Automated Store Ordering versus Manual Store Ordering at Jumbo

by

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I. Abstract

Since 2003 the Dutch retail market entered a fierce price war (van Heerde, Gijsbrechts, & Pauwels, 2008; van Woensel, van Donselaar, Broekmeulen, & Fransoo, 2007). Consequently, retailers are continuously forced to seek for opportunities to save costs while maintaining the high service level that is demanded by customers. Implementing an automated store ordering (ASO) system can reduce food waste up to 20% (Kiil, Dreyer, Hvolby, & Chabada, 2018), reduce stock outs (Avlijas, Simicevic, Avlijas, & Prodanovic, 2015), and it could save a significant amount of work in the stores, since store managers do not need to adapt orders manually anymore. Jumbo has currently implemented an ASO system. However, a major challenge with this implementation is that approximately 9% of the automatic generated order advices are manually adapted by the store managers without knowing why and whether these adaptions add value. By performing a logistic regression and taking interviews, this Master Thesis provides insights in why and when store managers are likely to adapt the order advices. Besides that, a logic introduced is which makes it possible to determine, afterwards, whether the order adaption added value. In general, results indicate that store managers are more likely to add value for perishable products than for non-perishable products. To guide stores to a hands-off policy, it is recommended for store support to use three KPIs: process trustworthiness, added value of order adaptions, and order acceptance. Besides that, it is recommended for forecasters and replenishers at Jumbo's main office to do an analysis on stock-keeping unit (SKU) level to discover those SKUs where store managers add, in general, a lot of value.

II. Executive Summary

Problem Definition & Research Design

Jumbo experiences deviations between the automatically generated orders and what the store managers actually order. This deviation exists since store managers have the possibility to manually adapt the automatically generated order advice. Jumbo's perception is that, ideally, store managers do not have to intervene in this automatic ordering process (the so called "hands-off" policy). However, it could be possible that store managers improve the order advice by manually adapting the order advice. Because of that, this Master Thesis report focusses on characteristics that are related to the probability that an order advice will be adapted and which of them are likely to add value.

The main question that this Master Thesis ought to answer is as follows:

How could Jumbo narrow the gap between their actual and automatically generated orders?

To answer this question, interviews at several stores and a logistic regression have been performed to establish insights in which characteristics are related to the probability that an order advice is adapted. Besides that, a logic is introduced and integrated into a model to determine whether the order adjustment added value. This logic for upward adjustments is based on the following reasoning; if the inventory of the adapted SKU would have gone below its centralized minimum shelf quantity with its original order advice, the upward order adaption added value. For a downward adjustment the logic is as follows; if the inventory of the adapted SKU would have stayed above its centralized minimum shelf quantity with the adapted order, the downward order adaption added value.

Results

Based on the interviews, there are five reasons that count for approximately 76% of all order adaptions. These reasons are: "product is in promotion", "product is on second placing", "weather/temperature changes", "inventory corrections, and "improving store view". By performing the logistic regression, promotions, second placing and inventory corrections also came forward as factors that correlate with the probability an order advice will be adapted. Weather/temperature change was not found as a characteristic that correlates with the probability that an order will be adapted. Besides that, improving the store view was not tested in the logistic regression, since there was no data available for this subjective characteristic.

Besides the reasons that came forward during the interviews, there were also some other characteristics tested during the logistic regression. Characteristics that are also correlated with the probability that an order advice will be adapted are: "Day of the week" (orders are most likely adapted on a Thursday), "franchise/affiliate" (franchisers are slightly more likely to adapt an order advice), "daily sales" (more sales of a product increases the probability of adaption), "minimum shelf quantity" (a lower minimum shelf quantity increases the probability of adaption), and "price" (a higher price increases the probability of adaption). Note that these relations are not necessarily causal relationships.

Finally, an analysis has been performed to gain insights in whether order adaptions added value. Results showed that approximately 75% of all order adaptions are up and 25% are down. For products without perishability issues, approximately 15% of the upward adjustments added value while this is 65% for downward adaptions. However, one should take into account that these downward adjustments are not that relevant for products without perishability issues. This because having an out of stock for these products is way more costly than having some extra inventory. Note that this is not the case for perishable products, since having extra inventory will also increase the probability for waste.

Compared to non-perishable products, perishable products are more likely to be adapted and the probability for a downward adjustment is also higher. The probability that a downward adjustment added value is lower while the probability for an upward adjustment to add value is higher. However,

one should be aware that downward adjustments that add value are way more relevant for perishable products than for non-perishable products.

Recommendations

Based on the results and experiences that were established during this Master Thesis, it is recommended to use the KPIs "process trustworthiness", "added value of order adaptions", and "order acceptance" to move to a hands-off situation. It is important to use these KPIs, since can use the KPIs to create insights in whether a specific store is able to move to a hands-off policy or not.

The first step that Jumbo should take is to alter its KPI "process trustworthiness". This KPI is used to conclude something about the inventory management which is a crucial aspect in moving to a hands-off situation. Inventory management is crucial, because F&R needs correct input data (e.g., inventory level of a SKU) to determine a proper order advice. A higher score on this KPI indicates a better inventory management and thus better input data for F&R to determine its order advices. However, currently the KPI "process trustworthiness" also depends on the KPI "order acceptance". It is recommended to make the "process trustworthiness" independent of the "order acceptance", since a lower "order acceptance" is not necessarily an indicator for poor inventory management. This because a low "order acceptance" could also be caused by order adaptions that add value.

After altering the KPI "process trustworthiness", this KPI should be combined with the KPI "added value of order adaptions". If the "process trustworthiness" of a store is sufficient and the "added value of order adaptions" high, one knows that the store manager adds value to F&R and should the store not move to a hands-off policy before further analyses are done on how this knowledge could be integrated into F&R. However, if the "process trustworthiness" is high and the "added value of order adaptions" is low, this store does not add a lot of value and it should move to a hands-off situation. Finally, if the "process trustworthiness" is not sufficient, the store should first improve that KPI, because F&R will never be able to give proper order advices if it does not get accurate input data. So even if the "added value of order adaptions" is high and the store "process trustworthiness" is low the focus should first be on its inventory management to give F&R the chance to determine accurate order advices.

Finally, Jumbo should use the KPI "order acceptance" to take the amount of order adaptions into account. This KPI is especially important for two reasons: 1) to know how much effort one should put into integrating the knowledge of the store manager into F&R and 2) to know how much effort one should put into change management if the store is "forced" to move to a hands-off situation. Regarding the first reason; if both the "order acceptance" and "added value of order adaptions" are high, it is less relevant to integrate the store managers' knowledge into F&R than when the "order acceptance" is low and the added value of order adaptions high. This because a low "order acceptance" indicates that a lot of orders were adapted while a high "order acceptance" indicates that less order adaptions were made. Besides that, it is recommended that this KPI is used to get an understanding for the required change management. If a store with a low "order acceptance" is "forced" to move to a hands-off situation, it has to change its way of working more than a store with a high "order acceptance". It is generally known that people resist against change and to take this into account, it is recommended to give store managers insights in the results of their order adaptions so that the understanding of F&R's capabilities will increase.

Besides these three KPIs that should be used to create insights in whether a store can move to a hands-off policy, it is vital to tackle the most important reasons for order adaptions. Based on the interviews and logistic regression, three of these important reasons are: second placing, improving store view, and inventory corrections. It is recommended to take these reasons into account by taking the following measures:

- Second placing: Standardize the most second placing possibilities for the store. Besides that, it is important to change the minimum shelf quantity automatically such that the store does not need to adapt this manually anymore.
- Improving store view: Increase the minimum shelf quantity for non-perishable products with high volume (e.g., beer or water). This because it came forward that stores especially increase the order advices to improve the store view for these products.
- Inventory corrections: To prevent order adaptions that are caused by inventory corrections, it is necessary to implement the re-run functionality. Which is to ensure that F&R determines the order advice again after an inventory correction has been made.

III. Acknowledgements

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Finally and most importantly, I would like to thank my parents and sister. They always supported me during my five years at the TU/e. Without them it would, without a doubt, be impossible to ever reach the situation of writing this master thesis.

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IV. List of definitions and abbreviations

ASO: Automated Store Ordering

DC: Distribution Centre

DV: Dependent Variable

F&R: Forecasting and Replenishment

IOH: Inventory On Hand

IOQ: Incremental Order Quantity; The minimum amount of consumer units that an order should be increased. Note that this is not necessarily the same as the case pack size.

IT: Inventory in Transit

IV: Independent Variable

OOS: Out Of Stock

Second placing: As the name already indicates, it is a second place for a product in the store. Second placing is especially used for products that are on sale.

SKU: Stock-Keeping Unit

POS: Point of Sales

PVF: The product group “Potatoes/Vegetables/Fruit”

1 Introduction

This Master Thesis is performed at Jumbo and mainly focusses on the difference between order advices and actual replenishment. Jumbo is a major Dutch retailer with a revenue of more than €7 billion in 2017 (Jumbo Jaarverslag, 2017). The aim of this thesis is to gain insights in:

- Why store managers adapt the automatically created order advices;
- If the manual adaption of order advices improve the order quality;
- How Jumbo can improve the quality of the orders in order to close the gap between order advices and actual orders.

In the introduction, there will be further elaborated on Jumbo, the problem definition, the current ordering processes, and the relevance for Jumbo.

1.1 Jumbo

With a market share of 19% and 65.000 employees, Jumbo is the second largest grocery retailer in the Netherlands (Jumbo Jaarverslag, 2017). During the years Jumbo grew significantly; in 2002 Jumbo had 36 stores with a revenue of €400 million while last year Jumbo's revenue was more than €7 billion with 585 stores. This year the grow keeps going on, since Jumbo took over Emté (a grocery retailer with a Dutch market share of 2.5%).

Jumbo wants to ensure that the customer is the core of all their activities. To ensure this, Jumbo uses seven certainties:

1. Euro's cheaper
2. Service with a smile
3. For all your groceries
4. Fresh is also really fresh
5. Easy shopping
6. Not satisfied? Money back!
7. Your wishes are central

From these seven certainties Jumbo's unique formula follows:

Best service + extensive assortment x lowest price

By focussing on these certainties and formula, Jumbo wants to ensure that customers experience the best service for the lowest price so that customers become loyal fans.

Besides regular supermarkets, Jumbo recently introduced other concepts/channels to satisfy the changing customer needs. These concepts/channels are the following:

- Jumbo Foodmarket: The Jumbo Foodmarket combines the regular supermarket and the possibility to buy fresh and prepared food by professional cooks.
- Jumbo City: A Jumbo store, in an urban area, where customers have the possibility to quickly buy regular and fresh products.
- Jumbo.com: Jumbo's online channel to sell products. Customers can order products online and pick them up at a Jumbo store or let them deliver at their home address.

1.2 Problem Definition

Jumbo experiences deviations between the automatically generated orders and what the store managers actually order. This deviation exists since store managers have the possibility to manually adapt the automatically generated order advice. Jumbo's perception is that, ideally, store managers do not have to intervene in this automatic ordering process. Therefore, they want to gain insights in whether these manual adaptions add value and how one should deal with this.

Although Jumbo's perception is that, ideally, store managers should not have to adapt order advices, this is not by definition the case as discussed by Kiil, Dreyer, Hvolby, and Chabada (2018) and Syntetos, Nikolopoulos, Boylan, Fildes, and Goodwin (2009). They discuss that especially for products with high perishability and intermittent demand store managers could add value to the order advice. Therefore, it is also relevant to gain insights in whether store managers have the ability to outperform the automated store ordering (ASO) system[1]. Another element why it is not trivial that store managers should not intervene in the ordering process is because of algorithm aversion. Algorithm aversion is the phenomenon that people are reluctant to use a forecasting algorithm that is known to be imperfect (B. J. Dietvorst, Simmons, & Massey, 2018). Ignoring algorithm aversion and forcing people to use an ASO system could have a depleting effect on the motivation of employees. Therefore, Dietvorst et al. (2018) suggest to give forecasters (i.e., in Jumbo's case the store managers) a possibility to change the algorithm's forecast. Besides that, they conclude that the maximum amount of this possible change is relatively unimportant to ensure that forecasters stay motivated.

Therefore, Jumbo's problem statement is defined as follows;

Jumbo experiences differences between the automatically generated orders and what the store managers actually order.

This thesis will focus on this problem statement, but it will also take into account that store managers could add value to the ASO system. Section 1.4 elaborates into more detail on why these differences are potentially problematic for Jumbo.

[1] Jumbo calls their ASO system "F&R"

1.3 Current Ordering Processes

The focus of this Master Thesis lies on the difference between order advices and actual orders. To focus on this difference, it is important to have an insight in the current ordering process (i.e., how are orders created and adapted). Therefore, this section elaborates on the current processes for the creation of an automatic order advice and how store managers could manually adapt this automatic order advice.

Before explaining the ordering process (see Figure 1 for more detail), one should understand the logic of it. The ovals in the middle represent specific steps in the creation of a final order. The squares on the left represent the information that should be available for that corresponding step. The times at the right represent when a specific action should be performed.

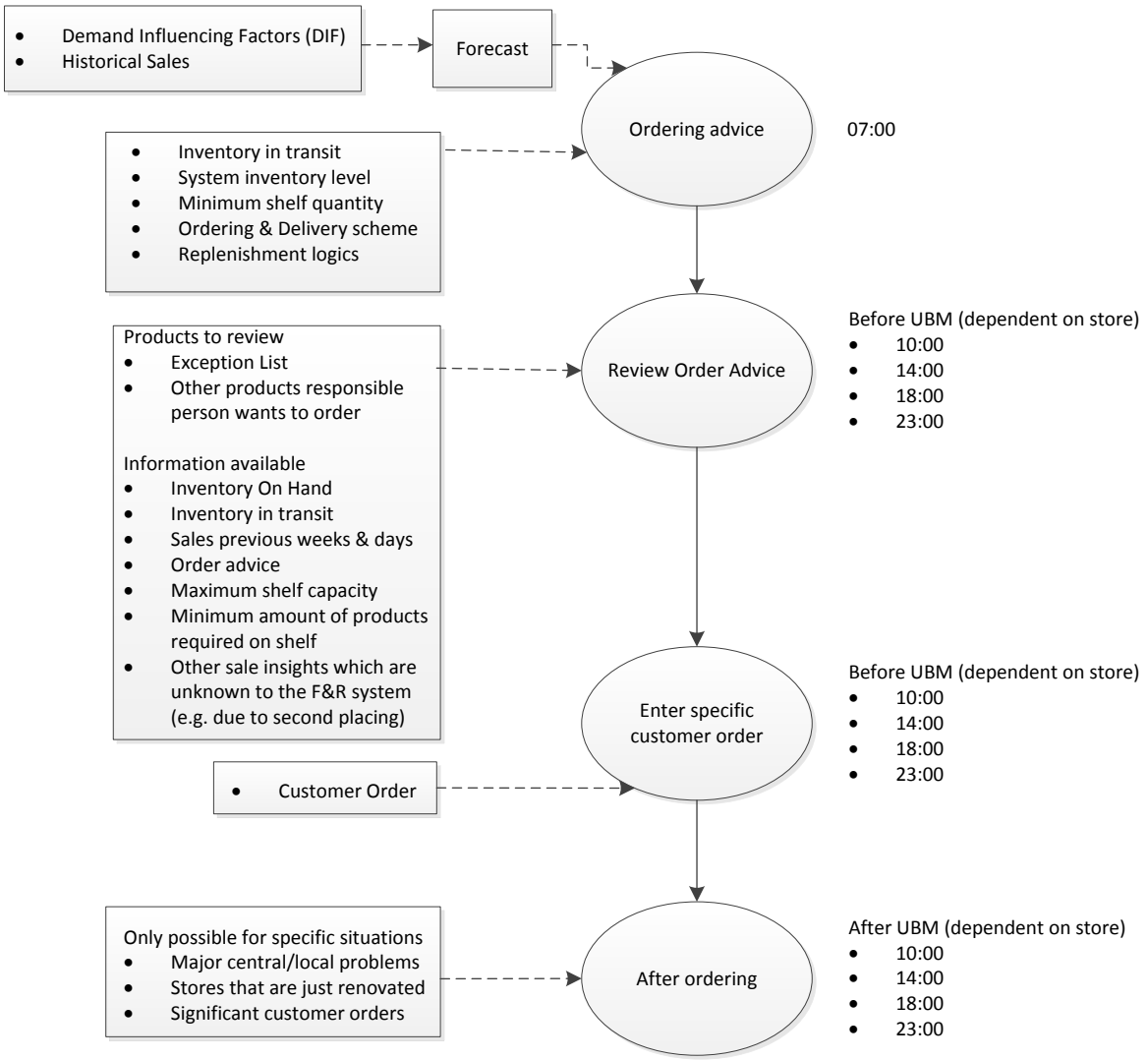

Figure 1: Jumbo's ordering Process

The first step for F&R (Forecasting & Replenishment) is to establish the order advice. Note that Jumbo's ASO system is called F&R and these terms are therefore used interchangeably. The order advice is dependent on the forecast and some other product-store specific information (as can be seen in Figure 1). Important note here is that the term ''system inventory level'' is used, since it is likely that, the inventory levels indicated by the system differ from the inventory levels in the store (DeHoratius & Raman, 2008). One can define the ''system inventory level'' as the inventory level indicated by the

system. Another matter that one should take into account is that the forecast itself is also dependent on some specific information. Final remark regarding the ordering advice is that it becomes available at 07:00 for all stores and for all F&R products[2].

The second step is that the reviewer (a store manager or any other staff member that is allowed to adapt order advices) has the possibility until their store specific UBM to manually adapt the order advice. The "Uiterste Bestel Moment" (UBM) can be defined as the latest time a store has the possibility to adapt an order advice. A store manager should always review an exception list, this is a daily list where the system basically tells ''I have not enough information to give a proper ordering advice for these products, so please check this manually''. These are typically new products, since for those products there is not enough historical sales data to establish a proper forecast. Besides the exception list, a store manager also has some other products he/she wants to review. These are typically local advertisement products or products on second placing. Local advertisement products are those products for which the promotion is not centrally managed. If a reviewer wants to adapt the order advice, he/she can just simply type another number on its PDA (see the selected number, ''384'', in Figure 2). The other information available for a store manager, as indicated by Figure 1, is also available via the PDA screen. An important note for this second step is that the store manager could have insights that the F&R system does not have. For example, a specific store can use second placing for some products which makes it very likely that products will sell more and that the minimum required inventory increases.

Figure 2: PDA screen where a store manager can change the order advice

The third step is all about a large customer order. If a customer wants, for example, 100 cans of sausages, a store needs to order this manually, since it is very unlikely it does have sufficient inventory on hand to fulfil this demand directly. So this is another way why the ordering advice can be adapted.

The fourth step is rare, but sometimes there are certain situations (see last step in Figure 1) where the store can adapt the order advices after its UBM.

1.4 Relevance For Jumbo

Order advices are created by an ASO system which recommends an order quantity per SKU for every order cycle (van Donselaar, Gaur, van Woensel, Broekmeulen, & Fransoo, 2010). Jumbo is currently implementing a new and improved ASO system called F&R.

The actual order at the store is usually the same as the order advice. However, based on numbers of this year (2018), the acceptance percentage of the total assortment is around 91%. In other words, around 9% of all orders lines are manually adapted by the stores. The week before Easter however, the overall acceptance percentage dropped to 87%. This is a trend that Jumbo typically experiences: during holidays, promotions, or any other demand influencing events the order acceptance level drops significantly. A probable reason for this is that the order advices become more inaccurate, because it is known that forecasts become more inaccurate during promotions (Ali, Sayın, van Woensel, & Fransoo, 2009). Because of this inaccuracy, people lose their trust in the ASO system and are more inclined to adapt the order advice.

One important problem that Jumbo experiences with these acceptance levels is that stores spend a lot of time with checking and adapting these order lines. On the other hand, Jumbo has no clear insight in

[2] F&R products:. Those products that get an ordering advice by the new Forecasting and Replenishment system. This thesis will only focus on the assortment for which an ordering advice is generated by F&R (i.e., the F&R products). In the scope (section 2.3) these relevant product groups are specified.

whether these manual order adaptions increase the quality of the order advice or decrease it. This Master Thesis provides insights whether and which order adaptions increase the quality of the order advice.

