model 1

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Figure 40 – Screenshot of Allocation model 2

Simplified application of the tool: tables

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Figure 41 – Simplified table used for allocation of HPC products

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Figure 42 - Simplified table used for allocation of Food products

1	Maximum impact
2	High impact
3	Severe impact
4	Limited impact
5	(nearly) no impact
	No data available

Figure 43 - Legend

Appendix M – Sales slides

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Figure 44 – Exemplary first slide for Customer Development

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Figure 45 – Exemplary second slide for Customer Development

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