Returns within Fashion E-Tailing:

Investigating Product-Related Return Drivers and their Impact on Profitability

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MASTER'S THESIS

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Abstract

The purpose of this master's thesis is to provide a contribution to the research body regarding consumer returns, particularly within the online fashion retail industry. A quantitative data analysis approach is chosen and two main methods are used: data study that aims to identify patterns and interesting relationships in the data, and a simulation study that uses real input data to attempt to identify how different fashion product categories are affected in various future scenarios regarding consumer return behavior. The five research questions posed are presented below.

1. How are different product categories affected in terms of profitability by increasing return rates?
2. How are different product categories affected in terms of profitability by increasing or decreasing return delay?
3. a) How are return rate, discount rate and time in sales period (TISP) connected?
   b) How is return rate affected by sales price?
4. Is it possible to find data to indicate the occurrence of "retail borrowing"?
5. To what extent does the data indicate the occurrence of multiple size ordering and return behavior?

The study provides the following abbreviated answers to each research question:

1. The study finds that the products that suffer the worst effects are those with an already high return rate, and low to medium base sales price. Sales period length does not seem to differentiate products in terms of profits between different return scenarios.
2. The results regarding return delay were inconclusive. The study provides suggestions for further investigation of the effects of return delay.
3. Discount rate correlates negatively with return rate and positively with TISP, while return rate correlates negatively with TISP. There is also a positive correlation between return rate and sales price.
4. This study could not find conclusive evidence indicating the occurrence of retail borrowing behavior.
5. The study found that multiple size ordering and return behavior is prevalent in the data. 2.26% of all orders and 12.9% of orders containing returns are associated with at least one instance of multiple size ordering and returning.

Keywords: Consumer returns, simulation study, fashion, online retail, e-tailing, e-commerce

Sammanfattning

Syftet med detta examensarbete är att bidra till forskningen kring konsumentreturer, specifikt gällande e-handel inom modebranschen. Ett kvantitativt tillvägagångssätt inriktat på dataanalys valdes för studien, och två huvudmetoder användes: dataanalys med målet att hitta mönster och intressanta samband i datan, och en simuleringsstudie som använder den verkliga datan som indata för att identifiera hur olika kategorier av modeprodukter påverkas i olika framtidsscenarier när det gäller konsumentreturer. Studien ställer fem forskningsfrågor, som presenteras nedan.

1. Hur påverkas olika produktkategorier i termer av vinst när returfrekvensen ökar?
2. Hur påverkas olika produktkategorier i termer av vinst när returfördröjningen ökar eller minskar?
3. a) Hur ser sambandet ut mellan returfrekvens, reagrad och försäljningstiden (TISP)?
   b) Hur påverkas returfrekvens av graden av försäljningspris?
4. Går det att hitta data som tyder på förekomsten av "retail borrowing"?
5. Hur vanligt förekommande är "multiple size ordering and return"-beteende enligt den analyserade datan?

Studien ger dessa förkortade svar på frågorna:

1. De kategorier som är utsatta i särskilt hög grad är de produkter som redan har en hög returfrekvens i kombination med lågt eller medelhögt försäljningspris. Försäljningsperiodens längd tycks inte differentiera produkter när det gäller vinst i olika returscenarier.
2. Resultaten gällande returfördröjning gav inget tydligt svar på frågan. Förslag ges för framtida studier inom detta område.
3. Reagraden korrelerar negativt med returfrekvensen och positivt med TISP, medan returfrekvensen korrelerar negativt med TISP. Det finns även ett positivt samband mellan returfrekvensen och försäljningspriset.
4. Inga tydliga bevis kunde hittas i den här studien som tydde på förekomsten av "retail borrowing".
5. Studien finner att "multiple size ordering and return"-beteende är vanligt förekommande i orderdatan. 2,26% av alla ordrar samt 12,9% of ordrar som innehåller returer kan kopplas till minst en instans av "multiple size ordering and returning".

Nyckelord: konsumentreturer, simulationsstudie, mode, e-handel

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We would also like to thank the company that provided us with order data that formed the basis for all analysis and valuable information about the online return process, without which the project would not have been possible.

Finally, we want to express our gratitude to friends and family for providing us with support and encouragement throughout the project.

Lund, March 2019

Christoffer Nordberg and Fredrik Schmidt

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List of Acronyms and Abbreviations

closed-loop supply chain	A supply chain where the producer of an item also takes care of its disposal and/or recycling
E-tailing	Online retailing
multiple size ordering	The phenomenon of ordering multiple sizes of the same fashion product, in order to determine which one fits at home (and then typically returning the one(s) that did not)
retail borrowing	The phenomenon of ordering an item, using it for some time period or for a specific occasion, and then returning it
return delay	The time interval between the customer picking up a delivered item and sending it back
sales period length	The "prime selling season" of an item, in this study defined as the time between the first sale of an item and the time when 90% of the total sales volume has been sold
SCM	Supply chain management
SKU	Stock keeping unit, a specific type of item for sale defined by its characteristics such as manufacturer, design, color, size etc.
TISP	Time in sales period, defined in this study as the relative time within the sales period, a value between 0 and 1.

1 Introduction

This chapter describes the background of the research area and gives the reader an idea of how this thesis is intended to contribute to the field of knowledge, as well as how it might find use in practice.

1.1 Background

Reverse logistics is a wide and rapidly expanding field within modern SCM. At its core, reverse logistics describes the process where goods/materials are returned from customer to supplier. These flows are common in industries forced by law to recycle (so-called closed loop supply chains), as well as retailers with a high share of sales coming from e-commerce, and pose a great challenge when trying to optimize the supply chain and reduce costs of logistic services. In recent years, the fashion retail industry has increasingly shifted towards online sales. In parallel with this trend, customer returns have become more common, and a greater expense for the retail companies. For example, recent surveys show that common customer practices include purchasing more products than they intend to keep and returning the rest, and even "retail borrowing", where the customer buys e.g. a party dress, uses it once and returns it without ever having intended to keep it. (PostNord, 2018a; PostNord, 2018b; Hjort and Lantz, 2012). According to Swedish industry studies conducted 2017 and 2018 the number of respondents having returned entire, or parts of, online purchases during the last month increased from 10% to 14% during this period (PostNord, 2018a; PostNord, 2018b). In the fashion retail industry these figures are believed to be even higher, approaching 30% (de Leeuw et al, 2016).

1.2 Problem Description

As these customer behaviors become more significant, they create of a new set of challenges for fashion e-tailing companies, which includes the cost for shipping and handling return flows and managing unpredictable stock levels of products with high rates of return. Another major challenge is late returns of seasonal products where the sales price is strongly related to the time of sale; e.g. a summer dress sold during autumn will likely have been sold at a steep discount. High return rates and long return delays would contribute to a higher proportion of these products being sold at a discount or not at all, since returned products must be sold again after being sent back, delaying the real time of sale by a significant amount. This delay could cause the retailer to either have to sell the product at a discount for a net loss, or in the worst case, dispose of it. Many retailers in this area have moved towards more generous return policies, such as allowing customers free, convenient returns up to six months after purchase. Questions have been raised both within the industry and academia if these policies are ultimately going to be sustainable (Janakiraman et al, 2015). However, little is known for certain about the cost effects of the issues described above, or how these effects might develop in the future as online consumer attitudes and behaviors continue to evolve. The authors argue that there is a need for more quantitative studies to show the cost effects of this phenomenon on the profitability of fashion retail companies, and what these effects might be in the future. Furthermore, there is a need to complement interview-based studies regarding different types of return behavior with quantitative data analysis, and to explore which product-related factors affect return rate.

As part of an initial literature study, the authors have reviewed a number of previous papers to get an overview of what aspects of fashion consumer returns have been studied. Here, these papers will be briefly described and the results summarized, in order to be able to perform a gap analysis identifying which aspects should be targeted for RQs related to data analysis methodology. The papers have been selected for maximum relevance to the focus of this paper; thus, only papers that attempt to identify consumer return behavior patterns will be included in the scope.

In their study (R)e-tail borrowing of party dresses: an experimental study, Hjort and Lantz (2012) use experimental data for return rates of different product categories within different return policies to identify retail borrowing behavior. Their study assumes the hypothesis that party dresses, due to their nature as a relatively expensive product that is not used often, should be more exposed to retail borrowing behavior, as opportunistic consumers may be able to use it once without leaving enough wear and tear for the retailer to reject the return. Their data supports this hypothesis, as return rates for party dresses greatly exceed other products for their overall data (31.5% vs 17.4%), and they also found that so-called average return time (the time between delivery and item return) is longer for party dresses compared to other items (15.8 vs 14.1 days), which could indicate retail borrowing behavior. This study inspired the authors to look for similar effects in the data studied in this paper.

Saarijärvi et al (2017) use interviews to explore consumer’s reasons for returning fashion products, while also relating these return decision reasons to a specific phase of the online purchase process. Other studies including Powers and Jack (2013) and Wachter et al (2011) have used similar methods to explore different dimensions of consumer behavior regarding returns, but aside from retail borrowing of party dresses, there appears to be a lack of studies focusing on investigating return behavior with respect to different product characteristics, rather than the traits or interview responses of different consumers. Therefore, the authors believe it would be prudent to attempt to fill this research gap by performing analysis of industry data in order to identify potential patterns regarding return behavior with respect to product and sale characteristics, such as product price and discount rate. Based on the gaps identified, the following phenomena were explored:

1.2.1 **Return Rate Relationship with Discount Rate and Sales Price**

The goal of this analysis is to determine how two characteristic factors related to the product at the time of sale affect the return rate of that product.

1.2.2 **Retail Borrowing Return Behavior**

Here the goal is to determine if there is evidence in the data that indicates occurrence of retail borrowing behavior.

1.2.3 **Multiple Size Ordering and Returning**

The goal of this analysis was to explore the behavior described in literature where customers purchase different sizes of the exact same product, in order to try them on at home, and then returning the one(s) that did not fit.

1.3 Purpose

There has been a significant amount of research published recently concerning consumer behavior and attitudes related to product returns, but not much research devoted to quantitative analysis of the profit impacts of higher return rates and longer return delays. The authors would like to contribute to filling this first part of the research gap described by proposing a generalized product-based profitability analysis framework that divides fashion products into categories, based on three parameters: sales period length, base profit margin and product-specific return rate. Sales period length is significant due to the difficulty of re-selling a returned product for full price if the demand is season-based or the window of opportunity for generating sales is otherwise limited. Sales price was chosen as a parameter since a product with low sales price, and therefore a lower possible maximum profit margin, can only withstand a smaller amount of additional cost and still be sold profitably. Product-specific return rate is important as a parameter since recent industry data shows that certain product categories in fashion retailing have far higher return rates than other categories. An example of this would be that a party dress is far more likely to be returned than an everyday product, such as a pair of socks.

The product categories will be subjected to a profitability what-if scenario analysis using a fashion e-tailing supply chain simulation model where two main factors are considered, corresponding to an overall change in customer behavior related to online fashion retail; overall return rate and average return delay. Product categories will be defined by setting each of the three product-defining parameters to a low, medium or high value, creating 27 distinct product categories. Then, the effects of different customer behavior scenarios on each product category will be summarized and developed into a framework that will hopefully be useful for managers trying to determine how the profitability of their product portfolio will be affected by changing return policy decisions as well as changing customer behavior concerning product returns. Whilst some of the proposed categories, for example products with low sales price, high return rate and a short sales period may not be commonly found in reality, it could still be of interest to find out how such products are affected by varying overall return rate or return delay.

There is also a lack of quantitative studies covering different types of return behavior and how different types of products are affected by returns. The authors want to address this gap by performing deeper analysis on the industry order data which is also used to develop input data for the simulation model. Four main areas of interest were identified, based both on theory and patterns that emerged during initial data processing. These areas are retail borrowing, the effects of discounts on return rate, the effects of sales price on return rate, and multiple size ordering and return behavior.

The purpose is to use simulation to determine which product categories are most vulnerable, in terms of profit, to increases in return rate and/or return delay, as well as using data analysis to find how return rate is affected by two critical product-related factors: discount rate and sales price. The authors have also identified two specific kinds of return behavior, retail borrowing and multiple size ordering and returning, and the goal is also to find out to what extent the data indicates the occurrence of such behavior.

1.4 Overarching Goal and Research Question

The goal of this thesis is to analyze the profitability effects of changes in return behavior, on different fashion product categories in an e-tailing situation as defined by the three parameters sales period length, sales price and return rate, where customers have the opportunity to return items with a stochastic return delay. This is done by comparing the profit per item sold by product category in different scenarios with varying average return rates and average return delay, in order to determine how changes in consumer behavior regarding returns affects profit margins of different types of fashion products.

In addition to this, the authors want to evaluate whether the obtained industry data indicates the occurrence of retail borrowing or multiple size ordering return behavior, as well as identify what effects discount rate and sales price have on return rate. The specific research questions are presented below.