Another reason why this Master Thesis is relevant for Jumbo is because the Master Thesis will conclude with suggestions to narrow the gap between automatic orders and actual orders. This is important because the automatic generated orders become then more trustworthy. Jumbo wants this data to be trustworthy since this information could, for example, be shared with suppliers (e.g., Unilever) so that they can adapt their production to it. This data sharing could lead to substantial improvements within the supply chain on the following aspects; uncertainty, bullwhip effect, inventory levels, and forecasting accuracy (Aviv, 2001; Costantino, Di Gravio, Shaban, & Tronci, 2015; Disney & Towill, 2003; Kelepouris, Miliotis, & Pramatari, 2008; Lee, So, & Tang, 2000; Titah, Shuraida, & Rekik, 2016).

In short, this thesis is relevant for Jumbo since:

- It provides new insights in when and which order adaptions are likely to add value;
- It quantifies reasons why store managers adapt order advices;
- It states recommendations on how to close the gap between order advices and actual orders.

2 Research Design

As discussed in the Introduction (Chapter 1), Jumbo experiences challenges with their newly implemented ASO system. Core of these challenges is the difference between automatic generated order advices and actual order advices. These differences are problematic, because they lead to extra work in the stores, interrupt the supply chain, and could decrease the order quality.

To deal with these challenges, this section translates these challenges into a research question and sub research questions.

2.1 Main Research Question

The main research question is defined as follows:

How could Jumbo narrow the gap between their actual and automatically generated orders?

Note that during the entire thesis it was kept in mind that it is not by definition beneficial to close this gap.

2.2 Sub Research Questions

To give an extensive and complete answer to the main research question, the following sub research questions were defined:

1. For which reasons do store managers deviate from the automatically generated orders?
2. Are there typical product characteristics or other characteristics (e.g., case pack size, perishability, price, or weather conditions) that could explain the difference between actual and automatic generated orders? If so, what are these characteristics?
3. If there are product characteristics or other characteristics identified at the previous sub question, how does this influence the difference between actual and automatic orders?
4. How could possible improvements and practical knowledge be integrated into F&R?
5. After identifying possible improvements; what is the added value per improvement and where is this improvement most effective?

Finally, sub research questions will be added to define a gap in the literature that this research ought to fill.

Van Donselaar, Gaur, van Woensel, Broekmeulen, and Fransoo (2010) investigated how the ordering behaviour of store managers influences the ASO system. However, their scope of SKUs excluded perishables. This Master Thesis also focussed on a major part of perishables within Jumbo's assortment. Besides that, they indicated that comparing order advices and actual orders could be used to gain new insights in the performance of store managers which is something that is investigated in this Master Thesis. Therefore, sub research questions 6 and 7 are defined as follows:

6. Are similar results found for perishables compared to non-perishables for the following aspects:
    - Shifting orders from peak to non-peak days
    - Products characteristics that drive this behaviour (if the shifting is notified)
7. Comparing the order advice and actual order, which of the two is a better prediction for actual demand? In other words, is the reviewer able to outperform the F&R system?

2.3 Scope

To keep the amount of data manageable, it was decided to collect data from 50 stores from week 13 until week 23. These 50 stores were chosen so that the UBM for their entire assortment was 10:00. Why the requirement for this specific UBM was chosen, will be discussed in more detail during section 4.3. Besides these 50 stores, the scope is further narrowed to focus only on those product categories that were already implemented on F&R. The product categories that are therefore included in this Master Thesis are (note that the Dutch translation of these product categories is given between brackets):

- Sweets (Zoetwaren)
- Grocery Goods (DKW)
- Dairy and Eggs (Zuivel en Eieren)
- Freezer Goods (Diepvries)
- Cosmetics (Cosmetica)
- Pre-packaged meat and salads (Vvp Vleeswaren/Salades)
- Wine and off-license shop (Wijn en Slijterij)
- Other non-food goods (Overig non-food)
- Pre-packed cheese (Kaas Verpakt)
- Beer/Soda/Juice (Bier/Frisdrank/Sap)
- Meat Service (Vleeswaren Bediening)
- Bread (Brood)
- Service Articles (Service artikelen)
- Potato/Vegetable/Fruit (A.G.F.)
- Cheese of the knife (Kaas van het Mes)
- Convenience (Convenience)
- Local Sale (Lokale Aktie)

To create the complete picture, one should be aware that there are currently two product categories in a F&R pilot. That is, in a small amount of stores these product categories are currently being tested on F&R. It is decided to keep these product categories completely out of scope for chapter 4, but to include them in the analysis in chapter 3. This is decided, since the required data that is required for chapter 4 was not completely available and trustworthy for these two product groups. The two product categories that are currently in a pilot are:

- Butcher (Slagerij)
- Fish (Vis)

Note that for similar reasons (i.e., required data is not trustworthy), the product groups meat service and cheese of the knife are held out of scope for chapter 4. Main reason for this unreliable data is that the products are weight articles which means they do not sell per piece but per gram. Therefore, it was decided to keep all weight articles out of scope for chapter 4. More information on this is given in chapter 4.

Besides the product categories butcher and fish, the product category tobacco is also held out of scope. Tobacco is already completely integrated within F&R, but it is kept out of scope, since there were some serious disruptions between F&R and the products that belong to the product category tobacco. Therefore, the data regarding this product category is not trustworthy and it was necessary to completely exclude this product category for the analysis.

2.4 Set Up Of The Report

To answer the main research question, Chapter 3 discusses the interviews to determine the most important reasons for order adaptions. Besides that, Chapter 3 discusses also the logistic regression which was performed to check whether there is quantitative evidence to support the findings of the interviews. Chapter 3 concludes with a discussion whether there are also other characteristics (e.g., case pack size or perishability) that correlate with the probability that an order advice will be adapted. After that, Chapter 4 discusses whether these order adaptions add value or not. Chapter 5 combines the findings from Chapter 3 and Chapter 4 where after Chapter 6 states the recommendations. This Master Thesis report concludes with the specific answers per sub-research question in Chapter 7 and recommendations for further research in Chapter 8.

3 Deviations From The Automatically Generated Orders

As explained in section 1.2, Jumbo experiences differences between their order advices and actual replenishment. The two most important problems caused by these differences are 1) more work for the stores, since they adapt these order advices manually and 2) data shared throughout the supply chain is not trustworthy which stimulates, for example, the bullwhip effect. For a more detailed discussion on these problems, see section 1.4.

This chapter discusses, both from a qualitative (section 3.1) and a quantitative (section 3.2) point of view, why store managers adapt order advices and how this could be explained. After that, section 3.3 combines insights from both analyses (i.e., do findings from the qualitative and quantitative analysis support each other).

3.1 Qualitative Research

3.1.1 Interviews for data collection

The qualitative part consists of interviews at ten different stores. In total, around 1200 order adaptions were discussed with store managers. The procedure for these interviews was as follows:

1. Selection of the stores was based on their willingness to participate and the possibility to visit.
2. Once a store was selected, a list with all order adaptions of the previous week was created.
3. At the store, this list with order adaptions was then discussed in order to discover the motives for these order adaptions. Basically, the list with order adaptations was discussed per order line with the responsible person for this order adaptions.

Note that it was not possible to discuss the entire list of order adaptions due to practical limitations. These practical limitations were as follows:

- Not all responsible persons for every order line were present at the store during the time of the visit.
- The responsible person did not have enough time to discuss all order adaptions. This makes sense, since, on average, one store has approximately 500 - 600 order adaptions per week.
- Although, the order adaptions were of the previous week it is understandable that the responsible person could not remember the motivation for each and every order adaption.

Consequence of these practical limitations is that the interviews are not necessarily representative for all order adaptions in general. This because some product categories are overrepresented and some are underrepresented. In Figure 3, one can see how much more or less a product category is represented during the interviews than in reality. For example, of all order lines that were reviewed during the interviews, approximately 24% of the product category beer/soda/juice, while in reality this product category represents only 11% of all order adaptions. Therefore, it is likely that the exact percentages presented in this section are not completely representative. However, it is still a good indication of what are important motivations for the stores to adapt their order advices.

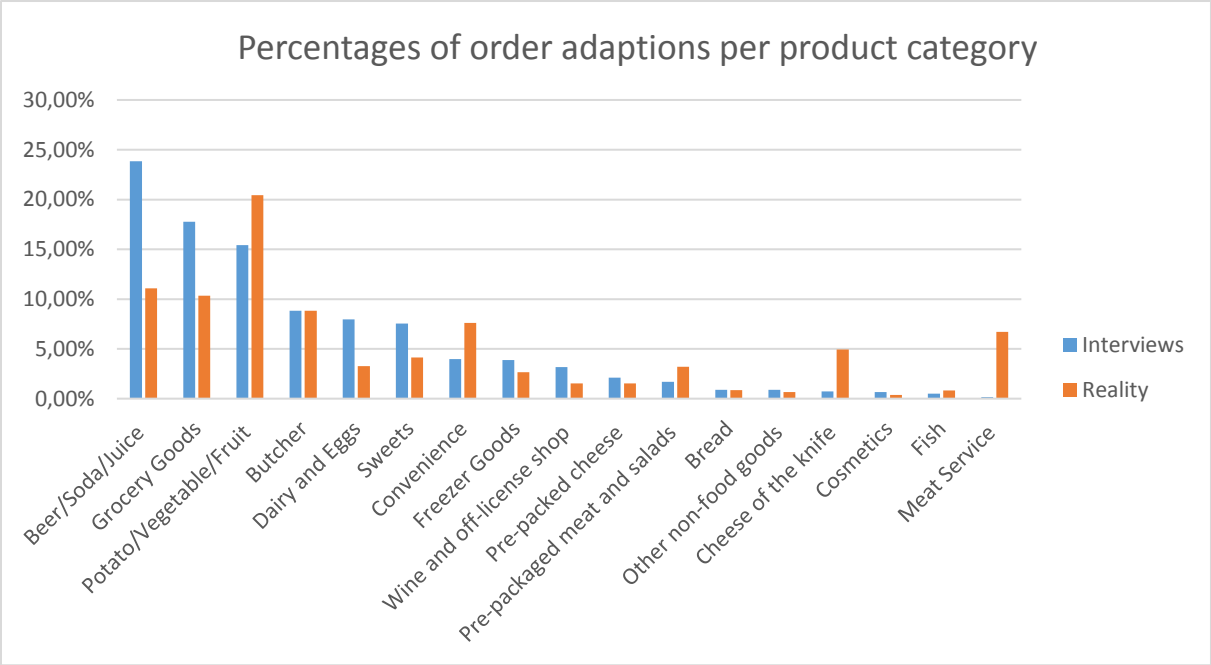

Figure 3: Proportion of representativity per product category for the interviews and in reality

During the interviews and discussions of the order adaptions, a separate list was presented with possible motives to adapt an order advice. This list is basically an enumeration of every reason that was noted why one could adapt an order advice. These reasons were discovered during informal discussions with the stores and employees at Jumbo's headquarters. These possible motives for adapting order lines are as follows (note that it is also possible that one chooses more than one reason for an order adaption):

1. Sudden weather change
2. Product is in central promotion
3. Local event at the specific store (e.g., funfair, road construction, or closing/opening of a competitor)
4. Improving store view (i.e., the store wants more inventory to give the store a more attractive view)
5. Local actions (i.e., store promotes a product locally)
6. Second placing
7. Inventory corrections
8. Promotions by competitors
9. Product is new in the assortment
10. Cannibalization (i.e., once a product, is in promotion it is likely that another similar product, which is not in promotion, is going to sell less)
11. Product does not fit on the shelf
12. Too many products of the entire product group together
13. Anticipating on perishability (The person who can adapt the order advice has the possibility to check the perishability date of the products that are on stock while F&R does not have this knowledge. Once he or she notices that a lot of the inventory will be thrown away, he or she can anticipate on it by increasing the ordering advice.)
14. Signing in for promotions (Stores need to order promotional products several weeks before the promotion actually starts. However, in practice stores are reluctant to do this, since this reduces the flexibility of the store. Most stores prefer to increase the order advice manually just a few days before the promotion starts. This has a, possible, positive effect for the store but a negative effect for the supply chain)

15. Product is out of stock
16. The store manager estimates that the inventory will not be enough to fulfil all the demand
17. High probability that product will perish
18. Changing shelf layout
19. Deficiency (i.e., product is out of stock at the DC)
20. Customer order (a specific customer order; for example, 100 crates of beer which then need to be ordered manually due to the large quantity)
21. Other reason

3.1.2 Results on highest aggregation level (i.e., no differentiation between product groups)

The five most important motives, according to the interviews, for order adaptions can be seen in Table 1. These five motives count for 76% of all discussed order adaptions. For the total distribution of all motives one can go to "Appendix A: Distribution For Motives Of Order Adaptions". It is decided to only show the top five here, since the sixth largest reason counts for only 3%.

Reason(s)	**Percentage**
Product is in central promotion and on second placing	19%
Improving store view	19%
Sudden weather change	15%
Second placing	12%
Inventory corrections	11%

Table 1: Most important motives for order adaptions regarding all product groups

As one can see in Table 1, there are five important reasons why store managers adapt order advice. These five reasons are a good starting point from where to start with possible improvement suggestions to integrate practical knowledge into F&R. Also note that second placing comes back twice; once with a central promotion and once without. Therefore, one can conclude that, according to the interviewed stores, second placing is an important reason why stores adapt order advices. Finally, one should take into account that the interviews were held during a period where the temperature suddenly increased. Therefore, it is likely that the reason "sudden weather change" is overestimated.

3.1.3 Results for items with a long perishability

The previous section (3.1.2) accumulated all product groups. However, to gain extra insights it is decided to make a distinction between product groups. To make this distinction, this section only focusses on product groups with a long perishability while section 3.1.4 focusses on product groups with a shorter perishability. For Jumbo, the relevant product groups with a long perishability are the following:

- Beer/Soda/Juice (40%)
- Cosmetics (1%)
- Freezer goods (7%)
- Grocery goods (30%)
- Other non-food goods (2%)
- Wine and off-license shop (5%)
- Sweets (12%)
- Bread[3] (3%)

In total, approximately 700 of the 1200 adapted order lines belonged to one of these products groups. The percentages after the product group name indicate which percentage that specific product group is represented in those 700 order adaptions. Also note that these percentages cannot be used to conclude anything about how much more or less a product group is adapted compared to another one,

[3] Note that this is pre-packed bread and not fresh bread.

since, as one can see in Figure 3, the interviews are not entirely representative. In Table 2 one can see the most important motives for order adaptions when only product groups with a long perishability are taken into account.

Reason(s)	Percentage
Product is in central promotion and on second placing	23%
Improving store view	18%
Second placing	17%
Inventory corrections	14%
Sudden weather change	9%

Table 2: Most important motives for order adaptions regarding the product groups with a long perishability

The next section consists of a similar analysis for product groups with a shorter perishability. After that, section 3.1.5 elaborates in more detail on the differences between the results for product groups with a long and short perishability.

3.1.4 Results for items with a short perishability

Now that the results for product groups with a long perishability have been presented, this section presents the results for product groups with a shorter perishability. For Jumbo, these are the following product groups:

- Potato/Vegetable/Fruit (36%)
- Convenience (10%)
- Cheese of the knife (2%)
- Pre-packed cheese (5%)
- Butcher (21%)
- Fish (1%)
- Meat service (4%)
- Dairy and eggs (19%)
- Pre-Packaged meat and salads (2%)

Obviously, the resulting approximately 500 (1200 minus 700) order lines belong to these product groups with a shorter perishability. The percentages behind the product group names correspond, again, to the amount of which that product group is represented in that 500 order adaptions. In Table 3, one can see the motives and corresponding percentages for the most important motives why a store manager adapted the order line.

Reason(s)	Percentage
Sudden weather change	24%
Improving store view	19%
Product is in central promotion and on second placing	13%
Anticipating on perishability	7%
Second placing	6%
Inventory corrections	6%

Table 3: Most important motives for order adaptions regarding the product groups with a lower perishability

3.1.5 Differences between product groups

Sections 3.1.2, 3.1.3, and 3.1.4 discussed, according to the interviews, the most important motives for order adaptions. Section 3.1.2 discussed this for all product groups, section 3.1.3 focussed on products groups with a long perishability while section 3.1.4 focussed on product groups with a shorter perishability. These results are combined and presented in Table 4.

Reason(s)	All Product groups	Long perishable product groups	Short perishable product groups
Product is in central promotion and on second placing	19%	23%	13%
Improving store view	19%	18%	19%
Sudden weather change	15%	9%	24%
Second placing	12%	17%	6%
Inventory corrections	11%	14%	6%
Anticipating on perishability	3%	0%	7%

Table 4: Most important motives for order adaptions regarding the different product groups sets

The most important observations from Table 4 are as follows:

- The difference between second placing for long perishable product groups and short perishable product groups is remarkable. Summing up the percentages for second placing; for long perishable product groups 40% (23% + 17%) of the order adaptions is caused by second placing while for shorter perishable product groups this is only 19% (13% + 6%). A similar difference holds for the inventory correction with 14% against 6%.
- According to these results, sudden weather change is more influencing for short perishable product groups compared to long perishable product groups. This observation can be made by comparing the percentages for sudden weather change in the columns for long and short perishable product groups. For short perishable product groups, 24% of the order adaptions is explained by sudden weather change compared to 9% for long perishable product groups. Cause for this could, for example, be that when the temperature rises customers demand more fresh products. This increase in demand is typically caused by customers that want to have a barbecue. During the period these interviews were held, the temperature was for the first time in the year good enough to barbecue which caused a lot of customers wanting to barbecue. As a consequence, customers are demanding more fresh products which led to more adaption in the order advices, since stores wanted to have enough for this demand peak. F&R should take this peak, that is caused by changing temperatures, into account but apparently, stores do not have enough trust in F&R regarding this subject. Note that this is also a good illustration of why it is relevant for Jumbo to know whether order adaptions add value or not. If this is known, appropriate advices to stores or forecasters could be given about how to improve their activities.
- Anticipating on perishability is a substantial reason for short perishable product groups (i.e., 7%), but for long perishable product groups this is not a factor at all (0%). This is logical due to that perishability is especially a problem for products with a shorter perishability.

3.2 Quantitative Research

Contrary to section 3.1 this section answers if and how order adaptions could be explained from a quantitative point of view. In other words, are there certain factors that have an influence on the probability that an order advice will be adapted? After the quantitative analysis is discussed, the results will be combined with the results of the qualitative analysis in section 3.3.

3.2.1 Remarks about used data.

Before discussing the actual analysis, this section discusses the modifications that were made to the initial dataset.

- Data with an incremental order quantity (IOQ) greater than or equal to 60 were excluded. This to ensure that weight articles are excluded. One wants to exclude weight articles, since the IOQ of these products is given in grams while the rest of the SKUs are given in consumer units. Weight articles are mainly represented in two product categories which are “Cheese of the knife” and “Meat service”. Together they count for approximately 93% of all observations that

were excluded, because they are a weight article (i.e., have an IOQ greater than or equal to 60). For the product group cheese of the knife, approximately 36% of the observations were excluded and for meat service approximately 72%. Therefore, one should be aware that the presented results for these two product categories are not completely representative.

- Some order advices were given on Sunday. Since this is not an official ordering day for stores they were excluded from the original data set. In total, approximately 0.01% of all orders were on a Sunday and, therefore, it is not expected that removing orders on Sunday affects the representativity of the data.
- Products with a minimum (system) perishability of 0 are converted to 999. This was done, since these were products without perishability, for example, a dishcloth or a sponge. This was done for approximately 3% of all observations.

The total initial dataset consisted out of 4,086,827 observations. After these modifications, 3,940,527 observations were left which were used to perform the actual analysis. So the cleaned dataset still consists out of approximately 96% of the initial observations which still seems a representative number of the initial dataset.

3.2.2 Binomial logistic regression

To analyse whether there are certain factors that have an influence on the probability that an order advice will be adapted, the binomial logistic regression technique was used. Note that it makes sense to use this technique, since the dependent variable consists of only two categories; 1) order advice adapted, 2) order advice not adapted. Two typical objectives of a binomial logistic regression are; 1) determine whether the independent variables have a significant effect on the dependent variable, 2) predicting the dependent variable. During this analysis the focus is on the first one, so are there certain factors that influence the probability that an order advice will be adapted. To carry out this binomial logistic regression analysis, an article of Laerd Statistics (2015) was mainly used. It was chosen to do this analysis in SPSS.