RQ1: How are different product categories affected in terms of profitability by increasing return rates?

RQ2: How are different product categories affected in terms of profitability by increasing or decreasing return delay?

RQ3: a) How are return rate, discount rate and time in sales period connected?

b) How is return rate affected by sales price?

RQ4: Is it possible to find data to indicate the occurrence of "retail borrowing" behavior?

RQ5: To what extent does the data indicate the occurrence of multiple size ordering and return behavior?

In addition to these research questions the thesis aims to contribute to understanding the phenomena identified as well as the complexity surrounding them, while also providing readers some suggestions on how to handle their negative effects.

1.5 Scope and Target Audience

This paper will be limited to focus on the Swedish online retail fashion industry. This is also where the underlying data comes from, upon which assumptions are made for the simulation model construction regarding the logic used for return rates, discount rates, typical return delays, product profit margins etc. The process modeling is limited to focus on the process between an order entering the system, and the product being finally sold (i.e., when the customer decides to keep it). Furthermore, this paper does not take into account cases where a product is sold online but returned to a store, which would otherwise add a new set of challenges. Only online purchases, returned to the central warehouse will be considered. Non-operational costs, such as investment costs and inventory carrying costs will not be considered. Neither does the paper consider stock-keeping levels or replenishment, as an item is only generated within the system upon its first sale. This delimitation was formulated since it would be difficult to implement in a generalized system and would introduce a large amount of complexity into the results analysis. At the same time, it would not add significant value since the purpose is focused strictly on the returns aspect of the supply chain and related costs.

One of the target groups that has been identified for this thesis is industry professionals who may benefit from a quantifiable method of understanding how different types of fashion products would be affected by changes in return behavior among consumers, as well as a data-based review of which factors affect return rates and how.

Furthermore, the thesis attempts to deepen understanding within academia for how firms might be affected economically by changing return behavior, and provide inspiration for further study of this relatively unexplored area. The authors believe that simulation can be a powerful tool for analyzing future scenarios within the field of consumer returns, and hope that this study might serve as inspiration for how simulation may be applied for this purpose. The study also aims to demonstrate how industry data can be analyzed to find insights regarding consumer return behavior.

1.6 Thesis Structure

1. Introduction

This chapter describes the background of the research area and gives the reader an idea of how this thesis is intended to contribute to the field of knowledge, as well as how it might find use in practice.

2. Methodology

This chapter describes the methodology used and steps taken in order to conduct the research project presented in the introduction. The research approach used will first be presented, followed by the chosen methodologies.

3. Theoretical Background

This chapter describes the findings from the literature review outlined in 2.2, and provides an overview of the theoretical background for the analysis that follows.

4. Initial Data Study and Results

This chapter goes into detail on the data study that was performed in order to answer suggested gaps. As some of the results of this data analysis were central to the simulation model, these are presented in this chapter. However, the implications of these results will be discussed further in later chapters.

5. Model Description

This chapter covers the simulation process, including a description of the model on a conceptual level, and then in terms of its implementation in the Arena simulation software. It also documents the initial data analysis process for the purposes of model input data.

6. Simulation Results

This chapter presents the results from the simulation study described in chapter 5. The presentation of these results will follow the structure of section 5.3.6.2, which means that the base scenario will be presented first, followed by the scenarios with percental increase of return rate, then the scenarios with percentage point increase in return rate, and finally the scenarios with decreased or increased return delay. Due to the number of product types being analyzed, graphs of the results for each product in each type of scenario will only be presented in the appendix. However, results tables with significance levels and correlation effect size for the difference in mean profit per sold item for each product category will be presented for each type of scenario, and the most significant findings will be highlighted.

7. Analysis and Discussion

In this chapter the project's results are analyzed and the implications for theory and practice are debated. The limitations of the study are also discussed, as well as the various sources of error in the data analysis and simulation.

8. Conclusions and Further Research

This chapter describes the contributions of the project findings to theory and practice and presents suggestions from the authors regarding future research within the field.

2 Methodology

This chapter describes the methodology used and steps taken in order to conduct the research project presented in the introduction. The research approach used will first be presented, followed by the chosen methodologies.

2.1 Research Approach

Jonker and Pennink (2010) describes research as "the deliberate and methodical search for (new) knowledge and insights in the form of answers to questions that have been formulated in advance" (Jonker and Pennink, 2010). According to them, research can be divided into scientific and applied. Scientific, or fundamental, research is conducted in order to contribute previously unknown insights and eradicate shortcomings in fields of research. This process always involves formulating a problem, presenting current research and knowledge on the subject, finding shortcomings or gaps in relation to the problem, and attempt to fill these gaps and adding the research findings to the existing knowledge within the field. (Jonker and Pennink, 2010; Novikov and Novikov, 2013; Bell, 2010)

On the other hand, applied research consists of applying knowledge, typically the results of previous scientific research, as a specific problem-solving approach in the real world, producing solutions that may then be presented to relevant stakeholders (Jonker and Pennink, 2010). According to Jonker and Pennink (2010), this paper can be defined as scientific research since it is intended to fill a gap in the currently established knowledge within the field.

Bell (2010) also discusses the terms quantitative and qualitative research, where quantitative research generally focus and rely on numerical facts as a mean to investigate relationships and draw conclusions within a certain field. Qualitative research on the other hand is more concerned with "softer" values and tend to study questions revolving around things like human behavior and social dynamics (Bell, 2010) As the aim of this study is to draw quantitative conclusions on the effects of changing consumer behavior in the online fashion retail industry, it is clear that it can be characterized as a quantitative research study. However, this does not mean that approaches closer linked to qualitative research must be avoided, as both methods have their advantages. Depending on what information is necessary, it may well be that quantitative as well as qualitative approaches are used. (Bell, 2010)

The methods chosen for this paper are a literature review, in order to gain a deeper understanding of the fields of online retailing, the fashion industry and customer returns, followed by a simulation study, which is appropriate when trying to determine what may happen in a range of what-if scenarios where results are time-sensitive, stochastic elements are present, and the system contains interdependent factors. To facilitate the simulation study, supply chain mapping, categorization and scenario analysis was utilized. Additional insights were collected by conducting an interview with a purchasing manager of an online fashion retailer and from historic order data gathered from the same retailer. This order data was processed using data set analysis and associated quantitative methods.

2.2 Literature Review

According to Arshed and Danson (2015), the purpose of a literature review is "to educate oneself in the topic area and to understand the literature before shaping an argument or justication (sic)". Further, they argue that there has emerged four distinct types of literature reviews. The first is the narrative review, which is a traditional approach where a background to the field of study is presented, along with identified gaps and inconsistencies in the body of knowledge. The second is the systematic review, which is typically more narrowly focused to answer a specific research question. The meta-analysis focuses on using statistical methods to analyze data gathered across multiple previous studies. The final approach is the meta-synthesis, which is more qualitative in its nature compared to the meta-analysis (Arshed and Danson, 2015). According to their paper, the primary literature review conducted in this thesis can be described as a narrative literature review. However, there will also be a more narrow aspect of the literature review that is focused on finding answers for RQs 3 through 5, and identifying gaps in the literature where a data analysis approach may be appropriate to attempt to fill these knowledge gaps. According to Arshed and Danson (2015), this part of the literature review may be described as a systematic review, since it is more focused on answering a research question.

In her 2018 paper "Writing an effective literature review", Lingard argues that the purpose of a literature review within a wider study is not merely to describe what is known within a field of study, but rather to describe a figurative "map" of the field, the purpose of which is to identify a knowledge gap or white space within, which can then be filled by the study presented in the rest of the paper (Lingard, 2018). There are several advantages to presenting a literature review in this way. One of them is that it can help avoid listing unnecessary facts, related to the field but that are irrelevant within the context of the study. Another advantage is that the text is written with the goal in mind of pointing out the identified knowledge gap, which helps keep it more focused and makes for an improved reader experience. Lingard (2018) suggests that the writer be aware of whether the field in question is well-studied or understudied. In the case of a well-studied field, the writer must be more meticulous in selecting which areas to cover since it would be impossible as well as unnecessary to cover everything within the field; instead the writer should focus on only those pieces of knowledge that help in pointing out the interesting research gap. Lingard (2018) also identifies several types of research gaps: a pure knowledge gap where no one has researched a specific area before, a philosophical or methodical gap where researchers may have overlooked some perspective of an issue, a controversy where researchers disagree, or a prevalent unproven assumption within the field (Lingard, 2018).

The authors of this thesis consider product return management within logistics to be a fairly unexplored academic area, especially in terms of quantitative studies. The research gap that this paper is intended to help fill can be considered a pure knowledge gap as the authors have not been able to identify published studies that aim to analyze the effects of changing return rates and return delays on profitability within the retail supply chain. Furthermore, this paper draws its theoretical basis from several different areas, including the history of e-commerce within retailing, the nature of the fashion retailing industry, reverse logistics in practice as well as research related to consumer mentality regarding fashion returns. This warrants a more thorough literature review and associated theoretical chapter in the study, to establish the links which define the problem being studied.

When performing the literature review, the following keywords were used in the search engine lubsearch: *Fashion returns, return rate, retail borrowing, e-tailing, e-commerce, online, discount, reverse logistics, consumer returns, customer returns, seasonality, gatekeeping, avoidance, multiple size ordering, returns management, return flow, returns strategy*. Additionally, results were limited to peer reviewed studies published 2000 or later, to attempt to ensure that the literature was relevant and of high quality. Based on the most relevant articles found using keyword search, snowballing was used to identify additional articles of interest within the scope.

2.3 Categorization of Fashion Products

Categorization is a way to divide entities into groups based on shared properties and can be used as a tool for analysis and pattern recognition (Conradie et al, 2017). This paper aims to provide insights into how different products are affected by changes in return policy and customer behavior, and in order to achieve this products will be divided into groups along with other products with similar parameter values. This categorization is necessary when analyzing results as it gives a large enough statistical basis to draw conclusions on how different products are likely to be affected by changes implemented in return policies and customer behavior. To successfully categorize products it is important to choose the right parameters that defines what category a specific product should belong to. Choosing the wrong parameters will group products in a way that gives a false basis for conducting category-common analysis and could consequently cause misleading results and conclusions. Furthermore, one might imagine a situation where one or several of the chosen parameters are correct in themselves but add little value to the categorization process, such as parameters that are very similar or equal for all entities or parameters that add no value when analyzing different categories. An example of the latter would be to have color as a parameter when categorizing cars for an analysis of CO_2-emissions, as it is unlikely that this parameter will add significant value to this analysis. Based on these guidelines, it is clear that choosing the parameters for this paper's product categorization must be done in a careful manner.

As a result, the products analyzed in this paper will be categorized by identifying key parameters based on how much they are expected to affect a product's profitability. The parameters chosen as characteristic of a certain product in this context were base sales price, return rate and sales period length, which can each assume the value ranges low, medium or high, creating 27 distinct product categories, to be used as the basis for analysis.

2.4 Scenario Analysis

Scenarios can be used to describe and illustrate different possible futures. According to Mietzner and Reger (2004) scenarios are often misunderstood as a tool for predicting or forecasting the future, while they argue that scenarios should be viewed as strategic tool that helps in understanding the effects of decisions or showcase alternative solutions to guide decision makers when facing uncertainties. This paper will use scenario analysis to better understand how different product characteristics affect the profitability of those products in order to provide insights into what risks and uncertainties may be important to have in mind moving forward. When formulating scenarios the five step model presented by Kosow and Gaßner (2008) will be followed. This model consists of the five steps or phases presented in Figure 2.1.

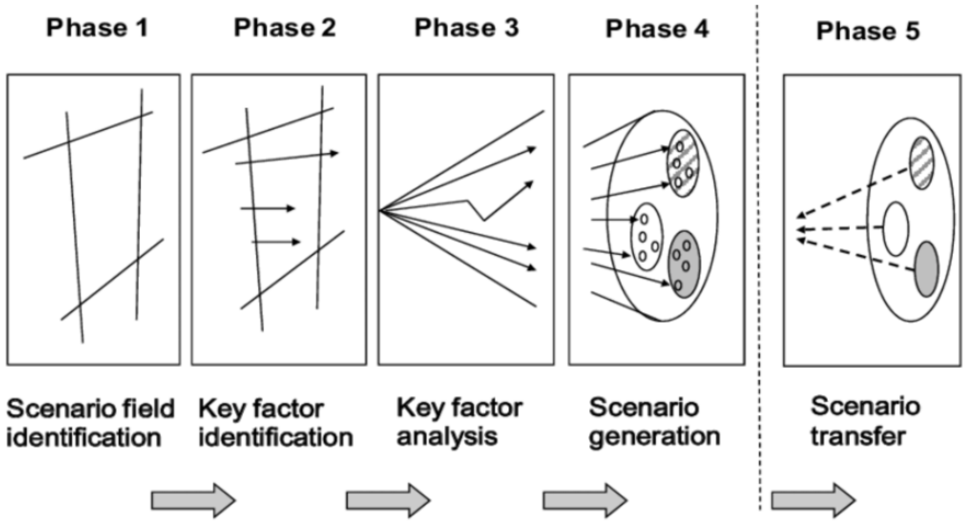

Figure 2.1 Five step scenario model adopted from Kosow and Gaßner (2008).

In the scenario identification phase the aim is to describe the purpose of creating a scenario analysis, e.g. "Why are we conducting this analysis?" or "What issues are we attempting to solve?". This phase of the scenario process also deals with factors such as limitation of scope, both in the sense of limiting the field that is to be studied, e.g. a single machine, the whole factory or the entire supply chain, but also what external factors should be taken into consideration, such as political and economic factors, environmental changes or cultural aspects. (Kosow and Gaßner, 2008)

The second part of the process deals with defining what key factors exist in the identified scenario field. This revolves around being able to identify the factors most important in the identified field and together are considered central to the performance of the entire process. These key factors can be anything from parameters or variables to sub-processes or trends within the scenario field and in order to successfully capture them, it is important to have a thorough understanding of the process. (Kosow and Gaßner, 2008)

The next step in the process is to analyze the identified key factors. This analysis specifically focuses on establishing what future values or characteristics each factor individually can be expected to assume. This step is central in a scenario analysis and the fact that it takes unknown, future aspects into consideration is perhaps what sets it apart most from other types of analysis techniques. (Kosow and Gaßner, 2008)

This brings on the fourth step in the scenario process, scenario generation. Using the individual analysis previously conducted on the key factors, they are now considered together and a variety of scenarios are constructed by using different values of their future parameters and characteristics. One of the most important aspects of the scenario generation is to create meaningful and comprehensible scenarios that add value when making future decisions connected to the field studied. One of the implications of this is that the number of scenarios should be kept small enough to ensure the ability to gain an overview of the entire process, without missing important perspectives. (Kosow and Gaßner, 2008)

Scenario transfer is the final step of the scenario process and deals with what happens after the scenarios have been generated. That is, “what do we do with the results generated from our scenarios?”. This step could include a wide variety of actions, everything from impact analysis of the field in question to roadmaps/backcasting, connected to the question “What actions do we need to take in order to reach this future scenario?”. The scenario transfer chosen is consequently closely linked to, but not exclusively limited to, the motivation behind the scenario analysis. If the aim from the offset was to evaluate how the current strategy is aligned with possible future scenarios, then it seems likely that a strategy assessment is good candidate in the scenario transfer phase (Kosow and Gaßner, 2008). Within the context of this study, scenario analysis was used in the simulation process in order to determine the effects of varying return rate and return delay on different product categories.

2.5 Simulation Study

This section outlines the sub-methods used in order to perform the simulation study and analyze its results.

2.5.1 **Simulation Study Outline**

Law and Kelton (2000) describe one of the advantages of simulation as being able to investigate real-world problems where the complexity and stochastic properties of the system renders it unfeasible for evaluation with traditional analytic methods. Furthermore, “simulation allows one to estimate the performance of an existing system under some projected set of operating conditions” (Law and Kelton, 2000). Considering the nature of this project where the system being studied is time-sensitive and contains heavily stochastic elements as well as interdependencies, a simulation study is suggested to be the most suitable approach.

This is also supported by Banks et al (2010), who state that a simulation approach is appropriate when trying to answer what-if questions, such as finding the effects of environmental changes for complex systems.

In his 2003 paper from the Winter Simulation Conference, Averill M. Law describes a seven-step approach for performing a successful simulation project. The steps and the associated process flow is outlined in Figure 2.2.

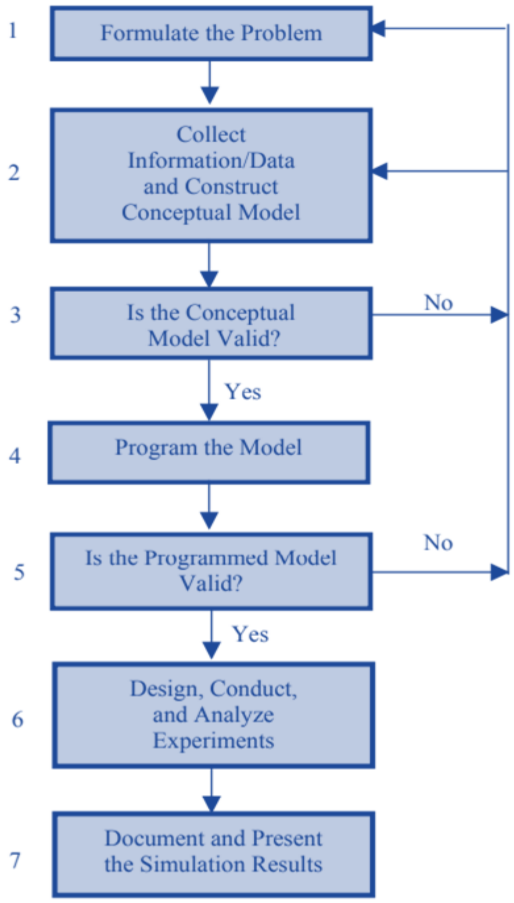

Figure 2.2 A flowchart overview of the seven-step approach (Law, 2003).

The first step is problem formulation. The project's overarching objective should be established, and it is also necessary to determine which specific questions the simulation project is to provide answers for. However, in many cases the problem will only be vaguely defined or understood at the start of a project, which means that this stage must be revisited and revised as the project proceeds and more details emerge regarding the problem. At this stage, the model's scope should also be determined, and KPIs (Key Performance Indicators) selected for appropriately measuring the performance of the model in the experimental scenarios.

The second step involves data collection and constructing the conceptual model. When collecting data on the more critical aspects of the system structure, it may be necessary to consider more than one document or expert since some data could be unreliable. It is also important to consider probability distributions rather than only absolute values (such as the mean value) of e.g. a process delay or machine failure rate. According to Law (2003), two common mistakes is to either use the mean value or use too rough of an approximation when determining the appropriate probability function, such as using a uniform or triangular distribution, when the real density function may have a “long right tail”.

The conceptual model and its associated assumptions, data usage and logic should be well documented in order to avoid errors and misunderstandings. If possible, performance data should be gathered from the real system for use in model validation (the fifth step). At this stage unnecessary model complexity should be avoided; instead, make the model simple and flesh out the most important parts later if necessary. Law (2003) suggests that the simulation team continuously remain in contact with the project stakeholders and decision-makers, in order to ensure that the right problem is being solved, whilst simultaneously improving the study’s credibility since the decision-maker’s involvement in and understanding of the project is maintained throughout.

In the third step, validation, the conceptual model should be presented before an audience consisting of those involved and familiar with the real system that is being studied. The purpose is to ensure that the model’s logic and assumptions are consistent with the real system and that any errors or gaps can be discovered and corrected as early as possible, saving valuable project time. This will also improve awareness and project credibility amongst all involved stakeholders (Law, 2003).

The fourth step consists of programming the model. The appropriate programming language or simulation software is selected and the conceptual model is implemented. Which language or software is appropriate in each case depends on the trade-off between ease of use and flexibility, as well as software availability. In the fifth step, the implemented model is validated, either based on performance data from the real system being studied, or by having experts familiar with the real system examine if the model behaves in a reasonable way. A combination may also be used.

In the sixth step experiments are designed and performed based on which real-world scenarios need to be examined. It is important to consider statistical reliability-related aspects such as run length, number of replications and, if applicable, warm-up and/or cool-down period. Law (2003) recommends that, to achieve statistical reliability, a confidence interval should be constructed using multiple replications. Then, the results are analyzed and if necessary additional experiments are performed.

The seventh and final step consists of model documentation for reuse and repeatability purposes, as well as presentation of the results and discussion of the model’s reliability and the building and validation process (Law, 2003).

2.5.2 **Supply Chain Mapping**

As this study focuses on a general fashion e-commerce returns supply chain the processes will be mapped using a combination of available literature describing best practices and case studies performed on companies similar to the ones described in the scope. Process mapping is not only used in order to provide these insights, but will also be an important tool when building a conceptual model of the system that is to be simulated.

The process mapping will consist of three steps. Firstly, it is crucial to determine the frames of the process. Knowing exactly where the process starts and ends is an important part before moving on to the next step. Secondly, all relevant activities in the process should be identified and described as thoroughly as possible as well as connections between the identified activities. Lastly, the process is viewed as a whole as a way of identifying any activities or connections that affect several parts of the process (Gardner and Cooper, 2003). Supply chain mapping is used in this study to identify the steps of the return process which should then be implemented in the simulation model.

2.5.3 **Data Collection**

This part of the thesis describes the data collection process within the study and details the associated methods that were used.

2.5.3.1 Interviews

In order to collect information otherwise not available in data or through literature review, interviews will be conducted with practitioners in return processes of online fashion retailers. The purpose of these interviews is primarily to better understand the decision making within the return process, but also to uncover new interesting issues and features of the process that have not been identified prior to the interviews.

Jennings (2005) presents that interviews can be divided into three categories; unstructured interviews, semi-structured interviews and structured interviews. Unstructured interviews can be described as more relaxed conversations where no questions are prepared in advance. This means that the interview flow is more similar to an everyday conversation and gives the interviewer a great deal of freedom to pursue interesting talking points that emerges throughout the interview. Structured interviews is in many ways the direct opposite of unstructured interviews, as the name suggests, and follow a clear and predefined protocol. If multiple interviews are conducted, all interviewees will receive the exact same questions and follow-up questions. The last type of interview, semi-structured, is a combination of the two previous. The interviewer will follow a question protocol and will ask these questions to everyone interviewed. However, once a question has been asked and answered follow-up questions may be asked as the interviewer see fit, ensuring some of the flexibility related to the unstructured interview technique while at the same time maintaining a fairly structured protocol. (Jennings, 2005)

The decision making process within returns management has seen little previous research, which according to Bernon et al (2013) calls for semi-structured interview as it is "flexible enough to allow an exploration of an under-researched phenomena". The semi-structured interview also provides the necessary structure to ensure that important areas aren't overseen in the case that an interview evolves into focusing heavily on a specific question. Based on these factors a semi-structured interview approach was chosen. The interview roughly followed the protocol presented in Appendix A.

An important aspect of conducting interviews is how the results are documented, e.g. by taking notes or using audio or video recordings. The different documentation methods have different advantages and disadvantages. Audio and video recordings are for instance much easier to reassess after the interview has been conducted and can better take into account the way in which the information was expressed (Al-Yateem, 2012). Video recordings have an additional advantage compared to audio by also giving the opportunity to analyze body language and facial expression. By only taking notes one tends to lose this dimension of the interview while at the same time increasing the risk that important information is overseen. However, audio and video recordings could prove problematic when conducting interviews on sensitive issues. Choosing documentation method is consequently a trade-off between quality of information and the ability to accurately document information that must be taken into consideration before conducting an interview (Al-Yateem, 2012). Based on the confidential nature of the interview and the fact that one of the interviewers was able to focus on taking notes, audio or video recording was not used for the interview performed within this study.

2.5.3.2 Data Set Analysis

An important part of conducting a quantitative analysis is the ability to collect, arrange and analyze data that will be used as input values or variables which will later serve as a base for further analysis. The first step of this method is collecting the data, which can be done in a number of ways. A few examples of how to receive such data is in the form of large data sets generated from business systems connected to manufacturing systems, point of sales data or shipment information. The next step is to structure and organize the data in a way that allows for easier analysis. This might involve deleting rows of data due to duplications and removing unnecessary information that does not add value to the analysis. It is important to have a structured approach when performing this step, as mistakes identified at a later stage of the project will take far more time to correct. The final step is to conduct the data analysis, where project-necessary input values are established. Exactly how this analysis is conducted varies depending of the nature of the collected data. (Sapsford and Wilson, 2006)

In this study the data was received in the form of order lines from an ERP (Enterprise Resource Planning) system. Before analysis was performed, lines with missing values or clearly erroneous data were removed. In the process of analyzing the data, as well as developing and testing values, distributions and equations for use in the model, a variety of quantitative methods were used, including correlation analysis, linear regression, distribution fitting, t-test, Chi-square test and Kolmogorov-Smirnov test. The quantitative analysis tool Matlab as well as Rockwell Arena Simulation Input Analyzer were used in the data set analysis for this study.

3 Theoretical Background

This chapter describes the findings from the literature review outlined in 2.2, and provides an overview of the theoretical background for the analysis that follows.

3.1 E-Tailing within the Fashion Industry

Initially, it is necessary to provide a background regarding the development of e-commerce as a completely different retail channel compared to the traditional brick-and-mortar form of retailing. This will provide context for the current situation in the retail industry with mounting costs regarding customer returns.