3.2.2.1 Assumptions binomial logistic regression

Before performing a binomial logistic regression one needs to be aware of the assumptions. During this section, these assumptions will be stated and, if already possible, discussed whether they are met.

The assumptions that should be met for a binomial logistic regression are as follows:

1. *There must be one dependent variable that has two possible outcomes*. This assumption is met due to the fact that the dependent variable is about whether an order advice is adapted or not. Therefore, there are two possible outcomes; 1) yes and 2) no.
2. *One should have one or more independent variables that ought to explain the dependent variable. Besides that, should these independent variables be measured on a nominal or continuous scale.* This assumption is met, since there are multiple independent variables and they are all measured on a continuous or nominal scale. See section 3.2.2.2 for a complete overview of the independent variables.
3. *All observations should be independent and nominal independent variables should be mutually exclusive.* Independence of observations is met, since an observation (an order advice) is adapted or not. So it could not be in both categories. Besides that, are all nominal independent variables mutually exclusive, since it is not possible that one observation belongs to multiple groups of one independent variable.
4. *The minimum amount of observations should be 50 per independent variable.* This is not a problem for this research, since there is enough data available. The dataset consists out of approximately four million observations.

Assumption 5, 6, and 7 are concerned with how the data fits the binomial logistic regression model. These assumptions can only be tested by actually analysing the data in SPSS. Therefore, these

assumptions will be tested and discussed during the analysis part (section 3.2.2.3). These three assumptions are as follows:

5. *The continuous independent variables should have a linear relationship with the logit transformation of the dependent variable.*
6. *There should be no multicollinearity (i.e., there is no linear relationship between two or more independent variables).*
7. *In the data set there are no significant outliers, leverage or influential points.*

3.2.2.2 Set-up of the analysis

The binomial logistic regression has been set up with the following logic:

$$\ln(Y) = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9 + b_{10}X_{10} + b_{11}X_{11} + e$$

Where Y is the dependent variable (DV) (i.e., is the order advice adapted or not), b_0 is the intercept, e represents the sample errors, b_1 is the slope of the first independent variable (IV), b_2 the slope of the second IV and so forth. As said before, the DV is about whether the order advice is adapted or not. This DV is chosen, since Jumbo wants to have insights in whether there are characteristics that systematically influence the probability that an order advice will be adapted. By taking interviews at the stores, section 3.1 answers this from a qualitative point of view while this section (3.2) analyses whether these reasons could also be explained from a quantitative point of view. Besides the reasons that were discovered during the qualitative research, also some other, possible, reasons for order adaptions will be introduced and tested as an IV. This section continues by introducing these IVs and why they were chosen:

1. X1 = Day of the week: This IV is included in the analysis to check whether store managers are more likely to adapt order advices on a specific day. Besides that, by introducing this IV the extent of order advancement could be explored. Van Donselaar et al. (2010) concluded that order advancement is an important reason for store managers to adapt an order advice. F&R should already apply order advancement to balance the workload in the stores more evenly. Therefore, it could be interesting to analyse whether store managers still show signs of order advancement. During the interviews at the stores it was asked several times whether order advancement is still an issue, but the answer, unanimously, was “no”. Thus, it is expected that order advancement is not an issue anymore for Jumbo.
2. X2 = Second Placing: The interviews revealed that, according to the interviewed store managers, second placing is an important reason to adapt the order advice. This claimed importance will be tested by making whether a product should be on second placing an IV.
3. X3 = Inventory Mutation: An ASO system uses, among others, the system inventory to determine how much it should order (van Donselaar et al., 2010). So the system inventory is important for an ASO to function properly. However, DeHoratius and Raman (2008) indicate that inventory record inaccuracy is a real problem for retailers and they found that around 65% of the inventory records are inaccurate. If a store manager notices that this system inventory does not match with the actual inventory, the store manager should correct this by making an inventory mutation. This inventory mutation makes it likely that the order advice is not accurate, since the ASO system did not get accurate input data. The store manager knows this and can react to this by making an order adaption. Therefore, it is expected that inventory mutations trigger an order adaption. To test this hypothesis, X3 is included as an IV in the regression analysis.
4. X4 = Promotions: Promotions are identified as a factor that makes it more difficult to create an accurate forecast (Ali et al., 2009). This could trigger a store manager to adapt the order advice, since for these order advices it becomes more likely that the store manager sees F&R making errors. Seeing an algorithm making errors is an important reason for algorithm aversion (B. Dietvorst, Simmons, & Massey, 2015) which will lead to

more adapted order advices. Therefore, it is expected that promotional products are adapted more frequently compared to products that are not.

5. X5 = Franchise or Affiliate: This is included as an IV, since during interviews at the stores a different way of working was noted. In essence, this makes sense since a franchiser runs his/her operations to maximize its own profit while an affiliate runs his/her operations to score good on its KPIs. To investigate whether this different way of working also influences the behaviour regarding order adaptions, X5 is included as an IV.
6. X6 = Ratio Incremental Order Quantity[4] to daily sales[5]: To determine how much it should order an ASO system uses, among others, the case pack size (van Donselaar et al., 2010). Besides that, is the case pack size of a product identified as a factor that has a significant impact on distribution logistics efficiency (Wensing, Sternbeck, & Kuhn, 2018). Therefore, it is decided to include X6 as an independent variable into the regression analysis. It is also decided to reflect the IOQ against the daily sales, since this gives more insight than just the IOQ by itself. This IV is also based on van Donselaar et al. (2010), they introduce the term "case pack cover" which is simply the ratio of case pack size over weekly sales.
7. X7 = Minimum Shelf Life[6]: Perishability is widely recognized as a factor that causes significant challenges regarding inventory control (Damgaard, Nguyen, Hvolby, & Steger-Jensen, 2013). Besides that, identified Kiil et al. (2018) products with a short shelf life as those products where an ASO system has the lowest or even a negative effect. Another reason to include X7 as an IV in the analysis is that during the interviews it was found that store managers could also adapt the order advice to anticipate on the perishability. Therefore, it is expected that order advices for products with a shorter minimum shelf life are more frequently adapted.
8. X8 = Price: During interviews it was noted that some store managers gave SKUs with an extreme high price extra attention to check whether they think the order advice is correct. This was only the case in a few stores and for a few products (e.g., baby powder) so it is not expected that the price of a product has a big effect on whether an order will be adapted. However, the price per SKU is easily retrievable from Jumbo's database which made it easy to check whether the price correlates with the probability than an order advice will be adapted.
9. X9 = Temperature Difference with yesterday: This IV is added, since during the interviews it was frequently noted that the reason to adapt the order advice was a sudden temperature change. Therefore, it is expected that stores adapt more if the temperature difference with yesterday is high. Note that F&R should already take differences into account. However, based on the interviews, it could be that stores are not aware or confident about how F&R deals with it.
10. X10 = Maximum Shelf Capacity compared to daily sales: Store managers at the stores frequently indicated that they could also adapt the order advice to increase the store view. In other words, they say that the shelf capacity is too high for that specific product. The reason that F&R does not give an automatic order advice to proper fill the shelf is that it does not expect enough sales. Therefore, there could be a correlation between the "maximum shelf capacity compared to daily sales" and the probability an order line will be adapted. To check for this correlation, X10 is added to the analysis.
11. X11 = Backroom Capacity: As indicated by Eroglu, Williams, & Waller (2013) backroom operations are crucial for a retail store. A cluttered backroom creates disorder for the inventory management of that specific store. For example, a specific shelf might be empty while there might still be products in the backroom without anyone knowing it. If the store

[4] Incremental Order Quantity: The minimum amount of consumer units that an order should be increased. Note that this is not necessarily the same as the case pack size.
[5] Daily sales is an average of the POS per day from 26th of March until the 7th of June
[6] Minimum Shelf Life: This is the minimum shelf life when a product arrives at the store.

manager has no clear view of the backroom he/she could adapt the inventory, because he/she cannot find the inventory that is indicated by the system and therefore thinks it is not in the store. This makes it assumable that cluttered backroom operations increase the need to adapt an order advice. Besides that, it is assumable that a larger backroom makes it easier to manage the backroom products properly. Therefore, it is hypothesized that stores with a larger backroom are less inclined to adapt the order advice. This hypothesis will be tested by introducing X11 an IV.

In short, the DV is whether the order advice is adapted and the IVs are as follows:

1. X1 = Day of the week
2. X2 = Second Placing
3. X3 = Inventory Mutation
4. X4 = Promotions
5. X5 = Franchise or Affiliate
6. X6 = Ratio Incremental Order Quantity to daily sales
7. X7 = Minimum Shelf Life
8. X8 = Price
9. X9 = Temperature Difference with yesterday
10. X10 = Maximum Shelf Capacity compared to daily sales
11. X11 = Backroom Capacity

3.2.2.3 Assumption testing

Before performing the actual regression analysis, there are still three assumptions (5, 6 and 7) that should be checked. Therefore, this section discusses these assumptions.

5. *The continuous independent variables should have a linear relationship with the logit transformation of the dependent variable.*

To test this assumption, it was decided to use the Box Tidwell approach (Box & Tidwell, 1962). The results of this approach are given in Table 5. In short, to perform the Box Tidwell approach one needs to determine the natural log transformations for all the *continuous* independent variables. After that, an interaction term for each continuous variable and their log transformed variable should be created. Note that these interaction terms are given Table 5. Once these interactions terms are created, one should run the binomial logistic regression with all original independent variables and the created interaction terms. Finally, one should check whether these interaction terms are statistically significant. If an interaction term is statistically significant, then the IV does not have a linear relationship with the dependent variable and does it fails assumption 5

Interaction Term	B	Standard Error	Significance
X6[7]: Ratio Incremental Order Quantity by Ln(Ratio Incremental Order Quantity)	0.000	0.000	0.000
X7: Minimum Shelf Life by Ln(Minimum Shelf Life)	0.003	0.000	0.000
X8: Price by Ln(Price)	-0.060	0.001	0.000
X9: Temperature Difference with yesterday by Ln(Temperature Difference with yesterday)	0.028	0.003	0.000
X10: Maximum Shelf Capacity to daily sales by Ln(Maximum Shelf Capacity to daily sales)	0.000	0.000	0.000
X11: Backroom Capacity by Ln(Backroom Capacity)	-0.002	0.000	0.000

Table 5: Results of the Box Tidwell approach. Note that only the continuous IVs are included.

As one can conclude from Table 5, all interaction terms are highly significant which indicates that the independent variables are not linearly related to the logit of the dependent variable. This implies that the assumption is violated for these six continuous independent variables. However, it is important to note that this could be caused by an overpowered dataset. Sakai & Tetsuya (2016) define overpowering as the effect of finding significant differences for even very weak relations, caused by large sample sizes (note that the sample size for this logistic regression analysis has around 4 million observations). This effect of overpowering was also confirmed by Sarah Gelper, who is an expert in this area and an Assistant Professor at the TUe. Therefore, one could doubt whether this assumption is really violated, since the high significance levels could also be caused by an overpowered dataset. However, for the remainder of this logistic regression analysis it is assumed that this assumption is violated, but one should keep in mind that these extreme significance levels could be caused by an overpowered dataset.

To ensure that this assumption is not violated, it is decided to transform these six continuous independent variables into categorical variables. By doing this, there are no continuous IVs anymore which ensures this assumption always holds. It is defendable to transform these variables like this, since the goal of this regression analysis is to gain insights in which characteristics increase or decrease the probability that an order advice will be adapted. In other words, the goal is to conclude, for example, that products with an higher price are more likely to be adapted and not that one euro increase in price leads to a certain extra probability that the order will be adapted. For the exact details on the grouping of these continuous independent variables can one go to "Appendix B: Grouping Of Independent Variables"

In short, all IVs are categorical variables which ensures that assumption 5 holds. These categorical IVs are as follows, note that the possible categories per category are given between brackets.

1. X1 = Day of the week (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday)
2. X2 = Second Placing (Yes, No)
3. X3 = Inventory Mutation (Yes, No)
4. X4 = Promotions (Yes, No)
5. X5 = Franchise or Affiliate (Franchise, Affiliate)
6. X6 = Ratio Incremental Order Quantity to daily sales (0-1 , 1.01-3 , 3.01 – 10, >10)
7. X7 = Minimum Shelf Life (1-8 days, 9-28 days, > 28 days)
8. X8 = Price (€0 - €1, €1.01 - €3, >€3)
9. X9 = Temperature difference with yesterday (0°C - 2°C, 2.01°C - 3°C, > 3°C)
10. X10 = Maximum Shelf Capacity compared to daily sales (0-3, 3.01-10, >10)

[7] X6: Here is X6 written down to indicate that this is the interaction term of independent variable 6. The same holds for X7, X8, X9, X10 and X11

11. X11 = Backroom Capacity (0-150m^2, 151-250m^2, >250m^2)

6. *There should be no multicollinearity (i.e., there is no linear relationship between two or more independent variables).*

To check whether this assumption holds one should check for multicollinearity. To check for multicollinearity, VIF values are determined for every independent variable. Hair, Anderson, Tatham and Black (1995) discussed that, for this assumption to hold, the maximum VIF level is 10. As one can see in Table 6, all VIF values are very low which makes it likely, that for this logistic regression analysis, the assumption of no multicollinearity holds.

Independent Variable	**VIF value**
X1: Day Of The Week	1.037
X2: Second Placing	1.006
X3: Inventory Mutation	1.002
X4: Promotions	1.006
X5: Franchise or affiliate	1.215
X6: Ratio Incremental Order Quantity to daily sales	2.130
X7: Minimum Shelf Life	1.119
X8: Price	1.016
X9: Temperature difference with yesterday	1.034
X10: Maximum shelf capacity compared to daily sales	2.066
X11: Backroom Capacity	1.214

Table 6: VIF values per independent variable

7. *In the data set there are no significant outliers, leverage or influential points.*

Final assumption to check is whether there are significant outliers, leverage or influential points. To detect possible outliers, studentized residuals were determined by using SPSS. Laerd Statistics (2015) advice to investigate observations where the studentized residuals are higher than 2.5. Following this advice, there were several observations inspected, but by doing this it came forward that they were all observations where the order advice was adapted. This could explain the high studentized residual levels, since an order advice is adapted for only 9% of all observations. However, adapting the order advice does, off course, not mean that it is an outlier (it is just an event that does not happen frequently). Therefore, it was decided to not remove any observations. Note that possible outliers already could have been deleted, since the data already has been cleaned (see also section 3.2.1).

3.2.2.4 Binomial regression results

Now that all assumptions have been discussed and explained, one can start with the actual binomial logistic regression. This section will start the discussion with which independent variables correlate with the dependent variable. Subsequently, the model will be evaluated by how much of the variance in the dependent variable can be explained by it. Finally, there will be a discussion on how different factors influence the probability that an order advice is adapted. This final discussion is important, since all correlations that were found are highly significant which is likely caused by the overpowered dataset as discussed in section 3.2.2.3. To overcome, possible, problems caused by this overpowered dataset and to make the interpretation more easily, the probabilities for order adaptions are discussed directly.

3.2.2.4.1 Exponential values per parameter

Let's start the discussion with the independent variables and their exponents. The "Exp(B)" value represents the multiplication factor, compared to the baseline group, for the probability that an order line is adapted. Note that baseline group and the exponential component are also included in Table 7. For example, an order on Monday is 1.095 times more likely to be adapted compared to an order on

Saturday and an order for a product with a minimum shelf life of 1 -8 days is 2.619 times more likely to be adapted compared to an order for a product with a minimum shelf life greater than 28 days.

Independent Variable	Category	Exp(B) value	Baseline Category	Significance level
Day Of The Week	Monday	1.095	Saturday	0.000
	Tuesday	1.207	Saturday	0.000
	Wednesday	1.145	Saturday	0.000
	Thursday	1.308	Saturday	0.000
	Friday	1.171	Saturday	0.000
Second Placing	No	0.286	Yes	0.000
Inventory Mutation	No	0.217	Yes	0.000
Promotions	No	0.510	Yes	0.000
Franchise or affiliate	Franchise	1.040	Affiliate	0.000
Ratio Incremental Order Quantity to daily sales	0-1	2.255	> 10	0.000
	1.01-3	1.187	> 10	0.000
	3.01-10	0.865	> 10	0.000
Minimum Shelf Life	1-8 Days	2.619	> 28 Days	0.000
	9-28 Days	1.760	> 28 Days	0.000
Price	€0-€1	0.459	> €3,-	0.000
	€1.01-€3	0.562	> €3,-	0.000
Temperature Difference with yesterday	0°C - 2°C,	1.095	> 3°C	0.000
	2.01°C - 3°C	1.030	> 3°C	0.000
Ratio Maximum Shelf Capacity to daily sales	0-3	1.611	> 10	0.000
	3.01-10	1.110	> 10	0.000
Backroom Capacity	0-150m^2	1.253	>250m^2	0.000
	151-250m^2	1.471	>250m^2	0.000

Table 7: Results binomial logistic regression

Using Table 7, one can get many insights. For example, franchisers are more likely to adapt an order advice, fresh products are more likely to be adapted, products with a low ratio between incremental order quantity and daily sales are more likely to be adapted etc. Besides that, all correlations seem, at first sight, highly significant. However, one should be aware that an overpowered dataset is likely to give very high significance levels even if the relationship is weak (see also section 3.2.2.3). To take this into account, section 3.2.2.4.3 contains a detailed discussion on how several variables impact the direct probabilities for order adaptions.

Furthermore, one should note that the IVs “ratio incremental order quantity to daily sales” and “maximum shelf capacity compared to daily sales” both depend on the daily sales. Therefore, it could be that, besides the incremental order quantity and maximum shelf capacity, daily sales is also a factor that influences the probability that an order will be adapted. This hypothesis was tested by deleting the IVs “ratio incremental order quantity to daily sales” and “ ratio maximum shelf capacity compared to daily sales” while “daily sales” was introduced as IV into the logistic regression. It appeared that SKUs that sell more than 3 consumer units per day are, approximately, twice as likely to be adapted than SKUs that sell less than 3 consumer units per day (see also Table 8). This indicates, that store managers tend to focus on those products that are frequently being sold. One should take this fact into account when interpreting the IVs “incremental order quantity to daily sales” and “maximum shelf capacity compared to daily sales”, since they could also have such a high “Exp(B)” value due to daily sales and not because of the incremental order quantity or maximum shelf capacity. If one is interested in the exact logistic regression results when daily sales is being introduced as an IV, one can go to “Appendix C: Introducing Daily Sales As An IV”.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Daily Sales	0-3	0.078	2991
	>3	0.145	949

Table 8:Direct probabilities of adaption for daily sales divided in two groups

To analyse the impact of daily sales into more detail it is decided to divide daily sales into three groups so that the largest group has approximately 250.000 observations. One can go to "Appendix D: Introducing Daily Sales As An IV With 3 Groups" for more details on this grouping and how the probabilities of the other IVs are affected by it. Most important finding of this extra analysis is that order advices of products that sell more than 8.6 consumer units a day are three times as likely to be adapted compared to products that sell less than 1 consumer unit per day (see also Table 9). Note that 8.6 consumer units is chosen as a bound such that the group with the largest daily sales consists out of approximately 250.000 observations. Therefore, this extra analysis clearly shows that sales of a product are heavily correlated with the probability that an order advice will be adapted. Note that the previous analysis showed that products that sell more than 3 consumer units are twice as likely to be adapted than products sell less than 3 consumer units. However, this analysis showed that there is only a small increase in the probability of adaption when a SKU sells on average 0-1 consumer units or 1-8.6 consumer units, but that there is a significant increase in likelihood when a products sells more than 8.6 consumer units per day. This finding indicates that store managers focus their attention, with respect to order adaptions, to those products that have higher sales.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Daily Sales	0-1	0.074	1578
	1.01-8.6	0.095	2113
	>8.6	0.214	248

Table 9: Direct probabilities of adaption for daily sales divided in three groups

Despite daily sales correlate with the probability for order adaption, it is decided to use the original regression analysis, as reflected in Table 7, for the remainder of this Master Thesis.