3.1.1 **The Rise of E-Tailing**

Since the early 1990s, the overall use of e-commerce has seen an explosive growth worldwide and has revolutionized the way people purchase goods and services. This development is noticeable also in Sweden, where the online share of retail sales has increased from 3 % in 2007 to 8,7 % in 2017, with total sales of 67 billion SEK. Industry analysts say that this shift will continue and predict that total sales will double in five years with the current growth rate. (PostNord, 2018a)

From a retailer's point of view there are several factors that can be used to explain why e-commerce has seen such an expansive growth during the past years, but the following are regarded as among the most important ones;

- Reduced facility costs – e-commerce gives the opportunity to eliminate the need for a physical store.
- Reduced personnel costs – with a well-developed e-commerce solution the need for staff to man the store and cash registers is eliminated.
- Digital sales – purchasing digitalized items, such as movies and books, makes it possible to receive the product instantly and reduces company's inventory cost
- Customer data – more recently, e-commerce has given companies a new way to collect data on customer behavior that can be used to focus advertising and increase sales
  (Kuhrana, 2018; Brain, 2000; Wagner, n.d.)

Despite these advantages compared to more traditional retailers there are still some disadvantages that have arisen with the emergence of e-commerce.

- Shopping experience – with e-commerce, consumers may feel that they lose the personal service and social aspect that is connected to shopping. Customers also miss the opportunity to feel and/or wear the products they are shopping for.
- Delivery times – consumers generally want their purchased products as quickly as possible. Apart from digital products, this time is naturally longer when using e-commerce than traditional retailers, as the purchased item has to be packaged and shipped. This discrepancy puts pressure on the speed in which online stores have to deliver orders to their customers.
- Return flows – if a customer is in some way unhappy with a purchase this is likely to cause a customer return. Some countries even have regulations that force companies to offer refunds on returned products that were purchased online. This process adds complexity in the logistics flow and results in increasing costs when handling returned products.
  (Kuhrana, 2018; Brain, 2000)

3.1.2 **The Online Fashion Industry**

The fashion market segment of e-commerce is defined as follows by Statista;

> *"The eCommerce market segment Fashion includes the online trade of articles of apparel (for men, women and children), shoes and shoe care products (e.g. cleaning products) as well as accessories and bags (e.g. hats, scarves, gloves and leather bags, suitcases, purses and briefcases)". (Statista, n.d.)*

Noteworthy is that sports and outdoor apparel and shoes as well as baby clothes are not included in this segment, but are instead part of other market segments. The clothing segment is by far the largest of the three main components and constitutes about 65 % of the total revenue. (Statista, n.d.)

The online fashion industry is often described as a fast moving market where it is considered key to decrease the so-called "time to market", that is, how long it takes for a company from that they pick up a new trend until it's available to customers. This type of business model is in many cases referred to as "fast fashion", where retailers focus on quickly providing consumers with affordable fashion trends. The emergence of fast fashion has in part been driven by the fact that consumers to a larger extent demand that the speed in every process is increased to make the shopping experience faster. Customers have grown more impatient and expect the gratification of shopping to come immediately. This consumer behavior has created situations where some companies have attempted to offer 90 minute deliveries on orders, which naturally leads to difficult supply chain challenges. (Friedman, 2017; Statista, 2018) In his article, Cohen (2011) states that this quick and responsive method has to rely on a "streamlined system involving rapid design, production, distribution, and marketing". Consequently, this business model sets high requirement standards on supply chains in order to be successful and profitable within the fashion industry (Statista, 2018).

The e-commerce fashion industry is currently a multi-billion dollar market with a revenue of $451 billion in 2017. As more and more people get connected to the internet and the number of smartphone users continues to increase the industry is projected to see a worldwide revenue of $788 billion in 2022, a growth of almost 75%. Another important explanation to the industry's fast growth is that large middle classes are emerging in several countries worldwide, giving them the opportunity to spend a larger part of their income on non-necessities such as fashion. Despite these opportunities, the industry is facing challenges during the upcoming years. One of the most difficult ones are related to environmental challenges. As more and more people are requesting green sourcing, constraints are put on everything from manufacturing materials to transport solutions. Another area of concern is customer returns, where rates sometimes as high as 50% are causing significant cost increases. Should this trend continue, retailers will need to find ways to revert the negative effect of returns on profitability. (Orendorff, 2018; Statista, 2018)

In Statista's report of the e-commerce fashion industry from 2018 Sweden ranks as the sixth largest market for online fashion sales in Europe with 3.1% of the total revenues, behind only much larger countries as the UK, Germany, France, Spain and Italy. The e-commerce fashion industry grew 13% in Sweden during 2017 and this growth is expected to continue, although not at the same pace as worldwide given that the market is far more mature in Sweden. (PostNord 2018a; Statista 2018)

3.2 Returns Management

Rogers et al (2002) define returns management in the following way:

> *"Returns management is that part of supply chain management that includes returns, reverse logistics, gatekeeping and avoidance."*

As consumer returns have become more and more prevalent during the past years, maybe most significantly within the e-commerce industry, many researchers have stressed the importance of practitioners focusing more on the processes involved in returns management. One of the main reasons is that they experience a lack of knowledge within the field and they argue that this causes the processes to be inefficient and ineffective, ultimately resulting in a sub-optimized supply chain. (Winkler, 2018; Hjort, 2013)

If the objective is to maximize the total value of the supply chain, many theorists argue that this can only be achieved by proper integration of the processes, both within the company and with other parts of the supply chain (Mentzer et al, 2001; Lummus et al, 2008; Croxton et al, 2001).

Röllecke et al (2018) define three types of returns management programs. Type 1 views returns primarily from a cost viewpoint and seeks to minimize returns in order to reduce returns-related costs, without considering trade-offs in terms of customer satisfaction and customer considerations when deciding on making a purchase. Managerial actions in this category might be charging the customer for returns, or making the return process purposefully difficult. Examples of the latter include refusing returns without a receipt or making the customer print the return label. These policies are typically implemented by smaller retailers who lack the capability to differentiate between profitable and unprofitable customers with regards to return and purchase behavior. (Röllecke et al, 2018)

Type 2 programs attempt to balance the need to reduce costly returns with maintaining customer satisfaction. Retailers implementing these programs usually try to leverage customer data in order to provide more leniency to profitable customers, while introducing a variety of measures to deal with habitual returners. One example cited by Röllecke et al (2018) is Amazon, who provide free and hassle-free returns in the case of returns triggered by some Amazon error, but charge a shipping fee and value-based refund deduction otherwise. Furthermore, Amazon have also closed customer accounts for repeat returners. Type 2 programs are most common in industries with lower profit margins for retailers, but where there is still a major need to consider customer satisfaction and retention due to high competition. One example brought up of such an industry is consumer electronics. (Röllecke et al, 2018)

The final category, Type 3, is wholly focused on improving customer satisfaction. The theory behind choosing this type of program is that the benefit in terms of customer acquisition and retention, and the resulting increase in sales, will outweigh all costs resulting from increased product returns. Röllecke et al (2018) cite the fashion industry as a typical case where this program is common due to the need for many customers to experience products physically before making a final decision on whether or not they want to keep it. Customers here expect something equivalent to the brick-and-mortar fitting rooms, to be provided without hassle and free of charge. Röllecke et al (2018) bring up Zalando as an example of a company implementing a type 3 policy. According to Zalando themselves, this is part of their overall core business goal of customer satisfaction. However, some return avoidance methods can be beneficial for both customer and retailer, such as improving text-based and visual product information regarding size, fit and color. (Röllecke et al, 2018)

Returns are a particularly significant challenge within e-commerce as retailers within various industries grapple with the fact that online purchases have far higher return rates than purchases made at traditional brick-and-mortar stores (Winkler, 2018). Some commonly cited reasons for the high return rates online include the inability of online customers to try the products on themselves and experience them visually and physically in a realistic way, which may lead a customer to order a product in a size or color that they did not actually want, or order a product they do not want at all (Saarijärvi et al, 2017). For reasons such as these, retailers that operate online implement generous return policies as a way for customers to mitigate purchasing risk. The idea is that lenient return policies will lead to an increase in demand of such a magnitude that it offsets the higher costs that an increase in return frequency will incur (Janakiraman et al, 2015). Recent studies provide some evidence that generous return policies do increase demand and drive customer retention and purchase amount, but it is still quite unexplored in research what the net effect is on profitability for companies in the online retail space, which in part could relate to difficulties in accurately describing the total cost of product returns.

As the online market share grows in importance for fashion retailers, return policy leniency has become a way of competing for customers and sales volume. Many customers today take hassle-free and/or free returns for granted and may shun retailers that do not provide them (Bower and Maxham, 2012). In this environment it is increasingly important to find what cost impacts these policies can have, in order to weigh them against increases in sales. Janakiraman et al (2015) state that return policies are used as a risk reliever for consumers, driving increased sales, but as demand increases, returns are likely to increase as well. Whilst it is widely believed that high return rates cut significantly into profit margins for retailers, these cost structures are not well defined, and the effects on profit are not well known.

Swedish fashion retailers implement a wide range of return policies, ranging from 14 to 365 days, where 14 days is the minimum legal requirement for online purchases (Konsumentverket, 2018). Additionally, there is close to a half-and-half split between those who provide free returns, and those who require the customer to pay a return fee (which roughly represents the shipping cost). Retailers also take different approaches in terms of marketing, where some are very up-front about their generous return policies and use it as a marketing tool, while others make it more difficult to find out which policy they implement on the website. Below, Table 3.1 illustrates the various return policies implemented by a wide range of online fashion retailers operating in Sweden.

Table 3.1 Presentation of return policies for 40 Swedish online fashion retailers.

Retailer	Number of days	Cost of returning
Adidas	30	Free
Bechic	14	Customer pays for shipping
Bon Prix	14	Customer pays for shipping
Boozt	30	Free
Brothers	14	Customer pays for shipping
Bubbleroom	14	Customer pays for shipping
Care of Carl	14	Free
Cellbes	14	Customer pays for shipping
Chiquelle	14	Customer pays for shipping
Cubus	100	Customer pays for shipping
Daniel Wellington	30	Customer pays for shipping
Dressman	180	Free
Ecco	30	Free
Footway	180	Free
Gant	30	Free
Gina Tricot	14	Customer pays for shipping
H&M	30	Customer pays for shipping
JC	21	Free
Joyshop	14	Customer pays for shipping
Junkyard	14	Customer pays for shipping
KappAhl	14	Free

Retailer	Number of days	Cost of returning
Lindex	30	Customer pays for shipping
Madlady	30	Customer pays for shipping
Man of a kind	14	Free
Mango	30	Free
Masai	14	Free
MQ	14	Free
Nelly	14	Customer pays for shipping
Nisses Herrmode	14	Free
Odd Molly	30	Customer pays for shipping
Paapi	21	Customer pays for shipping
Polar	14	Customer pays for shipping
Scorett	14	Customer pays for shipping
Sneakers point	30	Free
Stadium	365	Customer pays for shipping
Stayhard	14	Free
Stylepit	50	Free
Triumph	14	Free
Zalando	100	Free
Zara	30	Free

Even though companies implement such a wide range of different policies, the effects they have on return rates and return delay is still largely an unexplored area. Return delay is defined within the context of this paper as the time between customer pick-up of the delivered product, and the customer sending the product back to the retailer. The authors of this paper hypothesize that this return delay, in addition to high return rates, could have a significant effect on profits, particularly in an industry like fashion that is often heavily driven by short product sales windows and discounts (Zhang et. al, 2017). Based on the theory that lenient return policies that allow later returns could drive increased lateness in returning products, it would be prudent to investigate what effect this phenomenon might have in terms of profits.

Saarijärvi et al, in their interview-based 2017 study, discuss various reasons for consumers returning fashion products purchased online. The study focuses on categorizing returning behavior. They divide the consumer purchasing process into six phases: the searching and ordering phase, delivery phase, arrival phase, seeing, touching and feeling phase, experimenting phase, and finally usage. They associate different types of return decisions with each phase of the process. For the searching and ordering phase, there are several reasons for returning that can be associated with a decision to return being made prior to ordering the item. One reason associated with this phase is ordering one product in multiple sizes, or several very similar products, in order to try them out at home, and then returning all but one. Another is ordering an item for fitting, returning it, and then buying it later, possibly from a different retailer. In the next phase, delivery, consumers might return a product after ordering but before its arrival, because they found a better offer for the same product from another retailer. Some consumers might decide to return a product or neglect to pick it up, because they realize they may have ordered products they do not need and/or cannot afford. This behavior could also be observed in phase 3, arrival, which is defined as after the products have been picked up but before opening the package. (Saarijärvi et al, 2017)

In the fourth phase, when the customer first physically experiences the ordered product, some reasons cited for returning products include reclamations (associated with product defects), the wrong product being delivered, or some perceived discrepancy between the product description and reality. For returns associated with the fifth phase, experimentation, problems often arise from issues with size charts, where the size that the customer usually orders ends up not fitting them properly. Customers may also return a product for reasons that are difficult to define, such as it not matching some predetermined expectation, or just not matching their personal sense of style when trying it on. Finally, in the usage phase, the authors determine that customers may return products due to quality issues that arise first only after some period of use. An example given is of a pair of jeans whose color deteriorates after the first wash. (Saarijärvi et al, 2017)

The authors specifically focus on attempting to separate returning behaviors into "planned or unplanned", and the article highlights how the nature of online shopping may continue to drive an increase in returns because consumers make more impulsive decisions when shopping online, encouraged by lenient return policies to order more items than they may need, or order items they do not intend to keep at all (Saarijärvi et al, 2017). At the same time, most recent studies on the subject appear to have determined that lenient return policies generally drive demand to a higher degree than they increase returns, and therefore drive increased revenue overall (Hjort and Lantz, 2016; Bower and Maxham, 2012; Mukhopadhyay and Setaputra, 2007; Petersen and Kumar, 2010). However, not much is known about the effects on profits with regards to different product segments, where some have been found to have significantly higher return rates than the mean (Hjort and Lantz, 2012).

The two concepts gatekeeping and avoidance, mentioned earlier as the two main categories for specific strategies for reducing returns, are presented in more detail in the subsections below.

3.2.1 Gatekeeping

Gatekeeping refers to activities connected to screening whether a specific return is valid or not (Rogers et al, 2002). In order to implement a working gatekeeping solution it is important to provide customers with correct information regarding what requirements need to be met in order for a return to be considered valid. These requirements generally involve returning the product within a certain time window and restrictions on the condition of the product (Rogers et al, 2002; Hjort, 2013). Such restrictions may well differ for different types of products, e.g. that some product may be acceptable returns even if they have been used or assembled (for instance certain types of clothes or furniture), while other products are expected to be in their original packaging for a return to be accepted (for instance underwear and swimwear). According to Hjort (2013), a properly implemented gatekeeping solution can reduce costs and improve customer satisfaction while at the same time increasing the efficiency and effectiveness of the returns flow, ultimately resulting in an improvement of the entire supply chain's performance.

3.2.2 Avoidance

The basic concept behind avoidance is to minimize the number of returns by taking actions that make customers less likely to feel they need to return products they purchase (Rogers et al, 2002; Lambert, 2004). This can be done in numerous ways by for instance ensuring high quality of products sold and properly informing consumers regarding important aspects of the product, such as size, color and fit (Hjort, 2013). By successfully implementing an avoidance strategy, retailers can not only save money by reducing unnecessary orders that will ultimately result in returns, but could also improve customer satisfaction by providing customers with all information they consider important to make an informed purchasing decision

(Rogers et al, 2002). In his article, Hjort (2013) also mentions multiple size ordering as something that could occur if consumers are uncertain of what size to choose and consequently buy multiple sizes to increase the chance that one of them fits. Providing correct and clear information could therefore also help retailers avoid such purchasing behavior.

3.3 Seasonality and Discounts in the Fashion Industry

The fashion industry is characterized by unpredictable demand, seasonal products, and a diverse product portfolio leading to a very large number of different SKUs (Nenni et al, 2013). In their review of fashion industry demand forecasting, Nenni et al (2013) describe fashion demand as generally having a high degree of “erraticness” or “lumpiness” which makes more commonly used demand forecasting methods highly ineffective. Even if the total demand for a certain type of product can be accurately forecast, the variety of SKUs offered and the low sales volume associated with each SKU makes forecasting at such a low level “very difficult”. Furthermore, due to the competitive fashion market, some of the most prominent fashion companies have moved towards designing product lines with life cycles and “seasons”. According to Nenni et al (2013), companies like Zara may work with up to 20 “seasons” in a year, in which more or less the entire product lineup is refreshed.

In the context of an industry with such short selling seasons, Nenni et al (2013) claim that some within the industry are questioning whether it is even possible to accurately forecast demand, and are instead moving towards optimizing their supply chains to produce and distribute products “on the basis of ‘real-time’ demand”. This places high requirements on all parts of the supply chain, including the reverse logistics aspect, as return rates continue to soar within the online fashion sector. For a product that has gone out of season, so-called clearance discounts will often be used to get rid of excess stock, which squeezes profit margins (Caro and Gallien, 2012; Avittathur and Biswas, 2017). As seasons and sales windows for many product categories get shorter, the authors of this paper propose that companies may be forced to find new ways to reduce return rates as well as return delays in order to stay competitive, since returned products may already be past their sales window by the time they get back to the retailer to be put up for sale once again.

3.4 Statistical Methods

This section will provide the reader with some basic insight regarding a few statistical methods, as well as how and when they are appropriate to use.

T-test

A commonly used statistical analysis is to compare the means of two value samples. One such test used in order to see if there is a statistically significant difference between the means of two samples with unequal variances is Welch's t-test. This test is used to test the hypothesis that two samples have the same mean and is described by the following statistical expression presented in Equation (3.1) where $\overline{X}$ is the sample mean, s is the sample variance and N the sample size. (Welch, 1938)

$$t = \frac{\overline{X}_1 - \overline{X}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}} \qquad (3.1)$$

Correlation test

Another method used to discover relationships in data analyzed is the correlation test, which evaluates how strongly related two variables are to each other. The correlation coefficient measures the strength of the relationship and can assume values from -1 to +1, where ±1 indicates a perfect negative/positive relationship between the two variables. If the coefficient moves closer to zero the relationship weakens. (Bobko, 2001)

Regression analysis

Regression analysis is a statistical tool used to discover how independent variables affect and predict a dependent variable. It is often used to determine how this relationship looks and which of the independent variables have the most impact on the dependent variable. A regression model is then created in order to illustrate the relationship, along with a regression line representing the best line-of-fit. An example of a regression model is presented in Figure 3.1. (Bobko, 2001; Gallo, 2015)

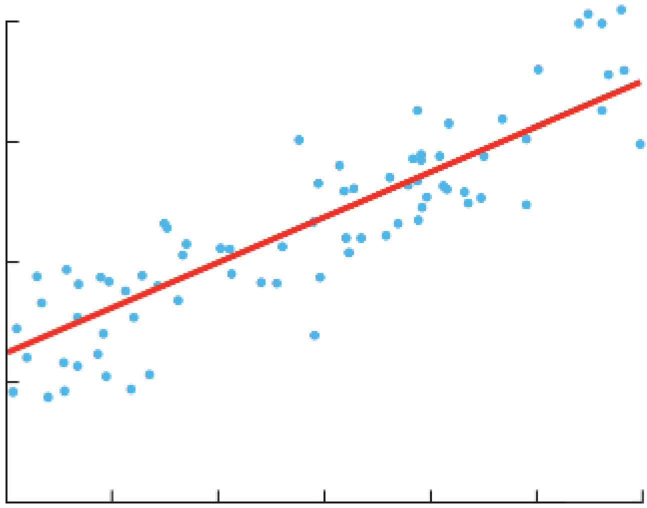

Figure 3.1 An example of a simple regression model (Gallo, 2015)

Kolmogorov-Smirnov test

A test that can be used to determine the goodness of fit for statistical distributions calculated from data is the Kolmogorov- Smirnov test. The test is performed by finding the largest vertical distance between the graphs for the data set and the distribution being tested, as seen in Figure 3.2, and from this calculating the test statistic, D, using Equation 3.2.

$$D = \sup_{x} |F_0(x) - F_{data}(x)| \tag{3.2}$$

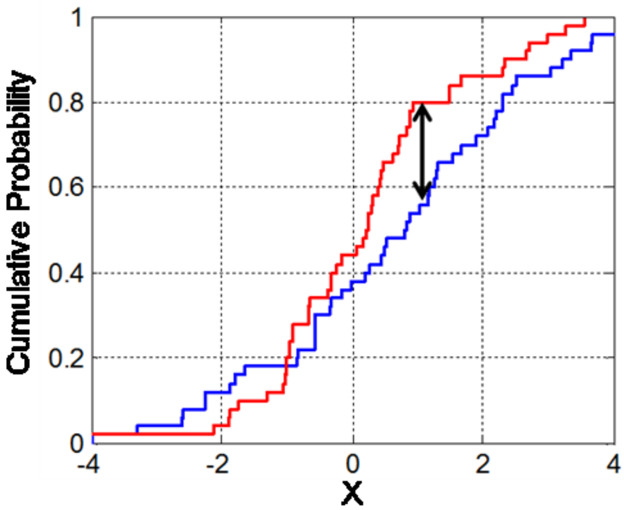

Figure 3.2 Illustration of the Kolmogorov-Smirnov test methodology. (Wikipedia, 2018)

This value is then compared with a so-called critical value, the size of which depends on the number of data points being tested, as well as the chosen significance level, in many cases 0.05. The critical value is equal to $1.36/\sqrt{n}$, where n is the number of data points the distribution is being tested against. If the D-value is larger than the critical value, the null hypothesis cannot be rejected. (Simard and L'Ecuyer, 2011)

4 Initial Data Study and Results

This chapter goes into detail on the data study that was performed in order to answer suggested gaps. As some of the results of this data analysis were central to the simulation model, these are presented in this chapter. However, the implications of these results will be discussed further in later chapters.

4.1 Initial Data Processing

Before conducting the data analysis, order lines with missing or erroneous vital data were removed. These data points comprised less than 0.5% of the total number of order lines. Furthermore, for those data purposes where product sales period length is involved, only one calendar year of data was used, from June to June, in order to prevent issues calculating sales period related to products that are sold periodically over multiple years. In addition to this, products whose final order took place during the first two months, as well as products whose first order took place during the final two months, were also removed in order to try and limit the range of analyzed products to only those whose sales period could be wholly contained within the year covered by the data. Generally, the range of products was also limited to only those with over 10 sales in order to avoid data anomalies related to products with very few sales. Based on this initial processing the data was analyzed in order to answer the gaps suggested in 3.4.

4.2 Retail Borrowing Return Behavior

Hypothesis Description

One of the suggested phenomena to investigate was the occurrence of retail borrowing, as presented by Hjort and Lantz (2012). In this article, the authors point out that a category of clothes they define as "party dresses" are more likely to be subject to this sort of consumer behavior. Consequently, the authors of this paper found it of interest to investigate whether or not a similar connection could be found in the data received. In order to investigate this, three different hypotheses were conceptualized.

The first one was that the closest similar category to the “party dresses” mentioned by Hjort and Lantz (2012), “dresses”, should have a longer average return delay than other items to indicate that they were being retail borrowed. The reasoning behind this hypothesis was that customers buying these dresses with the intent to return them would have a specific occasion in mind for when these products were to be used. Further, this would cause these consumers to order the dress a few days in advance to ensure that it would arrive on time, and also give them time to make sure that the size was correct and that it looked as they imagined it would. With the help of pivot tables in Excel the return delay for “dresses” were compared with the rest of the data using Welch's t-test to see if any statistically significant difference between the two means could be found. Using Excel’s data analysis tool the null hypothesis could then be tested on a desired significance level.

The second hypothesis was that the same data category, “dresses”, should be overrepresented when it came to products being returned with stains or other signs of use (in later parts only referred to as stains), as retail borrowed products likely would be used in a way that greatly increases the risk of them not being returned in perfect condition. This was also investigated using pivot tables along with the t-test, where the average of returns with stains for “dresses” was compared with the average of “non-dresses” returned with stains.

The third hypothesis was also connected to all products returned with stains, but was developed to see if these products had a longer return delay than other products. Likewise, this hypothesis was also based on the assumption that a product with stains is more likely to have been retail borrowed and that such products should have a longer return delay than others. This was then analyzed in the same way as hypothesis one, using pivot tables and a t-test comparing the mean return delay for returns with stains with those without.

An issue with hypothesis two and three was that the information available in the data concerning whether a product was returned with stains or not, also included other product-related problems, such as damaged (containing holes or similar flaws) and poorly sewn products. Another reason that this data could be a difficult source of information when investigating these hypotheses was that it was collected from the customers themselves, in the form of an answer to a question related to the return reason of the product being returned. One might argue that a customer who intended to retail borrow, and accidently put a stain on the product in question, most likely would pick something less conspicuous as their return reason. Based on the data analyzed and answers given in the interview with a company representative, it also seemed likely that most customers returning products actually didn’t bother to select the correct return reason, but rather picked the first one presented. This behavior was clearly visible in the data as a very large part of returnees had selected the first available option, “Did not meet expectations”.

Hypothesis Test Results

When testing the first hypothesis described in the section above, no difference was found between the average return delay for the category "dresses" compared to other categories. The test was conducted on a 95% significance level, resulting in the null hypothesis (equal sample means) being rejected with p-values smaller than 0.05. The results of the test are presented in Table 4.1 below.

Table 4.1 Results of retail borrowing hypothesis 1.

	Returned dresses	Other returns
Average return delay (days)	12.957	13.047
Variance	40.89	57.43
Test p-value	0.1132	
Null hypothesis rejected?	No	

The second hypothesis investigated whether there was a significant difference between the mean return delay of articles returned with stains. This test did result in a significant difference on a 95% significance level, as presented in Table 4.2. However, the mean value for dresses was significantly smaller than the one for other returns, contradicting the hypothesis presented.