3.2.2.4.2 Explained variance of the model

To establish an insight in the completeness of the model, this section discusses what amount of the variance in the dependent variable is explained by the independent variables. For this, the Nagelkerke R Square was determined which had a value of 0.089. This indicates that 8.9% of the variance in the dependent variable is explained by the independent variables (Laerd Statistics, 2015). Preferably one wants to have a higher R square, but note that that the goal is not to create a model that can predict whether an order advice will be adapted. The main goal is to create insights in which independent variables have an effect on the dependent variable. Therefore, discusses the next section how several variables influence the probability that an order advice will be adapted.

3.2.2.4.3 Probability of adaption per independent variable

This section discusses the direct relation between the sub-categories per independent variable and the direct probabilities that an order advice will be adapted. These direct probabilities are discussed, since the dataset is large and therefore it is likely to be overpowered. The probabilities in this section represent the average probability, for a specific sub-category, that an order advice will be adapted.

Table 10 shows the average probabilities per subgroup for each independent variable. For example, based on these results one can argue that orders are most likely adapted on a Thursday (note that this corresponds with the findings from Table 7). When interpreting these results, one should be aware that they are not necessarily causal relationships.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Day Of The Week	Monday	0.089	570
	Tuesday	0.096	648
	Wednesday	0.095	643
	Thursday	0.107	721
	Friday	0.098	755
	Saturday	0.078	604
Second Placing	No	0.093	3907
	Yes	0.262	33
Inventory Mutation	No	0.093	3930
	Yes	0.401	10
Promotions	No	0.094	3936
	Yes	0.181	4
Franchise or affiliate	Franchise	0.101	2403
	Affiliate	0.084	1537
Ratio Incremental Order Quantity to daily sales	0-1	0.239	259
	1.01-3	0.125	943
	3.01-10	0.071	1545
	>10	0.068	1194
Minimum Shelf Life	1-8 Days	0.201	475
	9-28 Days	0.114	745
	>28 Days	0.070	2721
Price	€0-€1	0.076	857
	€1.01-€3	0.089	2410
	> €3,-	0.135	674
Temperature Difference with yesterday	0°C - 2°C,	0.098	1932
	2.01°C - 3°C	0.091	1290
	> 3°C	0.089	719
Ratio Maximum Shelf capacity to daily sales	0-3	0.225	251
	3.01-10	0.107	1509
	> 10	0.070	2180
Backroom Capacity	0-150m^2	0.094	1223
	151-250m^2	0.110	1419
	> 250m^2	0.076	1298

Table 10: Direct probabilities that an order is adapted per subcategory

Table 10 gives insights in the probability that an order advice is adapted purely based on the category for one independent variable. In other words, the probability that an order advice is adapted because it is on a Monday is 8.9% and for a Tuesday 9.6%. Table 10 differs from Table 7, because Table 10 discusses the direct probabilities that an order will be adapted while Table 7 discusses the relative frequency/likelihood an order will be adapted for one sub-category compared to the baseline category. For example, from Table 10 one can conclude that an order advice on Monday is adapted with a probability of 8.9% while one can conclude from Table 7 that an order on a Monday is adapted 1.095 times more likely than an order on Saturday.

One can establish several interesting insights from Table 10. For example, products with a shorter shelf life are more likely to be adapted, franchisers are more likely to adapt the order advice, products that should be on second placing are more likely to be adapted etc. However, these results do not differentiate between whether the order adaption was up or down. It would be interesting to analyse whether the same relationships hold for down and upward adjustments, since one would, for example, expect that stores with a small backroom make more downward adjustments than stores with a large backroom. Therefore, Table 11 presents differentiated results regarding up and downward

adjustments. Note that, to make an easy comparison, the average probabilities which were already given in Table 10 are given again. Analysing Table 11, one can conclude that most IVs show similar proportions for the probabilities regarding up and downward adjustments. One IV that shows clear proportional differences between the probabilities for up and down is whether a product is in promotion. That is, if a product is in the central promotion it is more likely to be adapted upward and less likely to be adapted downward which is an indication that stores want to have more promotional products than F&R advices.

Independent Variable	**Category**	**Average Probability Up**	**Average Probability Down**	**Average Probability**
Day Of The Week	Monday	0.067	0.022	0.089
	Tuesday	0.072	0.024	0.096
	Wednesday	0.072	0.024	0.095
	Thursday	0.081	0.028	0.107
	Friday	0.073	0.026	0.098
	Saturday	0.055	0.023	0.078
Second Placing	No	0.069	0.024	0.093
	Yes	0.227	0.044	0.262
Inventory Mutation	No	0.070	0.024	0.093
	Yes	0.243	0.256	0.401
Promotions	No	0.070	0.024	0.094
	Yes	0.157	0.012	0.181
Franchise or affiliate	Franchise	0.074	0.027	0.101
	Affiliate	0.064	0.021	0.084
Ratio Incremental Order Quantity to daily sales	0-1	0.191	0.066	0.239
	1.01-3	0.093	0.037	0.125
	3.01-10	0.055	0.017	0.071
	>10	0.052	0.017	0.068
Minimum Shelf Life	1-8 Days	0.133	0.085	0.201
	9-28 Days	0.095	0.021	0.114
	>28 Days	0.055	0.016	0.070
Price	€0-€1	0.061	0.014	0.076
	€1.01-€3	0.070	0.020	0.089
	> €3,-	0.086	0.055	0.135
Temperature Difference with yesterday	0°C - 2°C,	0.074	0.025	0.098
	2.01°C - 3°C	0.067	0.025	0.091
	> 3°C	0.066	0.024	0.089
Ratio Maximum Shelf capacity to daily sales	0-3	0.175	0.065	0.225
	3.01-10	0.080	0.030	0.107
	> 10	0.054	0.017	0.070
Backroom Capacity	0-150m^2	0.072	0.024	0.094
	151-250m^2	0.082	0.029	0.110
	> 250m^2	0.057	0.021	0.076

Table 11: Direct probabilities that an order is adapted per subcategory. Differentiated for up and downward adjustments

3.2.2.4.4 Probability of adaption per product group

Besides the probabilities for adaption for all independent variables, it would also be interesting to analyse the probability of adaption differentiated on product group. The results of this analysis are given in Table 12.

Product Category	Average Probability	Number of observations *1000
Sweets	0.061	337
Grocery goods	0.063	1273
Dairy and Eggs	0.133	420
Freezer Goods	0.069	217
Cosmetics	0.070	72
Pre-packaged meat and salads	0.100	151
Wine and off-licence shop	0.097	90
Other non-food goods	0.058	25
Pre-packed cheese	0.081	112
Beer/Soda/Juice	0.088	547
Meat Service	0.149	36
Bread	0.108	31
Service articles	0.089	0.2
Butcher	0.252	6
Potato/Vegetable/Fruit	0.195	307
Fish	0.226	2
Cheese of the knife	0.111	78
Convenience	0.163	152
Local sale	0.098	0.1

Table 12: Direct probabilities that an order is adapted per product group

First remark to make is that the product categories "butcher" and "fish" are currently in a pilot. So these product categories are not fully integrated into F&R. Therefore, the number of observations is lower than expected for these categories and one should wonder whether these results are applicable to use. However, for every other product group one can intuitively interpret these probabilities as explained for Table 10. That is, the probability that an order advice in the product category sweets will be adapted is 6.1%.

3.2.2.4.5 Combining day of the week and minimum shelf life

As one could already conclude from Table 10, orders on Thursday are most likely to be adapted. However, one should be aware that the analysis was based on all products. To specify the analysis on certain sets of products, this section goes into more detail on how order adaptions depend on the day of the week. The focus will especially be on how the distribution over the week depends on the direction of the order adaption and the minimum shelf life. For this differentiation is chosen, since due to interviews at the stores and headquarters it is expected that stores increase their order advices just before the weekend. They do this to ensure that they have enough products in the store to satisfy the demand during the weekend. This hypothesis is partly supported by Table 11, since it was found that stores are most likely to adapt their order upwards on a Thursday. However, also according to Table 11, they are also most likely to adapt their orders downward on a Thursday which is an indication against this hypothesis. To analyse this into more detail, it is chosen to differentiate the products based on their shelf life. This to check whether the same relation, as found in Table 11, holds for products with a short, medium and long shelf life. The results of this analysis are given Table 13. The second column, "MSL 1-8, Up" represents the probabilities that, on a specific day, an order is upward adapted for products with a minimum shelf life of 1 until 8 days. For example, the probability that a product, with a minimum shelf life from 1 until 8 days, is adapted upwards on a Monday is 0.114. The other presented probabilities should be interpreted in a similar manner. So the probability that a product, with a minimum shelf life of 1 until 8 days, is adapted downwards on a Monday is 0.092.

Ordering day	MSL[8] 1-8, Up	MSL 9-28, Up	MSL > 28, Up	MSL 1-8, Down	MSL 9-28, Down	MSL > 28, Down
Monday	0.114	0.092	0.057	0.092	0.016	0.013
Tuesday	0.150	0.107	0.056	0.088	0.022	0.015
Wednesday	0.143	0.099	0.055	0.079	0.021	0.015
Thursday	0.154	0.101	0.066	0.075	0.024	0.020
Friday	0.130	0.085	0.061	0.093	0.020	0.014
Saturday	0.124	0.087	0.041	0.080	0.021	0.016

Table 13: Probabilities for order adaptions per day; based on minimum shelf life and direction

Note that the general distribution for order adaptions per day was distributed as follows (see Table 14) :

Ordering Day	Average Probability
Monday	0.088
Tuesday	0.096
Wednesday	0.095
Thursday	0.107
Friday	0.098
Saturday	0.077

Table 14: General probability distribution of order adaptions per day

Comparing the general distribution per day (Table 14) and the distribution per day based on the direction and minimum shelf life (Table 13), one can make the following observations:

- Minimum Shelf Life 1-8, Up: The probabilities for adaption follow approximately the same distribution as the general distribution. However, the relative gap from Monday to Tuesday is bigger in this subgroup than the general distribution. Possible explanation for this could be that store managers want to increase the freshness of their products for the weekend. By delaying the upward adaption from Monday to Tuesday one could achieves this.
- Minimum Shelf Life 9-28, Up: This group follows approximately the same distribution as the distribution in general. Only difference is that the order adaption on Friday and Saturday are almost equal while this is not the case for the general distribution.
- Minimum Shelf Life > 28, Up: This group follows approximately the same distribution as the probability distribution for order adaptions in general. That is; Monday, Tuesday and Wednesday have approximately the same probabilities. On Thursday the probability is the highest after which on Friday and Saturday the probability for adaption decreases.
- Minimum Shelf Life 1-8, Down: Considering this subgroup, one can observe that this probability distribution really differs from the distribution in general. By observing this subgroup, one can conclude that the probabilities for adapting are relatively high on Monday and Tuesday. This could be caused by that store managers want to receive fresh products just before the weekend. One wants to have an increased freshness during the weekend, since stores sell significant more during the weekend. This way of thinking could also explain why the probabilities for downward adjustments decrease on Wednesday and Thursday, since most orders on those days arrive just before the weekend such that they can be sold with a high freshness during the weekend.
- Minimum Shelf Life 9-28, down & Minimum Shelf Life > 28, Down: These subgroups follow approximately the general distribution for order adaption.

[8] MSL: Minimum Shelf Life in days when product arrives at the store

In short, based on these results it seems that store managers delay the orders for fresh products so that they arrive later during the week. By doing that, the freshness of those products during the weekend will be increased.

3.2.2.4.6 Combining product category and direction

Table 12 in section 3.2.2.4.3 discusses the average probabilities for order adaptions per product group. These probabilities are represented again in Table 15 which will be discussed during this section. Besides that, this section also gives insights in the probabilities for upward and downward adaptions per product group. By presenting these specific probabilities, one creates insights in which products groups are more likely to be adapted up or down. It is expected that all product groups are more likely to be adapted up, since it was found that approximately 75% of all adaptions are up (see section 4.4). However, it is also expected that there will be differences between product groups regarding how much more likely an adaption is up.

Product Category	**Probability of adaption**	**Probability Up**	**Probability Down**
Sweets	0.061	82%	18%
Grocery goods	0.063	79%	21%
Dairy and Eggs	0.133	78%	22%
Freezer Goods	0.069	77%	23%
Cosmetics	0.070	72%	28%
Pre-packaged meat and salads	0.100	81%	19%
Wine and off-licence shop	0.097	69%	31%
Other non-food goods	0.058	79%	21%
Pre-packed cheese	0.081	80%	20%
Beer/Soda/Juice	0.088	79%	21%
Meat Service	0.149	69%	31%
Bread	0.108	77%	23%
Service articles	0.089	63%	37%
Butcher	0.252	61%	39%
Potato/Vegetable/Fruit	0.195	64%	36%
Fish	0.226	63%	37%
Cheese of the knife	0.111	80%	20%
Convenience	0.163	62%	38%
Local sale	0.098	63%	37%

Table 15: Probabilities that an order is down or up per product category

Analysing the results that are presented in Table 15, it can be concluded that, in general, the product groups with a shorter perishability are more likely to be adapted downward. These product categories are especially Potato/Vegetable/Fruit, Convenience, Butcher, Fish and Meat Service. Note that according to this trend one would expect that the product category “Dairy and Eggs” would be adapted more frequently downward, since this is also a product group that consists mainly out of perishable products. However, as one can conclude from the Table 15, this is not the case. Possible explanation for this is that the same person who makes the order adaptions for grocery goods, makes usually also the order adaptions for “Dairy and Eggs”. Therefore, it could be the case that he/she uses a “grocery goods mind-set” when making order adaptions for “Dairy and Eggs”. Note that this explanation is extra likely, since the up and downward adaptions for grocery goods and “Dairy and Eggs” are almost similar.

3.2.2.4.7 Probability of adaption when comparing forecast error to forecast mean

The higher the forecast error, the more improvement possibilities store managers have to add value to F&R. To analyse whether store managers also recognize this increased improvement possibilities, the logistic regression analysis, as described in this chapter, was done again with “forecast error

compared to forecast mean" as an extra IV. The analysis has been done separately, since this analysis only focusses on product groups where perishability is a big issue (i.e., convenience, potato/vegetable/fruit and dairy and eggs). It was decided to only focus on these product groups, since for these product groups both up and downward adjustments could add a lot of value (see Chapter 5 why this is the case). The expectation is that forecast errors and the probability of adjustment are positively correlated. This because, with a higher forecast error the probability that store managers see F&R making errors increases and if people see forecast algorithms making errors they want to avoid this algorithm the next time (B. Dietvorst et al., 2015). To ensure that the assumptions of the logistic regression still hold it is also decided to transform this variable into a categorical variable. "Appendix E: Forecast Error Compared To Forecast Mean" discusses how this was done exactly and how it was ensured and tested that the other assumptions were met.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Forecast error compared to forecast mean	0 – 0.5	0.095	612
	0.5 - 1	0.124	14
	> 1	0.182	4

Table 16: Probabilities of order adaption for forecast error compared to forecast mean

Table 16 shows the results for the analysis whether store managers are more likely to adapt order advices where the forecast error is a larger part of the forecast mean. As one can conclude from these results, the "forecast error compared to forecast mean" and the probability of adaption are positively correlated.

3.3 Conclusion Qualitative Analysis (Interviews) And Quantitative Analysis (Logistic Regression)

This chapter gave insights in qualitative reasons for store managers to adapt order advices. Most important reasons were; second placing, improving store view, sudden weather change, inventory corrections and promotions.

Besides the qualitative analysis, also a quantitative analysis was performed by doing a logistic regression. This regression analysis gave insights in which variables are correlated with whether an order advice will be adapted. Caused by extremely high significance levels, it seems that all independent variables are correlated with the dependent variable, but one should take into account that these low significance levels could also be caused by an overpowered data set. Therefore, to take the possibility of an overpowered dataset into account and to make the results easier to interpret, the direct probabilities for an order advice to be adapted were determined per sub category. In Chapter 5, these insights are combined with an analysis whether the adaption of the order advice added value.

Combining the interviews and the logistic regression analysis one can indeed conclude that second placing, inventory corrections, and promotions are important reasons for a store to adapt the order advice. This because, both in the interviews (Table 1) and logistic regression analysis (Table 10), it came forward that these variables impact the probability that an order advice will be adapted. Two other important reasons to adapt the order advice that came forward during the interviews were improving store view and sudden weather change. It was not possible to test, with the logistic regression, whether improving store view had an impact on the probability that an order advice will be adapted. This was not possible, since during this Master Thesis it was not known how to translate something that subjective into data that could be used for the logistic regression. However, this was possible for sudden weather change, since the regression analysis includes the variable "Temperature Difference with yesterday". As one can conclude from Table 10 there is, according to the logistic regression, no big correlation between the temperature difference with yesterday and the probability that an order advice will be adapted. This finding does not support the finding of the interviews and therefore one should wonder whether sudden weather change is an important reason to adapt the order advice holds for all stores. Besides that, one should also take into account that this reason was, during the

interviews, probably over estimated in its importance due to the fact that the interviews were held when the temperature was increasing heavily. On the other hand, it could also be the case that store managers think it is an important reason, but that in reality there is another reason to adapt the order advice.

In short, some reasons that came forward during the interviews were supported by the logistic regression, some were not possible to investigate while for some no support was found after doing the logistic regression. However, there were also some factors found during the logistic regression that were not found during the interviews which correlate with the probability that an order advice will be adapted. These factors are as follows:

- Day of the week: Orders are more likely to be adapted on a Thursday than any other day
- Franchise or affiliate: Franchisers are more inclined to adapt an order advice than affiliates
- Ratio IOQ and daily sales: The smaller the ratio the higher the probability the order advice will be adapted
- Price: A higher price leads to a higher probability that the order advice will be adapted
- Ratio maximum shelf capacity and daily sales: The smaller this ratio the higher the probability an order advice will be adapted

4 Do Order Adaptions Increase The Accuracy?

While chapter 3 creates insight in why orders are adapted and whether there are certain characteristics that correlate with the probability for order adaption, this chapter focusses on the question whether order adaptions add value. First, the logic that was used to determine whether an order adaption adds value will be discussed. After that, the used data will be discussed and the chapter will end with a discussion of the results.

4.1 Added Value Upward Order Adaptions

This section introduces the logic that is used to determine whether store managers add value with an upward adjustment of the order advice. Crucial remark for this section is that it focusses on the effect of the order adaption with respect to the centralized determined minimum shelf quantity. Therefore, adding value is defined as follows: If, with the original order advice, the inventory on hand (IOH) would have gone below the centralized minimum shelf quantity, then increasing the order advice adds value. This because increasing the order advice in this case prevented an IOH below the centralized minimum shelf quantity, an out of stock (OOS), and/or increased sales. Note that a store manager could also have other reasons to increase the order advice, however, for this analysis these effects are not taken into account. What has been done, is cleaning the dataset so that these other effects affect the results to a minimum. An example of such another effect is that order advices could be increased to improve the store view. Note that how this exactly has been taken into account, is explained in section 4.3.

4.1.1 Used logic to determine whether an upward adjustment added value

To explain the logic that was used to determine whether store managers add value with an upward order adaption first, the so called ''comparing value'' is explained. This value is later on required to say something about the added value of the upward order adaption.

The comparing value can be expressed in words as follows: Assumed it is now day t, then the comparing value is the IOH one would have, without the adaption, just after the delivery moment of the next order moment. Where it is assumed that there were no sales, counting differences or waste of the product during the period "t until the delivery moment of next order moment".

- *Comparing value:* IOH(t) + IT(t) + OA(t) + Counting Differences(t) + Waste(t)
    - IOH(t) = inventory on hand at the beginning of day t
    - IT(t) = inventory in transit that will arrive during day t
    - OA(t) = ordering advice at day t that will be delivered the next delivery moment. Usually, the next delivery moment is day t+1 due to that most products can be delivered every day (except on Sunday).
    - Counting differences (t): the counting differences at the end of day t, can be a positive or a negative number
    - Waste(t): the waste at the end of day t, is equal to zero or negative

Using this comparing value, one can conclude that a store manager adds value in the following case:

- *Store manager adds value if:* POS(t, t+1) + centralized minimum shelf quantity > comparing value
    - POS(t, t+1) are the point of sales during day t and t+1
    - Note that by making the decision whether the store manager adds value, it is assumed that the product is delivered the next day. During the analysis other lead-times were also taken into account, but to explain the logic a lead time of one day is assumed (which is also the case for most products).
    - In words this formula can be expressed as follows: If the sales from day t *till* the day of the delivery moment of the next order moment plus the centralized minimum shelf

quantity are *greater* than the comparing value, then the store manager adds value. This because increasing the order advice, in this case prevented an IOH below the centralized minimum shelf quantity, an out of stock (OOS), and/or increased sales. Therefore, the order adaption is labelled as "adds value".