Table 4.2 Results of retail borrowing hypothesis 2.

	Returned dresses	Other returns
Proportion of returns with stains	0.007812	0.009546
Variance	0.007751	0.009455
Test p-value	0.023	
Null hypothesis rejected?	Yes	

The third hypothesis was similar to the second one but looked into if products returned with stains generally had a longer return delay than other returns, independent of what product category they belonged to. This test also resulted in a significant difference on a 95% confidence level. The results of the test is presented in Table 4.3.

Table 4.3 Results of retail borrowing hypothesis 3.

	Returns with stains	Other returns
Average return delay (days)	21.2473	12.9497
Variance	1012.24	44.03
Test p-value	$1.03 * 10^{-11}$	
Null hypothesis rejected?	Yes	

4.3 Product Return Rate Relationship with TISP and Discount Rate

This part of the analysis was intended to explore how other quantifiable factors affect a product's return rate. The hypothesis going into this analysis was that return rate might be negatively correlated with the time an item was sold, i.e. if it was early or late in that particular product's life span. If this turned out to be the case, it would also be interesting if this might be attributed to the product's increased likelihood of being discounted later on in its life span, or if there were other factors as well.

4.3.1 **Product Return Rate as a Function of TISP**

Hypothesis Description

In order to test the hypothesis described above, the first step was to analyze if the return rate did indeed decrease as products moved further into their sales period. This analysis was conducted by first categorizing identical products into 21 TISP bins with values ranging from 0 to 1 based on when they were sold relative to each other. This meant that products sold early in the sales period were placed in a bin with a lower value and products sold later in bins with higher values. Using this, it was then possible to measure the percentage of sold items that were returned in each bin. Further, the return rate for each bin was calculated using pivot tables and a correlation analysis could be conducted to determine whether or not the return rate correlated with TISP.

Hypothesis Test Results

The return rate over TISP is illustrated in Figure 4.1 below. A clear pattern can be observed as return rate decreases the later an item is sold, from 28% at the start of a sales period compared to 16% at the end.

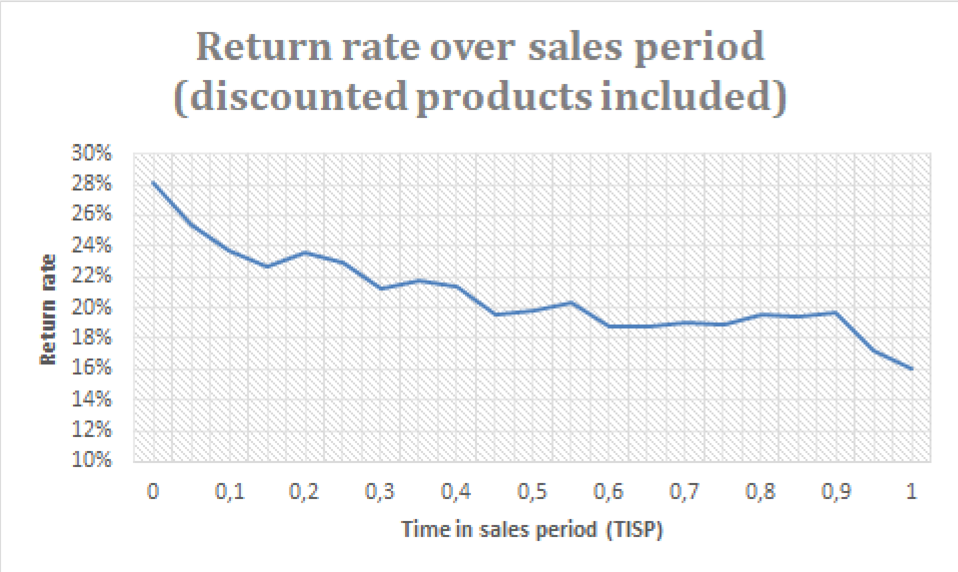

Figure 4.1 The return rate as a function of TISP, including discounted products.

A correlation analysis was performed, resulting in a correlation coefficient of 0.821 indicating that 82.1% of the variability of the return rate can be attributed to the time in the product's sales period. Using regression the significant value of this effect was calculated to $2*10^{-8}$, which is well below the critical value of 0.05, indicating that these results can be considered significant on a confidence level of 95%.

However, as the authors hypothesized that there is also a correlation between TISP and discount rate, the return rate reduction might be simply due to products sold "later" having a higher discount rate, and customers therefore being relatively more satisfied with their purchase due to getting a better perceived "deal". In order to investigate this, further analyses were performed related to discount rate and TISP.

4.3.2 **Impact of Discount on Return Rate**

This section investigates the effect of discount on return rate by analyzing the relationships between discounts, TISP and return rate.

4.3.2.1 Discounts as a Function of TISP

Hypothesis Description

The first step in testing if discounts were the underlying driver behind TISP reducing return rate was to confirm that discounts increase with TISP, and show by how much.

To accomplish this, products were divided into TISP bins using the same method as described in the previous subsection, and a two-step discount analysis was performed. The first step was to identify the likelihood of discounts, i.e. the ratio of discounted products out of the total number sold. The second step was to calculate their average discount rate. When calculating average discount rate, only discounted products were included.

Hypothesis Test Results

The analysis showed that TISP is associated with both an increase in the *likelihood of discounts*, and the *average discount rate*, as shown in Figure 4.2 and Figure 4.3, respectively.

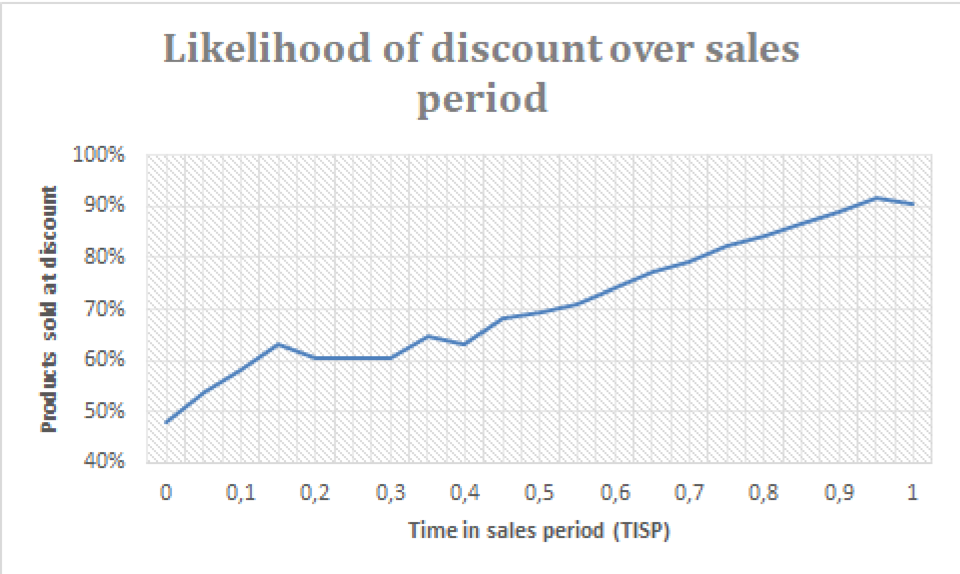

Figure 4.2 Likelihood of discount as a function of TISP.

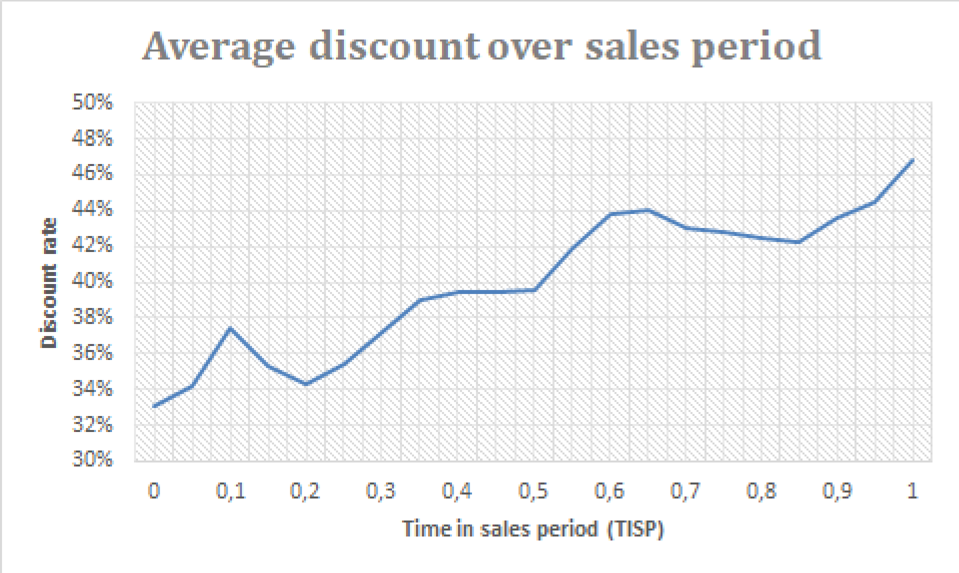

Figure 4.3 Average discount rate as a function of TISP.

The correlation analysis examining likelihood of discount and TISP gave an R-squared value of 0.968, which indicates that TISP has a very strong positive effect on whether a product is sold at a discount or not. The second analysis, investigating the relationship between level of discount and TISP, resulted in an R-squared of 0.884. These results indicate that TISP has a strong positive correlation with both likelihood of discount and discount rate. The significance of this effect was evaluated for both results using regression, resulting in values of $1.3*10^{-15}$ and $3*10^{-10}$ for likelihood of discount and average discount respectively. As both of these values are well below 0.05, the correlation effect can be considered significant on a 95% confidence level.

4.3.2.2 Return Rate as a Function of Discount Rate

Hypothesis Description

The next step was to determine the effect of discount rate on return rate. Using filtering to show only discounted items, products were divided into 10 bins according to their discount rate, i.e. how much they were discounted by. This was performed analogously to how products were divided into TISP bins in previous analyses.

Hypothesis Test Results

Using the above method, discount rate was shown to correlate with reduced return rate. Correlation analysis gave a correlation coefficient of 0.785, meaning that 78.5% of the variability in return rate could be said to be associated with the discount rate, for those products that were sold at a discounted price. However, the effect of TISP on average return rate for all products was slightly higher than the effect of discount rate on average return rate, which indicates that increases in discounts cannot fully explain the effect of TISP on return rate. Regression was also used in this case to evaluate whether or not the results effect could be considered significant on a 95% confidence level. This resulted in a value of 0.0006, which clearly indicates significant results. The effect is illustrated in Figure 4.4 below.

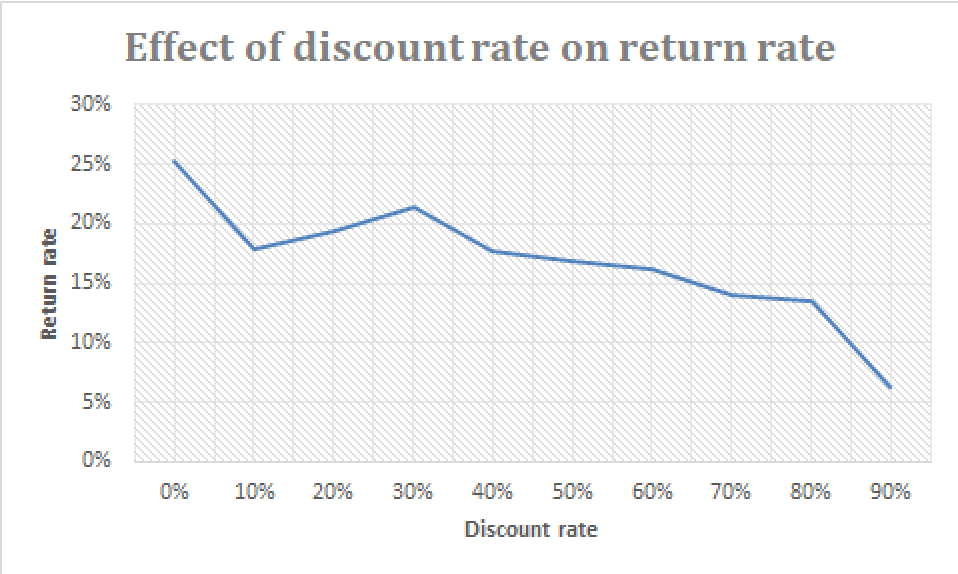

Figure 4.4 The average return rate for each discount rate bin.

4.3.2.3 TISP Effect on Return Rate Excluding Discounted Products

Hypothesis Description

As discounts were shown to have a similar effect on return rate when compared to TISP, the final step of this analysis was to determine the effect of TISP on products sold without a discount, to identify if there are indeed other factors driving reduced return rate over a product's life span. This analysis was performed by filtering out products sold at a discount and dividing the remaining products into TISP bins as done earlier.

Hypothesis Test Results

Results showed that there was still a significant TISP effect on return rate even when excluding discounted products, as shown in Figure 4.5 below.

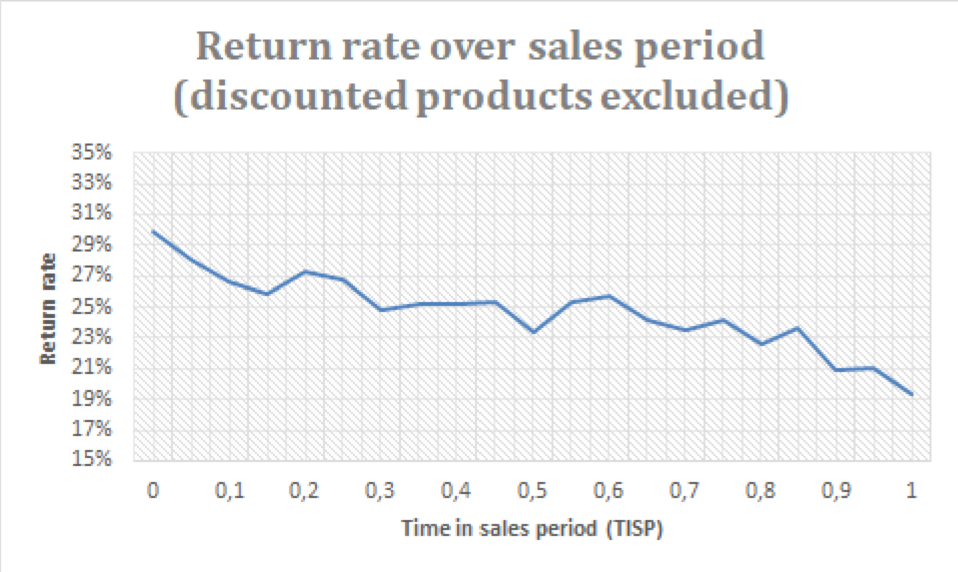

Figure 4.5 Return rate as a function of TISP, excluding discounted sales.

Correlation analysis gave a correlation coefficient of 0.817 indicating a strong correlation between TISP and return rate also in this case. Results from the following regression analysis gave a significance value of $2*10^{-10}$, indicating that the correlation effect can be considered significant on a 95% confidence level.

4.3.3 Impact of Sales Price on Return Rate

Hypothesis Description

The authors hypothesized that in general, products with a higher sales price should be returned more often than cheaper products. There are several reasons for the formulation of this hypothesis. One is that as a higher price means that the customer may be more inclined to return a product if they are "on the fence" and unsure about whether or not they are satisfied with their purchase, since the financial risk is higher. Another factor is that cheap products are often more basic products which are easier to evaluate without seeing it in person, such as socks, underwear or t-shirts. A third reason, indicated by theory, is that one factor driving returns is customers making purchases and later realizing they could not afford it or would rather have spent the money on something else, and thus returning the product even if they were not unsatisfied with the product itself. This should be more likely to happen if the product is expensive. For these reasons, the authors decided to use data analysis to determine if there was a significant effect of sales price on return rate. The test was performed by categorizing sold products into 25 bins according to their sales price, where the first 24 bins each consist of a price interval of 100 SEK, and the last one consists of all products above 2500 SEK, and using a pivot table to display the return rate for each bin.

Hypothesis Test Results

The results are shown in Figure 4.6 below. The horizontal axis labels show the average sales price within each bin.

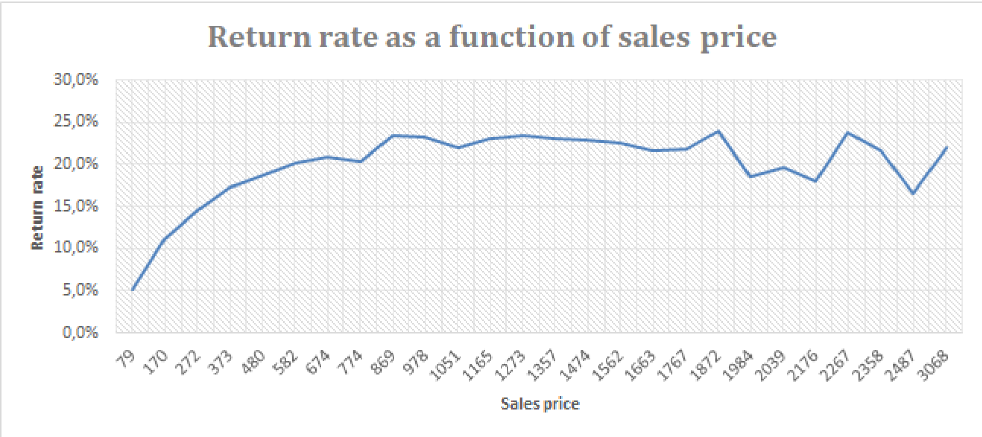

Figure 4.6 Return rate as a function of sales price.

The figure appears to show that there is a significant positive effect for the first few bins, but the return rate levels out as the sales price reaches around 700 SEK. There is some noise towards the end of the graph since the final bins (representing the most expensive sold items) are based on much fewer data points (sold items) than the lower price bins.

A correlation test was performed, resulting in an R-squared value of 0.212, showing that the correlation overall is quite weak. However, as can be seen in the graph, the effect is very noticeable between 0-700 SEK. A correlation analysis for the first ten bins, representing 0-1000 SEK, was therefore also performed. This gave an R-squared of 0.854, indicating a strong correlation. A regression analysis was again performed to evaluate the significance of both of these effects. This analysis resulted in a significance value of 0.018 when including all values and 0.00013 when only including the first 10. As both of these are below 0.05 the correlation effect can be considered significant on a 95% confidence level in both instances.

4.4 Multiple Size Ordering and Return Behavior

Hypothesis Description

The goal of this analysis was to identify behavior mentioned in literature where a customer orders multiple sizes of the same product in order to try on the different sizes at home, and then returning the sizes that did not fit. This was done using pivot tables in Excel, filtering to find only those orders where more than one of a certain individual product, with the same color but different sizes, was ordered, and at least one of these items was returned. Further, the percentages of orders that followed this pattern could be calculated, compared to both all orders as well as only orders containing returns.

Hypothesis Test Results

The results of the multiple size ordering test indicated that such a pattern was present in the data. Out of all orders 2.26% were orders containing at least two products identical apart from their sizes where one or more of them were later returned. When looking at only orders containing returns, they consisted of 12.9% such orders.

5 Model Description

This chapter covers the simulation process, including a description of the model on a conceptual level, and then in terms of its implementation in the Arena simulation software. It also documents the initial data analysis process for the purposes of model input data.

5.1 Return Process Description

In the context of this study, the online fashion retail return process can be considered a generalized process with a low level of detail, between first point-of-sale and the final sale or disposal of an item. These delimiters were chosen in order to avoid having the results affected by restocking policies, or any other factors which are not directly related to consumer returns. Furthermore, in-store returns are not taken into consideration in this study. This delimitation was chosen to reduce complexity and help focus the analysis on the interdependency effects on profitability between such factors as return delay, return rate and sales period length.

The process begins with an item being ordered by a customer. The item passes through order handling and transport to customer, incurring costs and time delays. Then the customer decides whether they want to keep the item or return it. In reality, this decision process may take anywhere from minutes (the customer immediately inspects the item and decides they do not want to keep it) to weeks, or even months (the customer may use the item for a while before deciding they do not want to keep it, or they may wait before opening and trying the item on, or their financial situation might change and they decide they cannot afford to keep the item). The maximum time depends on the retailer's return policy.

If the item is returned, it goes through return transport and return handling, incurring further costs and delays. If the item is determined to be resalable, it will be put up for sale again, but time will pass before it is purchased again. This process is repeated until the product is either sold and not returned, or it is returned and determined to be unfit for sale and therefore disposed of. The model assumption that all products are eventually sold relates to the delimitation that imperfect demand forecasting should not affect results since the analysis is only focused on the effects of product returns. In reality, a product that goes unsold for too long would most likely be sold to an outlet store to make room for new product launches. The initial cost, price and discount level of an item is set at the point of sale, but an item can incur further costs within the system, and the price may change due to further discounting when the item is returned and put up for sale again.

5.2 Product Categorization

In order to analyze how profitability is affected in the various scenarios on a more detailed level, products will be broken up into categories, based on their characteristics in three different dimensions: base sales price, product-specific return rate, and sales period (how long is the product's "season", or how much time does it take for the product to sell out, defined as the time from first sale to 90% of items sold). This definition of sales period was chosen since there were many cases in the data of one or two items being sold much later than the rest of the items sold of the same product type. With a 90% limit, most of these cases are excluded from the sales period, leading to a more accurate estimation of a product's prime selling season.

Sales period was chosen as a parameter since the length of a product's prime selling season should have a large effect on the average final sales price if it is returned often and/or is returned with a long return delay. Base price was chosen since a product with a higher price, and typically also a higher absolute profit margin, will be able to absorb more costs associated with returns as well as steeper discounts and still be sold profitably, whilst one with a low base price and low profit margin will be more heavily penalized in the same situation. Product-specific return rate is an important parameter in terms of profitability, and recent studies and industry data indicate that there are large gaps in return rate between different product categories, for example between "basic needs" products such as socks or t-shirts, and products such as expensive party dresses.

When analyzing the results of the simulation study, these parameter values will be divided into three ranges (low, mid and high) resulting in 27 different product categories. The categories are illustrated in Figure 5.1, where each product category is represented by a small cube, and the parameters are represented on each of the three axes. These ranges were derived from data, where each range represents the lowest, middle and highest third of SKUs in the data for each characteristic. The data is not weighted by number of sales for this purpose - instead, each specific product is given the same weight. This is because the purpose of the simulation analysis is to determine the effects on each product category, defined by these three parameters, regardless of how many sales or how much revenue can be attributed to each category. These range values for the three parameters are presented in Table 5.1. Additionally, the product's possible range of base profit margin was also derived from data in the same way, based on each sales price range and is available in Table 5.2. This value was then directly used to calculate the product's purchasing cost within the model. The specific methods used to develop these ranges from the underlying data is described in further detail later in this chapter of the thesis. All the 27 product categories, along with their respective range values, are presented in Table 5.3 below.

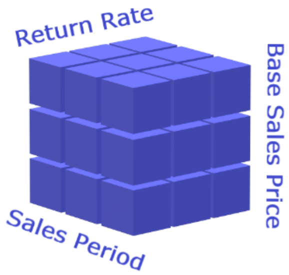

Figure 5.1 The 27 product categories, presented in a cubic format.

Table 5.1 Ranges derived from data for the three product parameters.

Range	Sales price (SEK)	Return rate (%)	Sales period length (days)
Low range	59 - 499	0 - 14.7	21 - 87
Medium range	499 - 799	14.7 - 25.5	88 - 141
High range	799 - 5999	25.5 - 78.6	142 - 362

Table 5.2 The three ranges of base profit margin for each sales price range.

Sales price range	Base profit margin range (%)
Low	52.7 - 95.5
Medium	53.1 – 89.1
High	53.4 – 84.0

Table 5.3 The 27 product categories and their associated values for each parameter, along with the proportion of total sales each category represents.

Product category	Sales price range	Return rate range	Sales period length range	Percentage of total sales
1	Low	Low	Low	4.80%
2	Low	Low	Medium	4.39%
3	Low	Low	High	9.57%
4	Low	Medium	Low	3.04%
5	Low	Medium	Medium	3.44%
6	Low	Medium	High	3.84%
7	Low	High	Low	2.56%
8	Low	High	Medium	2.01%
9	Low	High	High	1.55%
10	Medium	Low	Low	3.08%
11	Medium	Low	Medium	2.88%

Product category	Sales price range	Return rate range	Sales period length range	Percentage of total sales
12	Medium	Low	High	5.86%
13	Medium	Medium	Low	3.73%
14	Medium	Medium	Medium	5.66%
15	Medium	Medium	High	6.71%
16	Medium	High	Low	4.19%
17	Medium	High	Medium	4.17%
18	Medium	High	High	4.37%
19	High	Low	Low	0.94%
20	High	Low	Medium	1.48%
21	High	Low	High	2.47%
22	High	Medium	Low	1.94%
23	High	Medium	Medium	3.10%
24	High	Medium	High	4.20%
25	High	High	Low	2.62%
26	High	High	Medium	3.68%
27	High	High	High	3.75%

5.3 Simulation Study Process

This part of the paper describes the implementation of the simulation study framework presented in section 2.5.1.

5.3.1 **Problem Formulation**

The purpose of the simulation study is to determine the profitability effects of a change in industry-wide return rate and return delay on fashion products sold online with varying product-specific return rate, base sales price, and sales period length.