- Important note for this rule is the following: One should be aware that the store manager will already be labelled as "adds value" if the comparing value is 50 and the store sold 51. So it does not depend on how much the store manager increased his/her ordering advice. One could wonder whether you want to label the store manager as ''adds value'' for the case if he/she orders 500 and sold only 51 (when the comparing value is 50). However, results indicate that, according to this definition, in approximately 15% the store manager adds value and that approximately 50% of the upward adjustments are increased with only one case pack. Therefore, the negative effects of this limitation should be limited.
- Another remark is that F&R accepts, within certain boundaries, that there is not enough inventory to meet the demand. This is due the fact that F&R works with service levels that are lower than 100%. However, the effect of this will be small since service levels are high in general (about 95%). Besides that, one should be aware that orders are placed in case packs which, usually, forces the system to order more consumer units than is required to meet the service level.

Using similar logic, one can determine whether a store manager does not add value for an upward adaption. Note again that adding value is defined as increasing the order advice in case the IOH would have gone below the centralized minimum shelf quantity with the original order advice.

- *Store manager does not add value if*: POS(t, t+1, t+2) + centralized minimum shelf quantity ≤ comparing value
  - POS(t, t+1, t+2) are the point of sales during day t, t+1 and t+2
  - Note that, again, by making the decision whether the store manager adds value or not, it is assumed that the product is delivered the next day. During the analysis other lead times were also taken into account, but to explain the logic a lead time of one day is assumed.
  - In words this formula can be expressed as follows: If the sales *until* the day of the delivery moment of the next order moment plus the centralized minimum shelf quantity are *smaller or equal* than the comparing value, then one can be for sure that the increase of the order advice did not prevented an out of stock or inventory below the minimum shelf quantity and/or increased sales. Therefore, in this case the store manager is labelled as "did not add value". Note that for these order adaptions, the increase of the order just generated more unnecessary inventory.
  - So in this case one knows for sure that without the order adaption upwards, the store did not go out of stock or went below its minimum shelf quantity. Therefore, the store manager is labelled as "did not add value". What is not taken into account is that a store manager could increase its order advice, since he/she wants to improve its store view. However, as said before, this analysis does not take this into account, but the dataset has been set up in such a way to minimize the negative effects of this (see also section 4.3).
- *Cases of "doubt":* One should note that, according to the described criteria, not the entire set of possible upward order adaptions could be labelled as "add value" or "did not add value". So there will be order adaptions that are not labelled as store manager ''add value'' or ''did not add value''. This is due to the fact that the sets "POS(t, t+1) + centralized minimum shelf quantity > comparing value" and "POS(t, t+1, t+2) + centralized minimum shelf quantity ≤ comparing value" do not represent all possible upward order adaptions. This is caused by two practical limitations: 1) It is not possible to get the POS data distribution per day, since this

data is aggregated per day and 2) it is very hard to determine exactly when a store fills its shelves with a certain product. Therefore, it was necessary to determine the absolute lower bound and upper bound for the filling moment of the store with the freight of the delivery moment for the next order moment. These bounds were then determined as the start of day t+2 and end of day t+2 respectively. Note that this also why POS(t, t+1) and POS(t, t+1, t+2) are used to label the order adaption as "add value" or "did not add value". POS(t, t+1) are all sales till the start of day t+2 where POS(t, t+1, t+2) are all sales till the end of day t+2. In short, there is a case of doubt if the ''POS(t, t+1) + minimum shelf quantity ≤ comparing value'' and "POS(t, t+1, t+2) + minimum shelf quantity > comparing value".

4.2 Added Value Downward Order Adaptions

Section 4.1 discussed the logic to decide whether an upward order adjustment added value. This section discusses the same for downward order adaptions. A crucial remark for this section is that adding value for downward adjustments is defined as decreasing the order advice and not causing an IOH below the centralized minimum shelf quantity.

4.2.1 Used logic to determine whether a downward adjustment added value

To explain the logic that was used to determine whether a downward adjustment added value it is, again, necessary to first explain the so called ''comparing value''. It is necessary to explain this first, since this value is later on required to say something about the added value for the downward adaptions of the order advice. Note that the ''comparing value'' for downward order adaptions is not the same as the ''comparing value'' for upward order adaptions. In words the comparing value can be expressed as follows; assumed it is now day t, then the comparing value is the IOH one would have just after the delivery moment of the next order moment with the adapted order. Hereby, it is assumed that there were no sales, counting differences, or waste of the product during period t until the delivery moment of the next order moment. Note that the difference with the comparing value for upward adjustments is that here the adapted OA is used and for upward adjustments the actual OA.

- *Comparing value:* IOH(t) + IT(t) + Adapted OA(t) + Counting Differences(t) + Waste(t)
    - IOH(t) = inventory on hand at the beginning of day t
    - IT(t) = inventory in transit that will arrive during day t
    - Adapted OA(t) = adapted order advice at day t that will be delivered the next delivery moment
    - Counting differences(t): the counting differences at the end of day t, can be a positive or a negative number
    - Waste(t): the waste at the end of day t, is equal to zero or negative
- *Store manager adds value if:* POS(t, t+1, t+2) + centralized minimum shelf quantity ≤ comparing value
    - POS(t, t+1, t+2) are the sales during day t, t+1 and t+2
    - Note that by making the decision whether the store manager adds value or not, it is assumed that the product is delivered the next day. During the actual analysis, other lead times were also taken into account, but to explain the logic a lead time of one day is assumed.
    - In words one can express this formula as follows: The store manager adds value if the sales *until* the day of the delivery moment of the next ordering moment plus the minimum shelf quantity are *smaller than or equal to* the comparing value. In this case the store manager is labelled as "adds value", since one knows for sure that the decrease in the order advice did not cause an inventory below the minimum shelf quantity.
    - Important note with this rule is that one should be aware that it is expected that store managers will regularly be labelled as "add value" due to the safety stock F&R uses. In other words, F&R orders, deliberately, more inventory then that is expected to be

necessary to meet the demand. This extra inventory is necessary to meet the service levels.
    - Besides that, one also should note that this analysis does not take into account whether the order advice could be lowered more.
- *Store manager does not add value if:* POS(t, t+1) + centralized minimum shelf quantity> comparing value
    - POS(t, t+1) are the sales during day t and t+1
    - Note that, again, a lead time of 1 day is assumed to explain the logic
    - In words this formula can be explained as follows: If the sales *till* the day of the delivery moment of the next ordering moment plus the minimum shelf quantity are *greater* than the comparing value, one knows for sure that the store manager did not add value.
    - One can make a similar note like for the upward adjustments when the store manager added value. Namely, the logic to decide whether a store manager did not add value in case of a downward adjustment does already give a positive result if the inventory is only one lower than the minimum shelf quantity. So in case F&R orders 500 and the store manager decreases it to 50 which causes that the inventory goes only one unit below the minimum shelf quantity, the store manager is labelled as "did not add value". One could argue whether this reasoning correct, since in this example the store manager avoided a lot of unnecessary stock. However, results indicate that only 25% of all order adjustments are downward and that around 80% of the downwards adjustments is an adjustment of just one case pack. Therefore, it is likely that the impact of this limitation is limited.
- *Cases of "doubt":* Note that one will get, for the same reasons as explained in section 4.1, also some downwards adjustments that could neither be labelled as "add value" nor as "did not add value". This is due to the fact that the set of "POS(t, t+1, t+2) + minimum shelf quantity ≤ comparing value" plus "POS(t, t+1) + minimum shelf quantity > comparing value" does not include all possible downward adjustments. So for the analysis it was necessary to determine the absolute lower and upper bound for the filling moment of the store regarding the delivery moment of the next order moment. These bounds were then determined as the start of day t+2 and end of day t+2 respectively. Note that this also why POS(t, t+1) and POS(t, t+1, t+2) are used to label the order adaption as "add value" or "did not add value". POS(t, t+1) are all sales till the start of day t+2 where POS(t, t+1, t+2) are all sales till the end of day t+2. In short, there is a case of doubt if the ''POS(t, t+1) + minimum shelf quantity ≤ comparing value'' and "POS(t, t+1, t+2) + minimum shelf quantity > comparing value".

Finally, one should be aware that the used logic, as explained in section 4.1.1 and 4.2.1 is not the only logic one could use. The explained logic is used, since the POS data is only available per day and the exact moments that the store refills their products are not known. However, if one has POS data with the exact distribution over the day and it knows the exact filling moments of the stores it becomes possible to use another logic which eliminates the cases of doubt. Another possibility to eliminate these cases of doubt, is to make assumptions about the filling moment of the stores. If one wants more details about these logics one should go to "Appendix F: Other Methods To Determine Whether Order Adjustments Add Value".

4.3 Used data

To establish the initial dataset, data from 50 different stores for 11 weeks (week 13-23) was collected. By doing this, the original dataset consisted out of approximately 8.5 million unique observations. One observation is defined as: "One unique store, SKU, day combination". This original dataset was reduced to 8 million observations, since for some observations it was not possible to determine the lead time due to high complexity in the delivery schedules.

Of these 8 million observations there were approximately 1.8 million order lines and 360.000 of these order lines were adapted. So there were 6.2 million observations that did not lead to an actual order (i.e., there is no order created for that specific store, SKU, Day combination[9]). Besides that, note that this does not mean that the order acceptance level is just 80% (i.e., 360.000 adaptions over 1.8 million order lines). Reason for this is that the dataset consists only out of those products that were adapted at least once during the 10 weeks of data collection. So products that were not adapted once were deleted from the dataset to reduce its size and keep the data manageable.

Furthermore, it was not possible to analyse weight articles since, the POS, IT, and IOH were not measured in the same dimensions (i.e., the POS is measured in consumer units while the IT and IOH are measured in grams). For this reason, it was decided to exclude all weight articles out of the observations of adapted order advices. Since cheese of the knife and meat service represent 99.4% of all adapted order lines that were a weight SKU, it is decided to keep these two product groups entirely out of scope for this analysis. Butcher and fish were also excluded since they are in a pilot and, therefore, the data for these product groups is not representative. This because F&R is not properly "trained", since the amount of input data is scarce. Besides these four product categories, the product group tobacco was also excluded since there was a failure within F&R for this product category during these 10 weeks of data collection. Removing the weight articles and the product groups cheese of the knife, meat service, butcher, fish, and tobacco reduced the initial set of 360.000 adapted order lines to 290.000.

Sections 4.1 and 4.2 explained how it was determined whether a store manager added value. Due to the fact that the entire analysis was based on whether the inventory stays above or goes below the centralized determined minimum shelf quantity, the dataset should, ideally, consists out of order adaptions where the reason for adaption was to stay above the centralized minimum shelf quantity. As came forward during the interviews at the stores (section 3.1), store managers can also adapt the order advice for other reasons like second placing or improving store view. If this was the reason for adaption one cannot use the explained logic to determine whether the store manager added value, since the store manager used a different criteria. This is caused due to the fact that when a product is on second placing, the centralized minimum shelf quantity is not updated in the system. In short, for these two cases (second placing and improving store view) it does not make sense to use the described logic to determine whether the store manager added value. This because, the evaluation logic uses different criteria than the store manager.

Based on this information, the ideal situation is to have a dataset of order adaptions that excludes all products on second placing and products that are frequently adapted to improve the store view. To establish this, first all order adaptions that were in promotion are deleted from the dataset. This was done to limit the inaccuracy caused by order adaptions that were on second placing. Note that for the order adaptions that were discussed during the interviews approximately 30% was due to second placing. Of this 30% approximately 70% was on promotion and, therefore, excluding promotional products should significantly decrease the impact of second placement products. Of course, there will still be some impact due to these second placement products, but note that it is not possible to fully exclude this, since stores also decide second placing on their own. Another measure to increase the accuracy of the dataset is to exclude those products that were excluded by the stores. Stores typically exclude products if they promote the product locally which could also be a reason to put it on second placing. Removing adaptions for products that were in promotion or were excluded by the store reduced the dataset with another 2.5% which resulted in 283.000 adapted order lines. By taking these measures, the order lines that were adapted because they were on second placing were reduced to a

[9] Note that this not necessarily means that the store manager did not want to order, because not all products can be ordered every day.

minimum. In short, these measures were taken to ensure that the results, as presented in section 4.4, are trustworthy.

Another factor that should be taken into account is that store managers could adapt the order advice to improve the store view. For this situation, the logic as explained in section 4.1 and 4.2, does not give a fair indication whether the store manager's order adaption adds value or not. Therefore, in the ideal situation, all order adaptions that were made to improve the store view should be deleted. However, as one can probably imagine, it is almost impossible to find all order adaptions that were made because of improving the store view. This is especially hard because the 283.000 order adaptions that remain for this analysis are not discussed with a store manager as was the case with the interviews. Therefore, interviews were held at Jumbo's main office and the stores to ensure that this disturbance is not completely neglected during the analysis. Interviews at Jumbo's headquarters revealed that improving store view could especially be a valid reason for products where perishability is not an issue. This because Jumbo just finished an analysis for products with a high perishability that should have optimized the trade-off between availability and waste. Therefore, it was indicated that increasing the order advice for products with a high perishability because of the store view should not be necessary since this probably brings more disadvantages (waste) than advantages (improved store view). However, it was recognized that for products with a low perishability, adapting the order advice to improve the store view could definitely add value. This value would not be recognized if the explained logic would be used to determine whether the store manager adds value or not. Interviews at the stores revealed that adapting to improve the store view especially relates to large volume products and products that are on the ground instead of on a shelf (e.g., crates of beer or bottles water). This seems to be confirmed by the interviews that were discussed in section 3.1 since products that were most often mentioned for order adaption to improve the store view were indeed in the product category beer/soda/juice. Based on this information, it is decided to exclude this product category from the main analysis. This to reduce the impact of order adaptions that were made to improve the store view. However, this product group will still be analysed separately to keep the possibility to give advices regarding the beer/soda/juice product group. Deleting this product group, reduced the remaining dataset which had 283.000 observations to the final dataset of 231.000 observations.

The next section will use these approximately 231.000 observations to analyse if and where store managers add value compared to F&R. To interpret this analysis correctly, it is crucial to understand that the analysis is purely based on the logic as described in sections 4.1 and 4.2. Therefore, it will not take into account that an order advice could also be adapted for other reasons like improving the store view or that it is on second placement. Note that this is exactly the reason why, as described in this section, measures are taken as deleting promotional products, deleting products that are excepted by the stores, and deleting the entire product group beer/soda/juice. These measures were taken to narrow the dataset as much as possible to only those adapted order advices that were adapted to stay above the centralized minimum shelf view.

4.4 Results Of The Analysis Whether Order Adjustments Add Value

As discussed in section 4.3 there were in total around 231.000 order adaptions evaluated. This section discusses, by using the explained logic in section 4.2, the results whether an order adjustment added value.

To establish a first insight into the data, consider Table 17. In this table one can see all possible results and corresponding percentages whether the adaption added value. So from Table 17 one can conclude that, for this dataset, 77% of the order adaptions were upward and 23% downward. Besides that, 20% of all upward adaptions added value. The remaining percentages can be interpreted in a similar manner.

Adaption	Percentage	Result	Percentage
Upward	77%	Adaption adds value	20%
		Adaption did not add value	63%
		Case Of Doubt	16%
			Total: 100%
Downward	23%	Adaption adds value	49%
		Adaption did not add value	28%
		Case Of Doubt	23%
			Total: 100%

Table 17: Results whether the order adaption added value

4.4.1 Results per product group

Although Table 17 gives some interesting insights, it could also be interesting to split these results into more subcategories. The first subcategory to check is the product groups. By doing this, new insights could be established, like for which product group store managers add the most value. Therefore, Table 18 shows percentages, per product group, whether an order adaption added value. Note that, as discussed during section 4.3, some product groups were excluded. These excluded product groups are cheese of the knife, meat service, fish, butcher, and tobacco. Furthermore, note that the product groups local sale and service articles are also excluded. These were excluded since during the ten weeks of data collection there were only eight order adaptions in both these product groups. The percentages behind the name of the product groups refer to the relative size of that specific group. For example, 9% of the 232,000 order adaptions were made in product group sweets.

Product Group	Result	%Upward adaptions	%Downward adaptions
Potato/Vegetable/Fruit (27%)	OA[10] adds value	35%	36%
	OA did not add value	37%	34%
	Case Of Doubt	28%	29%
Grocery Goods (20%)	OA adds value	17%	61%
	OA did not add value	76%	24%
	Case Of Doubt	7%	15%
Dairy and Eggs (14%)	OA adds value	17%	56%
	OA did not add value	56%	19%
	Case Of Doubt	27%	25%
Convenience (9%)	OA adds value	24%	53%
	OA did not add value	58%	27%
	Case Of Doubt	18%	20%
Sweets (9%)	OA adds value	13%	66%
	OA did not add value	79%	18%
	Case Of Doubt	8%	16%
Freezer Goods (6%)	OA adds value	16%	65%
	OA did not add value	75%	23%
	Case Of Doubt	10%	12%
Pre-packaged meat and salads (5%)	OA adds value	15%	75%
	OA did not add value	72%	10%
	Case Of Doubt	13%	14%
Wine and off-licence shop (4%)	OA adds value	13%	70%
	OA did not add value	78%	20%
	Case Of Doubt	9%	10%
Pre-Packed Cheese (3%)	OA adds value	13%	75%
	OA did not add value	74%	9%
	Case Of Doubt	13%	16%
Bread (2%)	OA adds value	17%	56%
	OA did not add value	71%	29%
	Case Of Doubt	12%	15%
Cosmetics (1%)	OA adds value	35%	33%
	OA did not add value	63%	65%
	Case Of Doubt	2%	2%

Table 18: Results whether the order adaption added value per product group

Main observation one can make by studying Table 18 is the following:

- For most product categories, the percentages for "order adaption added value" and "order adaption did not add value" are approximately the opposite. Consider, for example, the product group convenience. For upward adaptions, 58% of the order adaptions did not add value while for downward adaptions 53% added value. This is similar for the other product groups except for cosmetics and potato/vegetable/fruit. This effect can be explained by the fact that product groups with less perishability issues have a higher service level than product categories where perishability is an issue[11]. Potato/vegetable/fruit is definitely the product group with the most perishability issues and has, therefore, a lower service level than, for example, grocery goods. A consequence of a high service level (i.e., 95-98%) is that an order adaption downwards has just, by chance, a high probability of being labelled as "add value".

[10] OA = Order Adaption

[11] Note that this argument does not hold for the product group cosmetics, since for cosmetics perishability is not an issue.

This is due to that F&R sends, on purpose, way more products than that are needed to fulfil the expected demand. Of course, for product groups with a high perishability F&R also sends more than the expected demand since most service levels are higher than 50%. However, it is not that high as for products with low perishability. Therefore, it is likely that high service levels are a cause for the major differences between the added value for upward and downward adaptions.

4.4.2 Results per store

As one can imagine not every store is the same. So one store can have twice the revenue of the other store while it is smaller. Besides that, there is also a great differentiation of the customers between the stores. A store can, for example, be located in a wealthy neighbourhood while the other is located in a poorer neighbourhood. These specific store characteristics influence, among others, the effort that is required to implement F&R successfully. Therefore, it seems reasonable to determine, per store, the results whether order adaptions add value or not. This is also extremely relevant for Jumbo since then insights can be established about how to implement a hands-off policy per store. Note that this does not always means that a store needs to change its processes. It could also be the case that a store adds a lot of value by adapting the order advices. If this is the case, then Jumbo's main office should improve the order advices for that store.

To create these store specific insights, three important KPIs are used: 1) Average order acceptance, 2) Average added value of order adaptions, 3) Average score process trustworthiness . These averages are determined over the same weeks as the data was collected (week 13-23). Before showing the results, these KPIs will be explained in more detail:

1. Average order acceptance: The percentage of order advices that is accepted by the store. That is, the percentage of order advices that is not adapted.
2. Average added value order adaptions: In section 4.1 and 4.2 is explained how it is determined whether an order adaption added value. This KPI is the average percentage of all order adaptions that add value.
3. Average score process trustworthiness: Jumbo uses this weekly KPI to establish insights regarding the inventory management per store. A higher score indicates a better inventory management. The, original, average process trustworthiness is based on the following aspects: 1) The size of the controlled counting list[12], 2) processing the controlled counting list, 3) number of SKUs counted more than once per week, 4) total number of SKUs counted, 5) order acceptance level. For this Master Thesis, it is chosen to remove the order acceptance level from the process trustworthiness. This was done since the order acceptance level is already represented as a KPI by itself and because it is doubted whether the order acceptance level is a proper indicator for the inventory management of a store. The maximum score for a store could get for this KPI is 11. The average percentage is then determined by dividing the score a store gets by 11 (and multiplying with 100).

Table 19 shows the results for these three KPIs for some of the stores. A remark to make regarding the average order acceptance is that this score is based on all product groups and the average percentage correct order adaptions only on those product groups as discussed in section 4.3. Therefore, there is a slight difference in product groups that are used to determine the average percentage order acceptance and average percentage correct order adaptions.

[12] Controlled counting list: Automatically generated list for the store which tells which SKUs have a negative system inventory. Obviously, a negative inventory is not possible so by counting these SKUs manually the system inventory could be corrected.

Store ID	Order Acceptance	Added value Order Adaptions	Corrected Process Trustworthiness	Original Process Trustworthiness[13]
3486	86%	40%	6,5	6.5
3655	85%	32%	9,5	9.5
4860	88%	35%	1,5	1.5
3458	96%	17%	3.5	9.8
Average	91%	27%	5,9	7.7

Table 19: Results whether order adaptions add value per store

To make these results more intuitive, one can consider Figure 4 that graphically represents the given numbers in Table 19. Note that the corrected and original process trustworthiness are given as a percentage of the total score one could get. So for the corrected process trustworthiness of store 3486 this is 6.5/11 = 0.59.

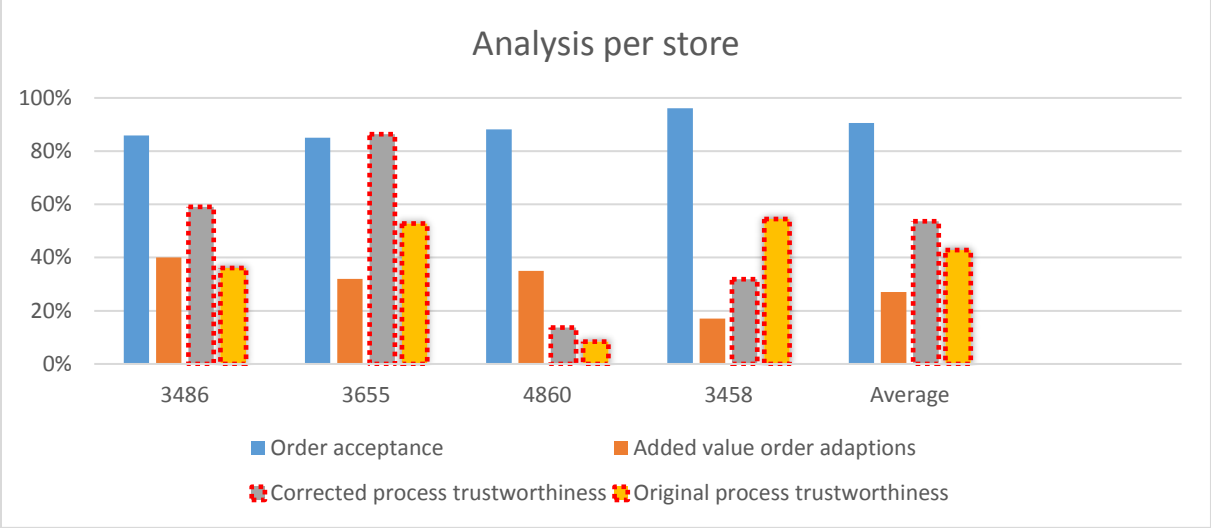

Figure 4: Results whether order adaptions add value per store

Based on these insights it becomes possible for Jumbo to establish an improvement plan per store in order to increase the order acceptance. To give Jumbo an insight in how these results could be used a short discussion per store, based on Figure 4, will be given:

- Store 3486: Order acceptance below average, added value order adaptions way above average, and the corrected process trustworthiness around average. This indicates that, despite, the seemingly sufficient inventory management the store sees and takes a lot of opportunities to improve the order advice that is created by F&R. Therefore, based on these results, it seems that this store deserves some extra attention to improve the order advices it gets from F&R. To determine where exactly the store adds the most value, one could create an overview for which product categories the added value is highest in that specific store as was done in Table 18 for all stores. Note the difference between the corrected and original process trustworthiness; it is likely that if the original process trustworthiness was used, the store would get the advice to first improve its own inventory management. However, using the corrected process trustworthiness one is more likely to conclude that the store's processes are not necessarily the cause for the low order acceptance level.
- Store 3655: Order acceptance below average, added value order adaptions somewhat above average, and the corrected process trustworthiness way above average. For this store basically a similar reasoning holds as store 3486. However, the corrected order process trustworthiness

[13] Note that for the original process trustworthiness, the points that a store could get for its order acceptance level are included. The maximum score a store could for this KPI is 18.

indicates that its inventory management is excellent and it still sees a lot of improvement possibilities by adapting the automatically generated order advices. Therefore, this store should get some extra attention to find the cause for it and, if possible, to take further actions.

- Store 4860: Order acceptance below average, added value order adaptions above average, and corrected process trustworthiness way below average. Similar to stores 3486 and 3655 this store scores pretty high on the added value on its order adaptions. However, there is one crucial difference which is the extremely low corrected process trustworthiness score. This indicates that F&R does not get the right input data to create its order advice since the inventory management at the store is not well organised. Therefore, it is likely that the inventory indicated by the system is not the same as the inventory in the store. Because of that, F&R is, obviously, not capable to give accurate order advices. Therefore, the first step to increase the order acceptance for this store is that it should improve its inventory management. If after the process trustworthiness score is improved, the added value of the store regarding the order adaptions is still that high, then it should be checked how that is possible. However, this store should first focus on improving its inventory management to increase the accuracy of its input data for F&R.
- Store 3458: Average order acceptance above average, added value order adaptions below average, and corrected process trustworthiness below average. So this store already adapts not that many order advices since its order acceptance is high and if the store adapts, it is likely that the order adaption does not add value. For these reasons, this store should get the advice to adapt even less. By doing an analysis for this store on product group or SKU level it could even be checked where the least/most value is added. Besides that, this store has still a lot of improvement possibilities for the order advices that are given by F&R. This because of the low corrected process trustworthiness which indicates that the inventory management is not sufficient. In short, this store should get the advice to improve its inventory management and to minimize its adaptions. Note that an actual visit to this store by a process manager might be useful. This because one could wonder how it is possible to have such a high order acceptance level and a relatively low corrected process trustworthiness which means that F&R does not get the correct input data. This could mean two things: 1) The store is extremely suitable to use F&R or 2) the store is a mess. To ensure it is not the second, one should visit the store. One can also take a look into the waste or wages amount of the store, however, for this Master Thesis these numbers are held out of scope.

As one can now imagine, not every store should get the same approach to increase its order acceptance level. By using the logic and KPIs discussed in this section Jumbo could create insights, per store, how it should cope with a specific store to increase its order acceptance level. Note that the overall goal of this Master Thesis is to give advices on how to increase this order acceptance and ,therefore, this analysis is relevant and extremely valuable to Jumbo.

Furthermore, note that not every store needs an unique approach to increase its order advice. It is likely that stores can be clustered into several groups which have similar scores on the discussed KPIs. By knowing which store should get which approach, process managers and forecasters at the main office should get a better idea on how the order acceptance could be increased.

4.4.3 Results differentiated on SKU level

Another possible manner to increase the order acceptance level of the stores is to check whether there are certain SKUs that are systematically, with added value, adapted by all stores. If there are such SKUs, one could wonder whether F&R gives appropriate order advices for it. To illustrate how this analysis can be done, the added value of the order adaptions for the product group potatoes/vegetables/fruit will be discussed. This product group is chosen since both order adaptions upwards and downwards that add value are relevant. For the product group grocery goods, one could wonder whether this is also the case since order adaptions downwards that add value seem less important than order adaptions upwards that add value. This is due to the difference in service levels that is a cause that

downward adaptions for low perishable products are more likely to be labelled as “adding value” (for more details on this, one can go to section 4.4.1).

To keep the analysis clear, it is decided to show the SKUs where the percentage of order adaptions that add value is relative high in Figure 5 (e.g., 52% of the order adaptions for SKU-ID 184937 add value). These insights can be used to establish insights where store managers add a lot of value to F&R. Therefore, it is a tool to discover those products where F&R has a lot of potential to be improved by the knowledge of the store managers. The next step is to know how the settings in F&R should be adapted to integrate this knowledge of the store managers. Which variables exactly should be changed cannot be recommended based on this Master Thesis and, therefore, following up research is necessary. Possible variables that could be changed are the minimum shelf quantity, case pack size, or lead time. The value of these results on SKU level is mainly that Jumbo creates insights on where store managers add value so that Jumbo knows where improvement possibilities are.

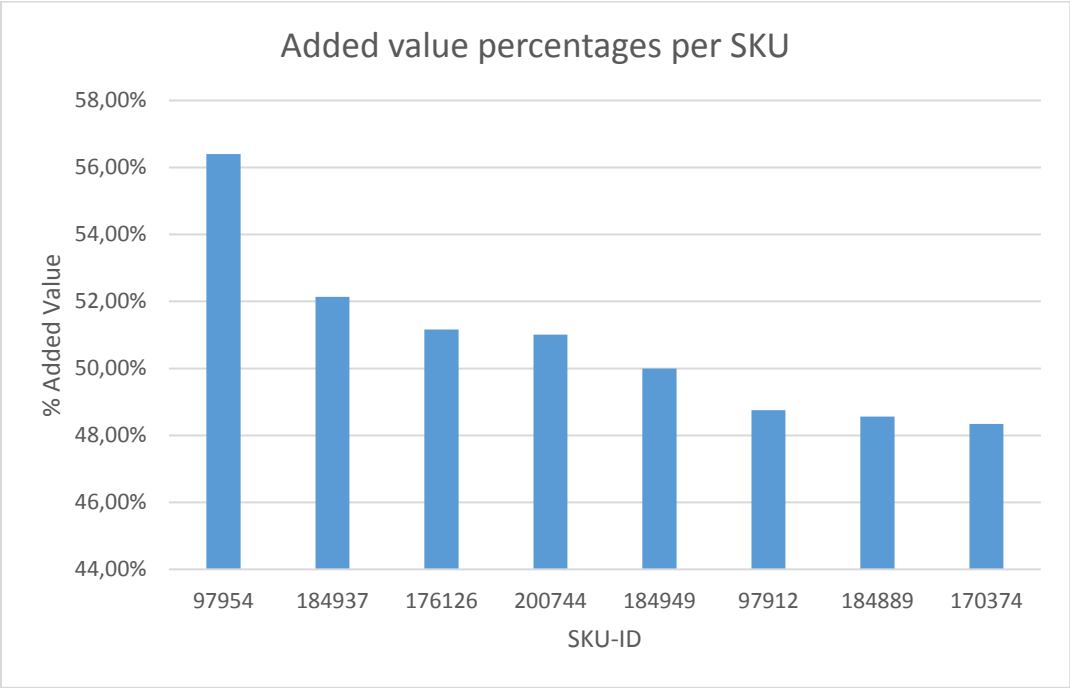

Figure 5: Added value percentages on SKU level over 50 stores

4.4.4 Results product group beer/soda/juice

As was discussed in section 4.3, the product group beer/soda/juice was excluded from the main analysis. This due to that most of the order adaptions that are made in this product category were cause by store managers wanting to improve the store view. Because of that, it is likely that there will be some disturbance regarding the results whether an order adaption added value. Nevertheless, the results could still give interesting insights and, therefore, it is decided to present the results of beer/soda/juice in Table 20. However, when one is interpreting these results, one should keep this note into account.

Product Group	Result	%Upward adaptions	%Downward adaptions
Beer/soda/juice	OA adds value	16%	65%
	OA did not add value	71%	20%
	Case Of Doubt	13%	15%

Table 20: Results whether the order adaption added value for beer/soda/juice

Considering Table 20, one can see a similar relation regarding the results as in Table 18 for non-perishable product groups (note that beer/soda/juice is an non-perishable product group). That is, the

percentages for “order advice adds value” and “order advice did not add value” are approximately the opposite for upward and downward adaptions. It is likely that this is an indication that the results are, despite of the discussed disturbance, still representative. Note that it is not said that these results have a perfect accuracy but the results that are given in Table 20 are not surprisingly if one considers the analysis that was given for Table 18.

4.4.5 Added value: forecast error compared to forecast mean

Section 3.2.2.4.7 discussed whether store managers are more likely to adapt order advices of those products where the forecast error is a larger part of the forecast mean. As was concluded in section 3.2.2.4.7, store managers are more likely to adapt order advices for those SKUs that have a larger forecast error compared to the forecast mean. This section analyses whether those products are also more frequently adapted with added value.

Independent Variable	Category	Probability of adaption	Probability added value
Forecast error compared to forecast mean	0 – 0.5	0.095	27 %
	0.5 - 1	0.124	29 %
	> 1	0.182	25 %

Table 21: Combining probability of adaption and probability of added value for forecast error compared to forecast mean

As one can conclude from Table 21, store managers are not more likely to add value for SKUs with a higher forecast error compared to the forecast mean. So they are more likely to adapt those SKUs that have a higher forecast error but they are not adding more value for products with a higher forecast error. That the probability of adaption increases with the forecast error is in line with B. Dietvorst's et al. (2015) results since they concluded that people avoid forecast algorithms after they see them making errors. However, according to these results, there is no indication that store managers are more likely to add value for those SKUs that have a larger forecast error compared to the forecast mean.

5 Integrating Likelihood Of Adaption And Added Value Of Adaption

5.1 Upward Adjustments

By combining the information that is presented in Chapter 3 and Chapter 4 one can create knowledge about the frequency and added value of an order adaption. Table 22 presents the probability of adaption and the probability of an upward adaption which were determined in Chapter 3. Besides that, it also gives the percentage of upward adapted order advices that added value (determined in Chapter 4). Note that only the product categories that were used for the analysis in Chapter 4 are given (including the product group beer/soda/juice).

Product Category	Probability of adaption	Probability Up	Added value Up
Potato/Vegetable/Fruit	0.195	64%	35%
Grocery goods	0.063	79%	17%
Dairy and Eggs	0.133	78%	17%
Convenience	0.163	62%	24%
Sweets	0.061	82%	13%
Freezer Goods	0.069	77%	16%
Pre-packaged meat and salads	0.100	81%	15%
Wine and off-licence shop	0.097	69%	13%
Pre-packed cheese	0.081	80%	13%
Bread	0.108	77%	17%
Cosmetics	0.070	72%	35%
Beer/soda/juice	0.088	79%	16%

Table 22: Combining probability of adaption and added value for upward adaptions

Analysing Table 22, one can observe/conclude the following for upward adaptions:

- Potato/Vegetable/Fruit, convenience, and cosmetics have a relative high percentage of order adaptions that add value. For potato/vegetable/fruit and convenience this can be explained due to the fact that they have lower service levels than the other product groups. However, for the product group cosmetics this is more remarkable since it is a non-perishable product group and, therefore, it has relatively high service levels. Due to these high service levels one would expect similar results as the other non-perishable groups like grocery goods or freezer goods. However, as one can see this is not the case for cosmetics. So despite the high service level, store managers see and take the possibility to add value by increasing the order advice. Possible explanation for this is that cosmetics consist mainly out of slow moving items which causes that the service level is somewhat lower than for fast moving non-perishable items. Another, probably more important, reason that could explain this finding for cosmetics is that 38% of all order adaptions within the product group cosmetics goes together with an inventory adaption (on average this is only 13%[14]). This is an indicator that a lot of products within this product are stolen and, therefore, the store manager is likely to add value with an upward adjustment since the actual inventory is lower from the system inventory that is used by F&R.
- For non-perishable product groups (except wine and off-licence shop), one can conclude that a major part (around 80%) of the order adaptions made in that product group are upward. Besides that, only around 15% of the order adaptions added value which indicates that most adaptions in these product groups do not add value.
- The product group dairy and eggs is definitely a product group with perishability. However, the results are similar to those product groups where perishability is not an issue (e.g., grocery goods). Therefore, one can conclude that, despite the lower service levels, store managers do not add that much value to the system. A possible explanation for this could be that, most of

[14] See "16Appendix G: Distribution Order Adaptions With Inventory Mutation" for the percentages per product group.

the times, the same person who does the order adaptions for grocery goods does the order adaptions for dairy and eggs. Therefore, it is possible that this store manager does the adaption for dairy and eggs with a similar mind-set as for grocery goods while a different mind-set is required.

5.2 Downward Adjustments

Now that upward adaptions have been analysed, the same analysis will be made for downward adjustments. The results are presented in Table 23.

Product Category	Probability of adaption	Probability down	Added value down
Potato/Vegetable/Fruit	0.195	36%	36%
Grocery goods	0.063	21%	61%
Dairy and Eggs	0.133	22%	56%
Convenience	0.163	38%	53%
Sweets	0.061	18%	66%
Freezer Goods	0.069	23%	65%
Pre-packaged meat and salads	0.100	19%	75%
Wine and off-licence shop	0.097	31%	70%
Pre-packed cheese	0.081	20%	75%
Bread	0.108	23%	56%
Cosmetics	0.070	28%	33%
Beer/soda/juice	0.088	21%	65%

Table 23: Combining probability of adaption and added value for downward adaptions

Analysing Table 23, one can observe/conclude the following for downward adaptions:

- For all product groups, the probability of adapting downwards is much lower than an adaption upwards. This is not remarkable since it was found that approximately 75% of all order adaptions are upward. Besides that, for most product groups (except cosmetics and potato/vegetable/fruit) the probability that a downward adaption added value is much higher compared to upward adaptions. In other words, for most product groups it is likely that a downward adaption did not result in an inventory below the centralized minimum shelf quantity. However, one should wonder whether for product groups with no perishability issues it is that important to not have more than is required to stay above the minimum shelf quantity. For those product groups it is assumable that the safety of having enough inventory to satisfy the demand, outweighs by far the importance to minimize the inventory.
- There are three product groups that, in general, have the most perishability issues. These are potato/vegetable/fruit, dairy and eggs, convenience, and “pre-packaged meat and salads”. For these product categories it is not that obvious that having enough inventory outweighs the importance to minimize the inventory. Having too much inventory for these product categories leads, in general, to more waste or at least to a decreasing freshness. This is something that Jumbo wants to prevent since one of their certainties to the customers is “fresh is also really fresh”. Therefore, downward adjustments that add value are for these product categories more important than for the other product categories. By analysing these downward adjustments, one can observe that especially for “dairy and eggs” convenience and “pre-packaged meat and salads” it is likely that they add value. From this, one can conclude that the adaption of store managers gives a good indication which products are ordered too much by F&R. For potato/vegetable/fruit the percentage is relatively low but with a percentage of 36% and knowing that this product group is most perishable, still a lot of waste is prevented with these order adaptions.

- There are three product groups that have a relatively high probability of being adapted downward; potato/vegetable/fruit, convenience, and “wine and off-licence shop’’. For potato/vegetable/fruit and convenience this seems logical since waste is a major challenge within these two product categories. Store managers experience this waste challenge in the stores and want to reduce waste by decreasing the order advice. Obviously, this argument does not hold for ‘’wine and off-licence shop’’. A reason that could explain this relatively high probability for a downward order adaption is that this product category tends to have high substitution levels.

6 Recommendations

Main objective of this Master Thesis is to answer the following question:

How could Jumbo narrow the gap between their actual and automatically generated orders?

This chapter answers this question by summarizing the most important results where after a recommendation plan to move to a hands-off policy will be given. This chapter will conclude with some general recommendations.

6.1 Summarizing Most Important Results

To narrow the gap between actual and automatically generated orders, it is key to know where and which store managers add value compared to F&R. To gain this knowledge, Chapter 3 and Chapter 4 analysed where order adaptions are likely to be made and where they are likely to add value. Chapter 5 brought these analyses together for the specific product groups. Using this analysis, one can say something about which product groups relatively have a lot of order adaptions and where they relatively add a lot of value. This section summarizes the most important results per product group where after section 6.2 uses this summary to set up a recommendation plan to move to a hands-off policy.

- Grocery goods, sweets, freezer goods, and beer/soda/juice: As one can conclude from Table 24, these product categories have similar values for the in Chapter 5 discussed indicators. In other words, the probability of an order adaption in these product categories is relatively low and if an order adaption is made, it is likely that is does not add value. Therefore, it is likely that store managers do not have a lot of unique knowledge regarding these product groups. Of course, the added value for downward adjustments is high but one should note that only 20% of the order adaptions is downwards. Besides that, downward adjustments for these product groups are not that important since perishability issues are negligible (as explained in chapter 5).

	Grocery Goods	**Sweets**	**Freezer Goods**	**Beer/soda/juice**[15]
Probability of adaption	0.063	0.061	0.069	0.088
Probability up	79%	82%	77%	79%
Added value up	17%	13%	16%	16%
Probability down	21%	18%	23%	21%
Added value down	61%	66%	65%	65%

Table 24: Key indicators for grocery goods, sweets, freezer goods and beer/soda/juice

- "Pre-packaged meat and salads", bread, pre-packed cheese, and "dairy and eggs": These four product groups show similar values (see Table 25) as grocery goods, sweets, and freezer goods except that the probability that they are adapted is higher. Therefore, one can conclude that for these product categories, store managers do not add a lot of value while they are relatively frequently adapted. One should be aware that "pre-packaged meat and salads" experiences moderate perishability issues which causes that downward adjustments that add value are relevant. Bread, pre-packed cheese, and "dairy and eggs" are less vulnerable for perishability which means that downward adjustments that add value are, similar to grocery goods, not that relevant.

[15] Note that there is some disturbance in the data for this product group, since most order adaptions that were made because of improving the store view belong to the product category beer/soda/juice

	Pre-packaged meat and salads	Bread	Pre-packed cheese	Dairy and eggs
Probability of adaption	0.100	0.108	0.081	0.133
Probability up	81%	77%	80%	78%
Added value up	15%	17%	13%	17%
Probability down	19%	23%	20%	22%
Added value down	75%	56%	75%	56%

Table 25: Key indicators for Pre-packaged meat and salads, bread and pre-packed cheese, and dairy and eggs

- Potato/vegetable/fruit and convenience: As one can conclude from Table 26, stores add value for potato/vegetable/fruit and convenience for, both, up and downward adjustments. Note that for downward adjustments the added value down is relatively low but this can be explained due to that these two product categories have relatively low service levels since they experience significant perishability issues. Although the added value down percentage is relatively low, the downward adaptions for these product categories are extremely relevant since waste is a significant challenge within potato/vegetable/fruit and convenience.

	Potato/vegetable/fruit	Convenience
Probability of adaption	0.195	0.163
Probability up	64%	62%
Added value up	35%	24%
Probability down	36%	38%
Added value down	36%	53%

Table 26: Key indicators for potato/vegetable/fruit, convenience

- Wine and off-license shop, and cosmetics: The key indicators for these product groups are given in Table 27. As one can conclude from Table 27, store managers add, regarding cosmetics, relatively a lot of value for upward adaptions and not that much for downward adjustments. This is remarkable since one would expect to find similar results for cosmetics as for other non-perishable product groups (e.g., grocery goods). Obviously, this not the case which is probably a consequence of the theft that takes place within the product group cosmetics (i.e., 40% of all order adaptions in cosmetics goes together with an inventory mutation). Theft is likely an explanation for this high percentage added value up since theft is a cause for a lower actual inventory level than the system inventory level which is a reason why upward adaptions are likely to add value.
  For wine and off-license shop it is remarkable that there are relatively many downward adjustments which are also likely to add value. The percentage of added value down is comparable with other non-perishable product groups (e.g., grocery goods) but especially the probability of a downward adjustment is higher. This could be caused by that customers are very willingly to substitute within this product group so that store managers are not that afraid that an OOS results in a lost sale.

	Wine and off license shop	Cosmetics
Probability of adaption	0.097	0.070
Probability up	69%	72%
Added value up	13%	35%
Probability down	31%	28%
Added value down	70%	33%

Table 27: Key indicators for wine and off license shop, and cosmetics

6.2 Recommendation Plan To Go Hands-Off

Based on the results and experiences that were gathered during this Master Thesis, this section describes a detailed plan on how Jumbo should move to a hands-off policy in order to close the gap between their actual and automatically generated orders.

First step Jumbo should take, is to change their KPI "original process trustworthiness" into the "corrected process trustworthiness". One can change this KPI by eliminating the order acceptance as a factor that influences the process trustworthiness. This order acceptance should be eliminated since a higher order acceptance is not by definition an indicator that the inventory management of a store is better. Besides that, the order acceptance is already a KPI on itself. Note that section 4.4.2 discusses in more detail why and how the original process trustworthiness should be changed.

Secondly, Jumbo should integrate the logic that determines whether an order adaption adds value into their information systems. Note that this logic is comprehensively discussed in sections 4.1 and 4.2. By integrating this logic, Jumbo creates insights, per store, where store managers add value to the F&R system which is crucial if one wants to close the gap between order advices and actual orders. This insight is crucial since one cannot integrate the knowledge of the store managers into F&R if one does not know if and where store managers add value.

Finally, stores should be assessed on the following KPIs:

- corrected process trustworthiness
- added value of order adaptions
- order acceptance

Stores that have similar scores for these three KPIs should be grouped together so that multiple stores can be approached in a comparable manner. Section 6.2.1 discusses the general approach how Jumbo stores should move to a hands-off policy. After that, section 6.2.2 discusses a more detailed and accurate approach for how stores should move to a hands-off policy. This detailed approach is mainly based on the three discussed KPIs: corrected process trustworthiness, added value of order adaptions, and order acceptance.

6.2.1 General Approach for Going Hands-off

Using the summarized results of section 6.1, this section describes a general approach on how Jumbo should move to a hands-off policy. This general approach will then be used in section 6.2.2 as the basis for customized, store specific, recommendations to move to a hands-off policy.

In general, store managers relatively add few value with order adaptions for the product groups grocery goods, sweets, freezer goods, and beer/soda/juice. Note that results show that downward order adaptions are likely to add value but it is also argued that these downward adaptions are relatively unimportant. These are unimportant since it is likely that the OOS costs outweigh, by far, the holding costs for these non-perishable product groups. Therefore, it is, in general, recommended that these four product groups should move to a total hands-off policy. One should be aware that the approach to move to this total hands-off direction could differ from store to store which will be discussed in the next section. However, in general, it is recommended to move to a hands-off policy for these product categories.

Product groups that experience significant perishability issues are potato/vegetable/fruit and convenience. Therefore, downward adjustments that add value are especially relevant for these product groups since they reduce waste probabilities. Considering these product groups, one can observe that they are relatively likely to be adapted and that the probability for a downward adjustment is also relatively high. Besides that, upward adjustments are also relatively likely to add value. Based on this information, it is recommended to first analyse where the value is added in these

product groups and after that, this information should be used to improve the order advices given by F&R. To analyse where store managers add value, it is recommended to perform an overall analysis on SKU level to detect those SKUs where store managers systematically add a lot of value (see section 4.4.3 for more details on this analysis). So this Master Thesis does not give recommendations on how one should deal with these products that are frequently adapted with added value, however, it provides recommendations on how Jumbo can identify those products that are systematically adapted with added value. Based on this recommendations, one knows where one can move to a hands-off policy and where further analysis is required.

For the product category "pre-packaged meat and salads" waste has a moderate impact. This means that it does not have such a significant impact as for the product group potato/vegetable/fruit but more than, for example, pre-packed cheese. Analysing the results of this product category, it can be observed that most adaptions are upward and that they are not likely to add value. However, the downward adjustments that are been made are likely to add value. Therefore, it is recommended before moving to a hands-off policy, to do a similar analysis as for potato/vegetable/fruit and convenience. By doing this, it becomes, especially for downward adjustments, clear where store managers add value.

For the product groups bread, pre-packed cheese, and "dairy and eggs" one can use similar reasoning as for the product groups grocery goods, sweets, freezer goods, and beer/soda/juice. So, in general, it is also recommended that these product groups should move to a total hands-off policy. However, this move to a total hands-off policy should be done more carefully since the downward adjustments that add value are relatively important if one compares them with grocery goods. That means that waste has also some impact on these product groups.

"Wine and off license shop" and cosmetics are the final product groups that will be discussed. The results for wine and off license shop are remarkable since the downward probability is relatively high compared to other non-perishable product groups. As discussed in section 6.1 this could be a result of substitution effects. However, the probability that a downward or an upward adaption adds value is similar to other non-perishable product group. Therefore, it is recommended to move this product group to a total hands-off policy as well. Generally, the same recommendation holds for cosmetics; however, Jumbo should be aware that upward adjustments are relatively likely to add value within this non-perishable product group which is probably caused by the amount of theft within this product group as was discussed in section 6.1. Therefore, before this product group can go hands-off, it is necessary that F&R determines immediately a new order advice after the inventory is adapted (i.e., re-run functionality) or that the amount of theft is reduced.

In short, the general recommendations per product group are as follows:

- For grocery goods, sweets, freezer goods, beer/soda/juice, bread, pre-packed cheese, "dairy and eggs", and "wine and off license shop" Jumbo should move to a total hands-off policy.
- Potato/vegetable/fruit, convenience, and "pre-packaged meat and salads" should first be analysed in more detail before moving to a total hands-off policy. "With more detail" means that it is required to do an analysis at SKU level to detect those SKUs where store managers add value. These SKUs can be detected by using the logic and recommendations that were given during this Master Thesis. However, to decide how one should cope with these SKUs to translate the knowledge of the store managers into F&R could be a new Master Thesis on itself. There are namely many factors that could influence this, e.g., case pack, lead time, perishability, shelf space etc. Besides that, Jumbo's assortment is continuously changing which causes that recommendations, on SKU level, could be irrelevant in a couple of months.

- It is only possible for cosmetics to move to a total hands-off policy if the amount of theft/inventory corrections can be reduced or if F&R updates the order advice immediately after an inventory correction (re-run functionality).

6.2.2 Store Specific Approach for Going Hands-off

Although the general approach (section 6.2.1) is a good indication on how Jumbo should move to a hands-off policy, it does not take store specific situations into account. Using the three discussed KPI's (i.e., percentage corrected process trustworthiness, percentage added value order adaptions, and percentage order acceptance), this section discusses how one can translate this general approach into a customized, store specific, approach to move to a hands-off policy.

Percentage corrected process trustworthiness:

This KPI should be used to determine whether the inventory management of a store is sufficient. A higher percentage for this KPI indicates a better inventory management which ultimately leads to more accurate input data for F&R. Obviously, F&R needs accurate input data otherwise F&R is not capable to give accurate order advices. Therefore, before moving a store to a hands-off policy, it is important to ensure that a store has a sufficient score on this KPI. Otherwise, F&R gets a lot of incorrect input data and the KPI "percentage added value order adaptions" does not say anything. It might be that the percentage added value order adaptions is high but if the percentage corrected process trustworthiness is low this has less/no value since F&R cannot give proper advices if it gets the wrong input data.

Therefore, if a store scores low on this KPI it is recommended to first focus on the store's inventory management so that this KPI increases. After that, one can use the next KPI (percentage added value order adaptions) to determine how and where this store can move to a hands-off policy and where further analysis is necessary.

Percentage added value order adaptions:

If the percentage corrected process trustworthiness is sufficient one should use this KPI. The lower this KPI, the faster a store should move to hands-off. It is also recommended, before using the general approach for a specific store, to check whether the percentage added value shows similar values to the average percentage added value per product group. If this is not the case, the general approach is not going to work for that specific store product group combination. For example, a specific store could have a much higher added value percentage for upward adjustments regarding grocery goods. Obviously, these adaptions are then important, otherwise the store would have gone OOS on these SKUs. If this is the case, it is necessary to do a similar analysis as for perishable product groups to discover where this high percentage of added value adaptions is coming from. If the key indicators, as discussed in section 6.1, are similar to the key indicators of that specific store, the general approach can be used to move to a hands-off policy.

Percentage order acceptance:

This KPI gives insights in the relative amount that orders are being adapted: the lower this percentage, the more orders are being adapted. It is important to use this KPI since by going hands-off, employees need to change their way of work. The lower the percentage is for this KPI, the more employees at the stores need to adapt their way of work if a hands-off policy is implemented. It is strongly recommended to guide stores in their process to implement a hands-off policy because it is generally known that people resist against change (Ozdemir, Karakose, Uygun, & Yirci, 2016; Seyyedi, Moosavi, & Zendehdel, 2014). To overcome this resistance against change by implementing a new algorithm (i.e., F&R), B. J. Dietvorst et al. (2018) advice to give forecasters (i.e., store managers) the possibility to adapt the forecast (i.e., order advice) slightly. They conclude, namely, that the size of the order adaption is

relatively unimportant to overcome resistance against chance. Jumbo should follow this by giving stores possibilities to design some of their second placement possibilities. This will then contribute to overcome the resistance against change and it will lead to a better consumer-tailored store since it is believed that employees in the stores know their customers best.

Another recommendation is to give store managers feedback on their order adaptions. This has two advantages: 1) Overcoming resistance against change and 2) increase the accuracy of the forecasters (i.e., store managers) (Legerstee & Franses, 2014). It is believed that the resistance against change can be reduced by giving store managers feedback since, during this Master Thesis, this was actually tested with one store. That is, a store manager was given feedback regarding his order adaptions. The results of this test are given in Figure 6. Note that the feedback to the store manager was given in week 23 and that after the given feedback the order acceptance is systematically higher than before.

A, sometimes, noticed contra-argument against providing feedback to stores is that stores (especially franchisers) could use this as leverage for claims against Jumbo since they now could have evidence that the system advised the wrong orders. Taking this argument into account, it is recommended to start a pilot with a few (e.g., 10) affiliates to check whether providing feedback really increases the order acceptance and accuracy.

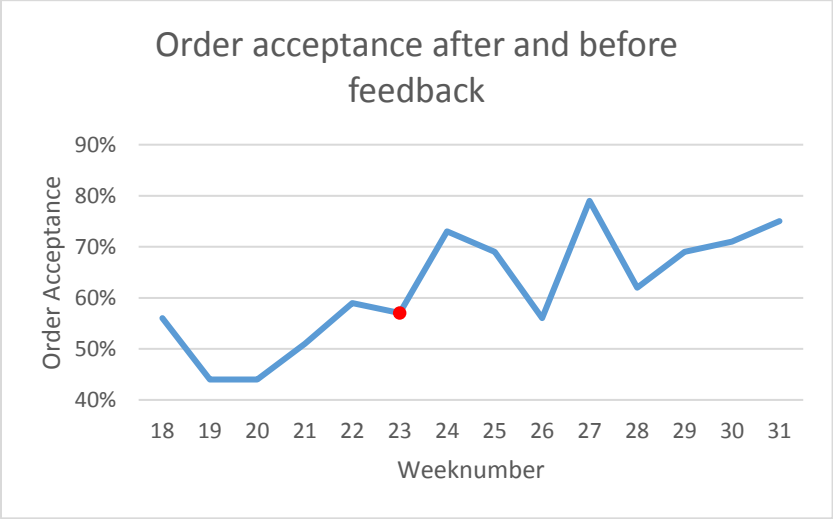

Figure 6: Order acceptance before and after providing feedback (feedback provided in week 23)

6.3 General Recommendations

During interviews at the stores (chapter 2) it came forward that the most important reasons for order adaptions were: second placing, improving store view, sudden weather change, inventory corrections, and promotions. These reasons count together for 76% of all investigated 1200 order lines. To increase the order acceptance and to move to a hands-off policy, it is necessary to take measures that reduce the probability that these reasons are the cause for an order adaption. Recommended measures per reason for adaption are:

- Second placing: To ensure that order adaptions because of second placing are reduced, Jumbo should standardize and improve their second placing plans. To realize this, Jumbo should know exactly how much second placing possibilities there are per store. After this is determined, Jumbo can automatically send the products that should be on second placing to the stores. Besides that, it is recommended to automatically change the minimum shelf quantity for the products that should be on second placing. Of course, it is also necessary that the minimum shelf quantity is automatically changed back to its original level after its second placing time. By doing this, stores are not required to systematically check and adapt the order advices for

second placement products. However, before doing this, it is vital that the second placement plans are improved since currently those plans do not make sense for a lot of stores. Possibilities to improve this are to make second placing dependent on the kind of store (e.g., is the store located in a poor or richer neighbourhood?). Another possibility is to make several central second placement plans where a store can choose from.

- Improving store view: Jumbo should take this important reason for order adaptions into account by increasing the minimum shelf quantity for large volume products (e.g., crates of beer, six packs cola, or water bottles that are on the ground) within the product group beer/soda/juice. Interviews (section 3.1) revealed that especially for this product group, orders were adapted to improve the store view.
- Inventory corrections: To prevent order advices that were made because of an inventory correction, Jumbo should implement the re-run functionality. That is, F&R determines a new order advice immediately after an inventory mutation has been made. By implementing this, F&R uses updated data to determine an updated order advice so that store managers do not need to update/adapt the order advice manually.
- Sudden weather change and Promotions: Based on this Master Thesis, it was not possible to give clear and well-funded recommendations to prevent order adaptions caused by sudden weather change or promotions. Therefore, it is decided not to give any recommendations on how Jumbo can reduce the impact of these two reasons.

7 Specific Discussion Per Sub-Research Question

In contrary to chapter 6, this chapter discusses all the sub research questions specifically. Chapter 6 also, implicitly, discusses some of these sub research questions; however, for clarity it is decided to discuss these sub-research questions specifically during this chapter.

1. For which reasons do store managers deviate from the automatically generated orders?

This sub research question is mainly answered in section 3.1. The most important reasons for store managers to deviate from the automatically generated orders are: 1) Second placing, 2) improving store view, 3) weather change, 4) inventory corrections, and 5) product is in promotion.

2. Are there typical product characteristics or other characteristics (e.g., case pack size, perishability, price or weather conditions) that could explain the difference between actual and automatic generated orders? If so, what are these characteristics?

To explore which characteristics could explain the difference between order advices and actual orders the binomial logistic regression technique was used. Section 3.2 comprehensively discusses this technique and the results. Most important characteristics that correlate with the probability whether an order advice will be adapted are: 1) Day of the week, 2) second placing, 3) inventory mutation, 4) promotion, 5) franchise/affiliate, 6) daily sales, 7) minimum shelf life, and 8) price.

3. If there are product characteristics or other characteristics identified at the previous sub question, how does this influence the difference between actual and automatic orders?

Sub research question 2 definitely identified characteristics that correlate with the probability that an order advice will be adapted. These characteristics that correlate with the probability of adaption are as follows (one can find more details regarding these results in section 3.2.2.4):

- Day of the week: Orders on Thursday are most likely to be adapted and orders on a Saturday have the lowest probability for being adapted. An order on a Tuesday, Wednesday, and Friday have similar probabilities for being adapted while the probability of adaption for an order on Monday is between Saturday and Tuesday/Wednesday/Friday.
- Second placing: An order advice for a product that is, according to the central second placing plan, on second placing is three times as likely to be adapted as a product that is not.
- Inventory mutation: Order advices that have an inventory mutation on the same day are more than 4 times as likely to be adapted compared to order advices for products that do not have an inventory mutation.
- Promotion: An order advice of a product that is in central promotion is twice as likely to be adapted compared to a product that is not.
- Franchise/affiliate: An order advice at a franchiser has a probability of 10% of being adapted while an order advice for an affiliate has a probability of 8% for being adapted.
- Daily sales: Products that sell more than 3 consumer units per day are twice as likely to get an order advice adaption than products that sell less than 3 consumer units per day.
- Minimum shelf life: The shorter the minimum shelf life, the higher the probability an order advice is adapted. Products that have a minimum shelf life of 1-8 days have 20% probability of getting an order adaption, products with a minimum shelf life of 9-28 days 11%, and products where the minimum shelf life is greater than 28 days 7%.
- Price: Order advices for products that are more expensive are more likely to be adapted. Approximately 8% of the products cheaper than €1 is adapted, 9% of the products between €1 - €3, and 14% of the products that are more expensive than €3.

An important remark regarding these results is that they do not necessarily indicate a causal relationship since the results are correlations.

4. How could possible improvements and practical knowledge be integrated into F&R?

Two specific improvement recommendations given in section 6.3 are: 1) Increasing minimum shelf quantity for large volume products and 2) standardize second placing. Besides that, as discussed in section 6.2.1, this Master Thesis is especially relevant for Jumbo since it gives recommendations on how to identify the practical knowledge that adds value. Once that is known, further research/analysis is necessary to determine how this knowledge should be integrated in F&R.

5. After identifying possible improvements; what is the added value per improvement and where is this improvement most effective?

Similar to sub research question 4, this Master Thesis does not give a complete and final answer to this question. However, as discussed in chapter 6, it does recommend where and when Jumbo can implement a hands-off policy. Because of that, it becomes possible to identify where measures to improve order advices are most effective (i.e., they are most effective where store managers add the most value). In other words, this Master Thesis gives an extensive analysis where store managers do not add value such that a hands-off policy can be implemented for those stores product groups combinations. Besides that, this Master Thesis also creates an overview where store managers do add value so that it becomes clear where improvements are most effective.

6. Are similar results found for perishables compared to non-perishables for the following aspects:
    - Shifting orders from peak to non-peak days
        - As one can conclude from chapter 3 and especially section 3.2.2.4.5, there are no indications found that store managers shift orders from peak to non-peak days. These findings were also supported by the interviews at the stores since not one store manager indicated that orders are adapted to shift orders from peak to non-peak days. Therefore, similar results are found for perishable and non-perishables regarding the shifting of orders from peak to non-peak days (i.e., no shifting is noted). However, the results differ from van Donselaar et al. (2010) since they concluded that shifting takes place from peak to non-peak days. This difference is most likely caused by the fact that Jumbo's ASO system (i.e., F&R) takes order advancement into account while this was not the case for the ASO system that was relevant for van Donselaar's et al. (2010) study.
    - Products characteristics that drive this behaviour (if the shifting is notified)
        - Since it was concluded that no shifting takes place, there are also no characteristics noted that drive this behaviour.

7. Comparing the order advices and actual orders, which of the two is a better prediction for actual demand? In other words, is the store manager able to outperform the F&R system?

Considering the logic and definition of adding value that are introduced in sections 4.1 and 4.2, the store manager is definitely able to outperform F&R. However, as discussed in chapter 6, one can argue about the actual added value for, for example, downward adjustments for non-perishable items. Nevertheless, there are still a lot of product groups (especially perishable product groups) where store managers make a significant amount of relevant added value order adaptions. Therefore, it can be concluded that, in some cases, store managers are able to outperform F&R. See section 6.1 for a summary where store managers are likely to outperform F&R with relevant order adaptions.

8 Recommendations For Future Research

- Once the logic to determine whether an order adaption added value is integrated into Jumbo's information systems, one can use this to discover those SKUs that are systematically adapted with added value. After that, a standardized analysis should be established to know how this specific knowledge of store managers should be translated into F&R. This is especially relevant for the product categories potato/vegetable/fruit, convenience, and "pre-packaged meat and salads" and those stores that add a lot of value for specific product groups. This following up research would be a great extension to this Master Thesis.
- During this Master Thesis there was no specific relation between temperature and probability of order adaption found. However, it is possible to test this in a different way than was done during this Master Thesis. During this Master Thesis this was tested by taking the absolute actual temperature difference with yesterday. One could, for example, also test this with the temperature prediction or absolute temperature change if the temperature is above 25 degrees Celsius.
- This Master Thesis does not give recommendations on how Jumbo could prevent order adaptions that were made because of sudden weather change and promotions. Therefore, further research could focus on how these two reasons could be taken into account.
- Recommendation of this Master Thesis is to alter the KPI "process trustworthiness". Although it is believed that by making the process trustworthiness independent of the order acceptance the KPI is improved. There might also be other factors that should be included in the process trustworthiness. Such a factor could be, for example, how long it takes before a store manager corrects the inventory.
- Chapter 3 gave an extensive discussion on the factors why store managers adapt order advices. These factors were found and tested by interviews and a logistic regression. However, the regression analysis only confirmed that certain factors correlate with the probability that an order advice will be adapted. Therefore, it would be interesting to test these factors, in further research, also on causality.
- This Master Thesis discussed, according to a certain logic, whether an order adaption added value. However, it is not analysed how much value is added with an adaption that added value. In further research, this added value could, for example, be expressed in monetary units to make the results easier to use/interpret.
- Based on the logistic regression it seems that store managers delay orders for fresh products such that they arrive later during the week (as discussed in section 3.2.2.4.5). Store managers delay orders for fresh products to increase the freshness of those products during the weekend. Further research on this aspect is necessary to determine whether this delaying of fresh products is useful. If it comes forward that this delaying of fresh products is useful, Jumbo should integrate this into F&R.

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10 Appendix A: Distribution For Motives Of Order Adaptions

This Appendix shows the total distribution for the store managers' motives for order adaptions (Table 28). Note that one can find the meaning per reason in section 3.1.1.

Reason	Frequency	Percentage
1	188	15%
2	21	2%
4	227	19%
5	18	1%
6	149	12%
7	134	11%
9	32	3%
10	3	0%
11	7	1%
12	3	0%
13	37	3%
14	5	0%
15	21	2%
16	41	3%
17	7	1%
18	6	0%
19	27	2%
20	9	1%
21	27	2%
1&5	1	0%
1&6	5	0%
11&17	1	0%
2&6	230	19%
4&16	4	0%
4&18	1	0%
4&20	1	0%
4&7	1	0%
5&6	19	2%
Total	1225	100%

Table 28: Store managers' motives for order adaptions

11 Appendix B: Grouping Of Independent Variables

The independent variables were grouped are as follows.

- X1 = Day of the week (Monday, Tuesday, Wednesday, Thursday, Friday and Saturday)
- X2 = Second Placing (Yes, No)
- X3 = Inventory Mutation (Yes, No)
- X4 = Promotions (Yes, No)
- X5 = Franchise or Affiliate (Franchise, Affiliate)
- X6 = Ratio Incremental Order Quantity to daily sales (0-1 , 1.01-3 , 3.01 – 10, >10)
- X7 = Minimum Shelf Life (1-8 days, 9-28 days, > 28 days)
- X8 = Price (€0 - €1, €1.01 - €3, >€3)
- X9 = Temperature Difference with yesterday (0°C - 2°C, 2.01°C - 3°C, > 3°C)
- X10 = Maximum Shelf Capacity compared to daily sales (0-3, 3.01-10, >10)
- X11 = Backroom Capacity (0-150m^2, 151-250m^2, >250m^2)

The relative size per subgroup per IV are discussed during the remainder of this Appendix. E.g., 14.4% of all observations in the dataset is on a Monday.

X1: Day of the week:

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
X1	14.4%	16.4%	16.4%	18.3%	19.2%	15.3%	0.01%

Table 29: Relative size per subgroup for IV "day of the week"

X2: Second Placing:

	Yes	No
X2	0.8%	99.2%

Table 30: Relative size per subgroup for IV "second placing"

X3: Inventory mutations:

	Yes	No
X3	0.3%	99.7%

Table 31: Relative size per subgroup for IV "inventory mutations"

X4: Promotions:

	Yes	No
X4	0.1%	99.9%

Table 32: Relative size per subgroup for IV "promotions"

X5: Franchise or Affiliate:

	Franchise	Affiliate
X5	60.9%	39.1%

Table 33: Relative size per subgroup for IV "franchise/affiliate"

X6: Ratio Incremental Order Quantity to daily sales

	0-1	1.01-3	3.01-10	>10
X6	6.3%	23%	37.8%	32.8%

Table 34: Relative size per subgroup for IV "ratio incremental order quantity to daily sales"

X7 = Minimum Shelf Life:

	1-8 days	9-28 days	>28 days
X7	12.2%	21.1%	66.7%

Table 35: Relative size per subgroup for IV "minimum shelf life"

X8 = Price:

	€0 - €1	€1.01 - €3	> €3
X8	21.1%	59%	20%

Table 36: Relative size per subgroup for IV "price"

X9 = Temperature Difference with yesterday

	0°C - 2°C	2.01°C - 3°	> 3°C
X9	49%	32.7%	18.3%

Table 37: Relative size per subgroup for IV "temperature difference with yesterday"

X10 = Ratio Maximum Shelf Capacity to daily sales:

	0-3	3.01-10	>10
X10	6.2%	36.9%	59.9%

Table 38: Relative size per subgroup for IV "ratio maximum shelf capacity to daily sales"

X11 = Backroom Capacity:

	0-150m^2	151-250m^2	>250m^2
X11	31%	36%	33%

Table 39: Relative size per subgroup for IV "backroom capacity"

12 Appendix C: Introducing Daily Sales As An IV With 2 Groups

Before performing the actual logistic regression one should ensure that the assumptions are met. To ensure this the IV daily sales was transformed into a categorical variable with 2 groups.

	0 – 3	> 3
Daily Sales	76 %	24 %

Table 40: Relative size per subgroup for IV "daily sales" (2 groups)

Next assumption to meet is that there should be no multicollinearity. To test this, VIF values were determined which are shown in Table 41.

Independent Variable	**VIF value**
X1: Day Of The Week	1.036
X2: Second Placing	1.006
X3: Inventory Mutation	1.002
X4: Promotions	1.006
X5: Franchise or affiliate	1.211
X7: Minimum Shelf Life	1.031
X8: Price	1.038
X9: Temperature difference with yesterday	1.034
X11: Backroom Capacity	1.213
Average Daily Sales	1.027

Table 41: VIF values with the new IV "daily sales" (2 groups)

As one can conclude there are no extreme VIF values and thus it was concluded that there is no multicollinearity.

Finally, one should check for potential outliers. However, most potential outliers were adapted order advices. Therefore, also for this analysis, it was decided to not remove any outliers.

In Table 42 one can see the regression results with the direct probabilities that an order will be adapted per sub category.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Day Of The Week	Monday	0.088	570
	Tuesday	0.096	648
	Wednesday	0.095	643
	Thursday	0.107	721
	Friday	0.098	755
	Saturday	0.078	604
Second Placing	No	0.093	3907
	Yes	0.262	33
Inventory Mutation	No	0.093	3930
	Yes	0.401	10
Promotions	No	0.094	3936
	Yes	0.181	4
Franchise or affiliate	Franchise	0.100	2403
	Affiliate	0.084	1537
Minimum Shelf Life	1-8 Days	0.201	475
	9-28 Days	0.114	745
	>28 Days	0.070	2721
Price	€0-€1	0.076	857
	€1.01-€3	0.089	2410
	> €3,-	0.135	674
Temperature Difference with yesterday	0°C - 2°C,	0.098	1932
	2.01°C - 3°C	0.091	1290
	> 3°C	0.089	719
Daily Sales	0-3	0.078	2991
	>3	0.145	949
Backroom Capacity	0-150m^2	0.094	1223
	151-250m^2	0.110	1419
	> 250m^2	0.076	1298

Table 42: Direct probabilities that an order is adapted per subcategory with the new IV "daily sales" (2 groups)

13 Appendix D: Introducing Daily Sales As An IV With 3 Groups

Before the actual logistic regression was performed one should ensure that the assumptions are met. To ensure this, the IV daily sales was transformed into a categorical variable with 3 groups. Note that the boundary of 8.6 consumer units was chosen such that the group with the largest daily sales consists out of approximately 250.000 observations.

	0 – 1	1 – 8.6	> 8.6
Daily Sales	31 %	53 %	6 %

Table 43: Relative size per subgroup for IV "daily sales" (3 groups)

Next assumption to meet is that there should be no multicollinearity. To test this, VIF values were determined which are shown in Table 44.

Independent Variable	**VIF value**
X1: Day Of The Week	1.037
X2: Second Placing	1.006
X3: Inventory Mutation	1.002
X4: Promotions	1.006
X5: Franchise or affiliate	1.212
X7: Minimum Shelf Life	1.026
X8: Price	1.027
X9: Temperature difference with yesterday	1.034
X11: Backroom Capacity	1.213
Average Daily Sales	1.052

Table 44: VIF values with the new IV "daily sales" (3 groups)

As one can conclude there are no extreme VIF values and thus it was concluded that there is no multicollinearity.

Finally, one should check for potential outliers. However, most potential outliers were adapted order advices. Therefore, also for this analysis, it was decided to not remove any outliers.

In Table 45 one can see the regression results with the direct probabilities that an order will be adapted per sub category.

Independent Variable	Category	Average Probability	Number of observations(*1000)
Day Of The Week	Monday	0.088	570
	Tuesday	0.096	648
	Wednesday	0.095	643
	Thursday	0.107	721
	Friday	0.098	755
	Saturday	0.078	604
Second Placing	No	0.093	3907
	Yes	0.262	33
Inventory Mutation	No	0.093	3930
	Yes	0.401	10
Promotions	No	0.094	3936
	Yes	0.181	4
Franchise or affiliate	Franchise	0.100	2403
	Affiliate	0.084	1537
Minimum Shelf Life	1-8 Days	0.201	475
	9-28 Days	0.114	745
	>28 Days	0.070	2721
Price	€0-€1	0.076	857
	€1.01-€3	0.089	2410
	> €3,-	0.135	674
Temperature Difference with yesterday	0°C - 2°C,	0.098	1932
	2.01°C - 3°C	0.091	1290
	> 3°C	0.089	719
Daily Sales	0-1	0.074	1578
	1.01-8.6	0.095	2113
	>8.6	0.214	248
Backroom Capacity	0-150m^2	0.094	1223
	151-250m^2	0.110	1419
	> 250m^2	0.076	1298

Table 45: Direct probabilities that an order is adapted per subcategory with the new IV "daily sales" (3 groups)

14 Appendix E: Forecast Error Compared To Forecast Mean

Before performing the actual logistic regression one should ensure that the assumptions are met. To ensure this the IV "forecast error compared to forecast" was transformed into a categorical variable with 3 groups.

	0 – 0.5	0.5 - 1	>1
Forecast error compared to forecast mean	97 %	2 %	1 %

Table 46: Relative size per subgroup for IV "forecast error compared to forecast mean"

Next assumption to meet is that there should be no multicollinearity. To test this, VIF values were determined which are shown in Table 47.

Independent Variable	**VIF value**
X1: Day Of The Week	1.035
X2: Second Placing	1.004
X3: Inventory Mutation	1.001
X4: Promotions	1.004
X5: Franchise or affiliate	1.203
X6: Ratio Incremental Order Quantity to daily sales	1.757
X7: Minimum Shelf Life	1.104
X8: Price	1.013
X9: Temperature difference with yesterday	1.032
X10: Maximum shelf capacity compared to daily sales	1.639
X11: Backroom Capacity	1.201
Forecast error compared to forecast mean	1.032

Table 47: VIF values with the new IV "forecast error compared to forecast mean"

Finally, one should check for potential outliers. However, most potential outliers were adapted order advices. Therefore, also for this analysis, it was decided to not remove any outliers.

15 Appendix F: Other Methods To Determine Whether Order Adjustments Add Value

15.1 Logic to determine whether upward adjustments add value if one makes two assumptions about the filling moment

Section 4.1.1 discussed a logic to determine whether an upward order adjustment added value. However, if one uses this logic there will be cases of doubt (i.e., order adjustments that are neither labelled as "add value" or "does not add value").

It is, however, good to note that these cases of doubt could be eliminated if two assumptions are made.

1. All products with a short perishability are filled before any demand of that day takes place
2. All products with a long perishability are filled after all demand of that day has occurred

A substantial part of Jumbo's stores gets their fresh freight at 08:00, if this is the case it is reasonable to assume that most of the freight is processed and available on the shelf before any demand took place. On the other hand, products with a long perishability are usually filled in the evening (after 18:00). So here the assumption could be defended that all demand has occurred before filling takes place. In practice, these assumptions will not hold perfectly but they will not be that far of if a store gets its fresh freight early in morning.

Using these assumptions the following logic for products with *short perishability* can be used to determine whether the upward adjustment added value. Note that due to making these assumptions there will be no cases of doubt anymore.

- Store manager adds value: POS(t, t+1) + minimum shelf quantity > comparing value
- Store manager does not add value: POS(t, t+1) + minimum shelf quantity ≤ comparing value

The logic for products with a *long perishability* will then become as follows:

- Store manager adds value: POS(t, t+1, t+2) + minimum shelf quantity > comparing value
- Store manager does not add value: POS(t, t+1, t+2) + minimum shelf quantity ≤ comparing value

Note that, due to the assumptions, for short perishable products some order adaptions will be labelled, incorrectly, as "store manager does not add value". For long perishable items this will be the exact opposite (i.e., order adaptions will be labelled, incorrectly, as "store manager add value").

15.2 Logic to determine whether downward adjustments add value if one makes two assumptions about the filling moment

Similar to section 15.1 one has also the possibility to ensure that are no causes of doubt anymore for downward adjustments. To achieve this, one needs to make the same assumptions as in section 15.1. These assumptions were

1. All products with a short perishability are filled before any demand of that day takes place
2. All products with a long perishability are filled after all demand of that day has occurred

With these assumptions the logic for products with short perishability would be as follows:

- *Store manager adds value:* POS (t, t+1) + minimum shelf quantity > comparing value
- *Store manager does not add value:* POS (t, t+1) + minimum shelf quantity <= comparing value

For products with long perishability the logic can be established as follows:

- *Store manager does not add value:* POS (t, t+1, t+2) + minimum shelf quantity > comparing value
- *Store manager adds value:* POS (t, t+1, t+2) + minimum shelf quantity <= comparing value

The consequences of these assumptions will be that some adapted order lines for products with short perishability will be labelled as ''store manager adds value" while they are not. For products with a long perishability the consequences will be exactly the opposite (i.e., some will be labelled as "store manager does not add value" while they add value)

15.3 Logic to determine whether upward adjustments add value if one has the exact distribution of POS data over the day and knows the exact filling moments per store.

Section 4.1.1 describes a logic to determine whether an upward adjustment was add value or not. Two important practical limitations that were taken into account are: 1) it is not possible to get the POS data distribution per day, since it is aggregated per day and 2) it is very hard to know exact when a store fills its shelves with a certain product. However, if one knows the exact POS distribution over the day and the exact filling moment one can use the logic as explained in this section.

The logic here is similar as the logic described in sections 4.1.1 and 4.2.1, but in this case the exact POS distribution and filling moments are known. Therefore, one can use the following logic to determine whether a store manager adds value or not.

- Store manager adds value: POS(t, fill moment) + minimum shelf quantity > comparing value
- Store manager does not add value: POS(t, fill moment) + minimum shelf quantity ≤ comparing value

15.4 Logic to determine whether downward adjustments add value if one has the exact distribution of POS data over the day and knows the exact filling moments per store.

Sections 4.2.1 describes a logic to determine whether an downward adjustment added value. Two important practical limitations that were taken into account here are: 1) it is not possible to get the POS data distribution per day, since it is aggregated per day and 2) it is very hard to know exact when a store fills its shelves with a certain product. However, if one knows the exact POS distribution over the day and the exact filling moment one can use the logic as explained in this section

The logic here is similar as the logic described in section 4.2.1, but in this case the POS distribution over the day and the exact filling moments per store are known. Therefore, one can use the following logic to determine whether a store manager adds value or not.

- Store manager adds value: POS(t, fill moment) + minimum shelf quantity ≤ comparing value
- Store manager does not add value: POS(t, fill moment) + minimum shelf quantity > comparing value

16 Appendix G: Distribution Order Adaptions With Inventory Mutation

This Appendix (Table 48) shows the amount of order adaptions with an inventory mutation per product category. E.g., 12% of all order adaptions within the product category bread goes together with an inventory mutation.

Product Category	**% Order adaptions with inventory mutation**
Potato/Vegetable/Fruit	16%
Bread	12%
Convenience	9%
Cosmetics	38%
Freezer Goods	4%
Grocery Goods	12%
Pre-packed cheese	7%
Pre-packaged meat and salads	8%
Wine and off-licence shop	6%
Sweets	8%
Dairy and Eggs	8%

Table 48: Percentage order adaptions with inventory mutation per product category