5.3.2 **Conceptualizing the Return Process**

This part of the simulation process provides a conceptual overview of the return process in the context of this study, which can later be implemented in a simulation software tool.

5.3.2.1 Conceptual Model

This section describes the layout of the simulation model step-by-step and the fundamental underlying logic behind each block. First Figure 5.2 is presented to provide a visual representation as a basis for the rest of the section.

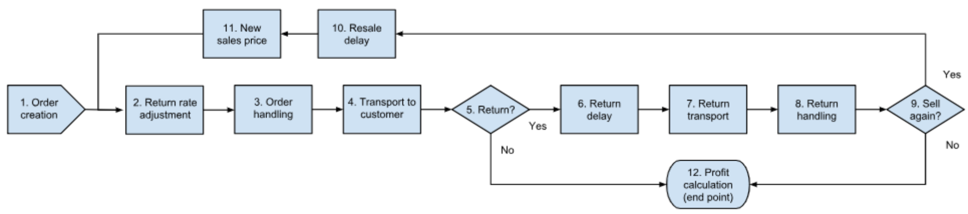

Figure 5.2 Visual representation of the conceptual simulation model.

1. Product Order Creation

In this block, customer product orders are created. Based on our scope and limitations, every product order placed will be immediately available to process and ship to the customer. For simplicity, product orders will be generally referred to as “products” from this point onwards.

Products will be created for each of the product categories separately and will be given the following attributes:

- Sales Price – each product will be assigned a base sales price from a category-specific uniform distribution (SEK)
- Base profit margin – each product will be assigned a base percentage profit margin from a uniform distribution specific to its sales price category which will be used to calculate its purchasing cost (%)
- Cost – each product will be immediately assigned a base cost based on sales price and base profit margin which will then additively increase as the order makes its way through the system (SEK)
- Sales period length – each product will be assigned a sales period length from a category-specific uniform distribution of values. (days)
- Sales period offset – each product is assigned a value between 0 and 1 indicating how late into its sales period it was first ordered. This value is only assigned once for each product. The value is based on order data regarding when items were sold, relative to other items belonging to the same product type. (days)
- Time in sales period (TISP) – this value represents the product's current relative time within its sales period. TISP is updated each time the product is sold again after being returned. For example, a product with a sales period length of 50 days, sold 10 days after the product was launched, will have a TISP value of 0.2.
- Return rate – each product will be assigned a return rate value from a category-specific uniform distribution that indicates the probability that the order is returned to the company. (%)
- Order bundling factor – each product is assigned an integer number that the transportation cost is to be divided by in order to take into account that some products are ordered together with others, reducing transportation cost for each item. This value is based on order data regarding how many products each order contained, and is identically distributed for all products. (Integer)
- Return bundling factor – each product is assigned an integer number that the return transportation cost and return handling is to be divided by in order to take into account that some products are returned together with others, reducing fixed return-related costs for each item. This value is based on data regarding how many products each return package contained, and is identically distributed for all products. (Integer)

2. Return Rate Adjustment

This block adjusts the product's return rate based on its TISP, in accordance with data presented in Chapter 4, showing that return rate is heavily affected by the product's time of sale.

3. Order Handling

Once a product has been ordered it will move on to order handling. The order handling process will add a set value to the product's accumulated cost. In real life terms, this process relates to the time and cost associated with picking and preparing the order for shipment.

4. Transport to Customer

This block adds a transport cost to the total accumulated cost of the product, adjusted by the order bundling factor. The product is also delayed according to the transport time distribution.

5. Return Decision Logic

This block represents the customer's decision on whether to keep the product or return it. Products are returned based on their return rate (probability) value. If a customer is satisfied with the purchase and decides to keep the product, it will exit the system and profit will be calculated for the specific product and recorded for its category's total profit. Should a customer decide to return an order, it will proceed through the system to the return process.

6. Return Delay

This block is tasked with assigning the time it takes for the product to reach the customer, as well as the time it takes for the customer to reach a decision about whether to return the product and send it back. This time is stochastically distributed, based on real order data (in the base scenario). The order handling time, transport time to customer, return transport time and return handling time is included in this block, since this total time between order picking and return to stock is the time that can be observed in the underlying data for returned products.

7. Return Transport

This block is similar to the "Transport to customer" block described earlier, with a fixed return transport cost added to the product based on data, adjusted by the return bundling factor. The product is also delayed according to the return transport time distribution.

8. Return Handling

This block adds a return handling cost to the product's total accumulated cost, based on data. The return handling time is included in the return delay.

9. Sell Again?

This block determines whether the order should be put up for sale once more, or if it should be disposed of. This disposal rate is based on the proportion of items that are disposed in the data after being returned.

10. Reorder Delay

This block determines how much time should pass before the item corresponding to the returned order is sold again, based on data regarding time between sales within each product type.

11. New Sales Price

This block sets the new sales price for returned products. This is based on real life sales data, corresponding to discount pricing for products as the product lifespan progresses. The new sales price will be a percentage of the order's base sales price, and will depend on the product's current TISP value.

12. Profit Calculation (termination point)

This block is the end point where products exit the system. When they reach this point, either because they have been sold and the decision has been made by the customer to not return them, or because they have been disposed of by the company after being returned, their total profit (i.e. final sales price minus total accumulated cost) will be added to the total profit of the product category that the product belongs to.

5.3.3 **Input Data Collection and Analysis**

After conceptualizing the simulation model, key input values were identified. The following values were considered necessary in order to construct a model as realistic as possible.

- Transportation cost – for the initial transport to customer as well as for the return transport.
- Order handling cost – cost of receiving and preparing an order for transport
- Return handling cost – cost of receiving returned product and making it available for sale.
- Purchase price – cost of purchasing or producing a product
- Sales price – initial sales price.
- Discount rate – logic for setting the discount rate for products based on when they were sold.
- Order handling time – time of preparing an order for transport.
- Return handling time – time of handling a returned order and making it available for sale.
- Transport time – for the initial transport to the customer as well as for the return transport.
- Return delay – time between the customer receiving an order and deciding to return it.
- Products per order – the average number of products an order consists of.

- Sales period length – time a product can be considered to be "in-season".
- Return rate – likelihood of a product being returned upon sale, on a product category basis.
- Return rate adjustment – the relationship between return rate and TISP describing how the likelihood of returns decrease when products are sold later in the sales period.
- Discount rate – the decision-making logic behind which products go on sale and how much they are discounted by.
- Disposal rate – the logic behind and likelihood of disposing of a product.
- Reorder delay – the time that passes between a product being returned and sold again.

5.3.3.1 Basic Costs, Purchase and Sales Price

The values for transportation cost, order handling cost, return handling cost and product purchase and sales prices were directly gathered from the raw data provided by the company. The ranges of possible sales prices were defined by splitting the products in the raw data into three equally large bins, in order to distinguish between "low-priced", "mid-priced" and "high-priced" products. The bin intervals were based on the top, middle and bottom third of SKUs in the data in terms of sales price. This means that the volume of sale for each SKU did not affect how the intervals were designed.

5.3.3.2 Return Delay, Order Handling Time and Transport Time

The data provided by the company was limited to providing the time of order picking as well as the time of order return handling (assuming the order was returned by the customer). This meant that it was not possible to distinguish between transport time to customer, order handling time, "return delay", return transport time and return handling time. For this reason the decision was made to include all transport times and order handling times in the simulation model return delay. Furthermore, the data provides information on the time of day products are sent to customers but does not include time of day for return arrival times, so for the purposes of data analysis, all returns were approximated to arrive at noon when calculating return delay. By plotting the times for this new return delay the Arena distribution fitting tool came up with the following distribution, as seen in Figure 5.3 and Equation 5.1, with a square error of 0.000073.

$$Return\ delay = 1 + \mathrm{Logn}(11.9, 6.3) \tag{5.1}$$

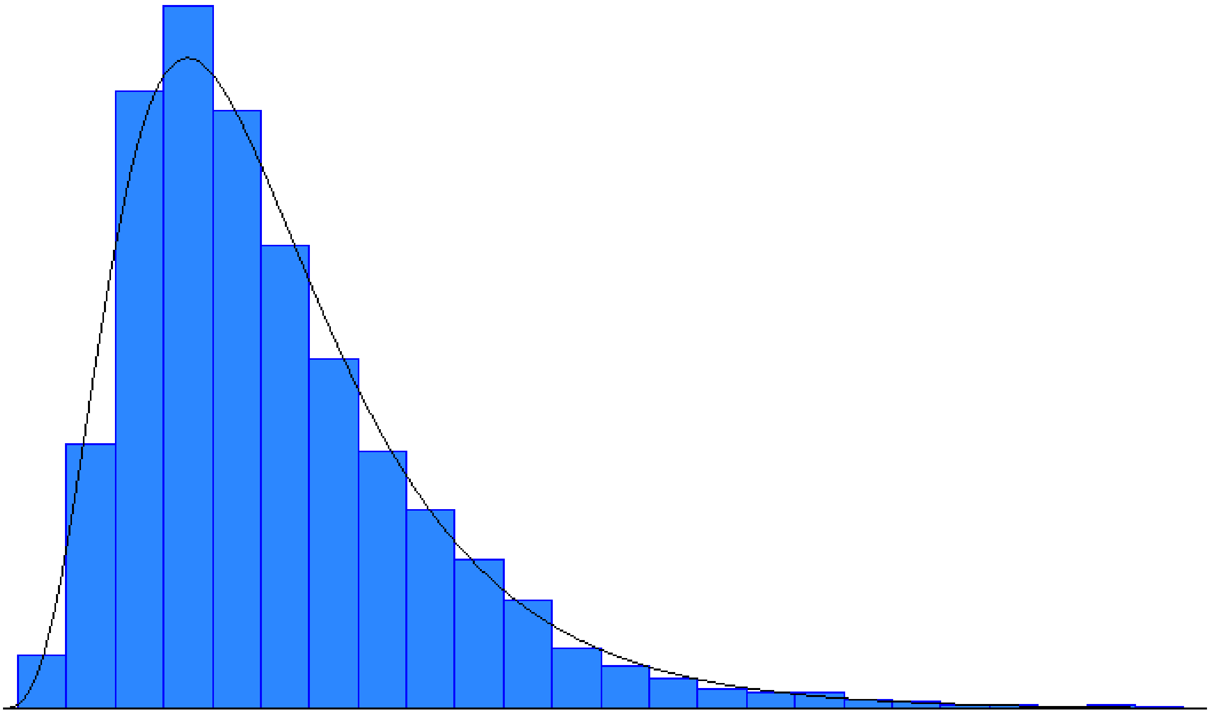

Figure 5.3 The return delay distribution along with a histogram showing the data it was based on.

5.3.3.3 Products per Order

The number of products included in each order was calculated from the underlying data and compiled into a list. This list was then directly used to provide the input data for the model, by drawing random values.

5.3.3.4 Sales Period

After identifying outliers in the raw data, such as single products being sold months after all other products of the same product type, a product type's sales period was defined as the time until 90% of all sales of that particular product have taken place. The 90% cutoff, while somewhat arbitrary, was nonetheless considered necessary to reduce the distortive effect of outliers such as those described earlier. Furthermore, based on the interview data, there was no process in place at the company for precisely determining a product's sales period ahead of time. Based on this definition, the range of possible season lengths was determined for each third of the product types (short, medium and long sales period lengths). The same binning method was used as described earlier in the case of sales price and only products with ten or more sales were considered. Since the data used only covered one year of sales, the maximum possible value for sales period length was 365 days. Furthermore, whilst there were products that sold out in fewer days, the minimum effective sales period was considered to be 21 days. A significant weakness of this definition is that it does not consider that many of the products with a shorter sales period length sold out before demand was satisfied, without the possibility of replenishing stock to fully satisfy demand. This means that in the model their profitability will be negatively affected by discounts very quickly, whereas in real life, they would most likely have still sold at full price at that time. However, this way of calculating sales period length to determine whether or not products are “in season” was still considered the best method based on the available data. The ranges for each category are illustrated in Table 5.1 in section 5.2.

5.3.3.5 Return Rate

Values for the return rate of the three product categories (low, medium and high return rate) were calculated based on the return frequency in the raw data. The same binning method as previously presented was used also in this case. The ranges for each category are presented in Table 5.1 in section 5.2.

5.3.3.6 Return Rate Adjustment

As Figure 4.1 indicated in 4.3.1, the return rate decreases the deeper into the sales period a product is sold. Consequently, further analysis was conducted to conceptualize this pattern for use in the model, as seen in Figure 5.4. As this pattern only represented an average of all orders' change in return rate over time, it was considered of interest to evaluate if there was any difference in how return rate decreased for products with higher or lower average return rates, respectively. In order to investigate this, products were split into three categories depending on their average return rate, with an equal number of products in each. The same binning method was used as before. Category 1 consisted of products with the highest return rate, followed by category 2 and 3. The return rate as a function of TISP for these categories, as well as the overall average, is presented in Figure 5.5.

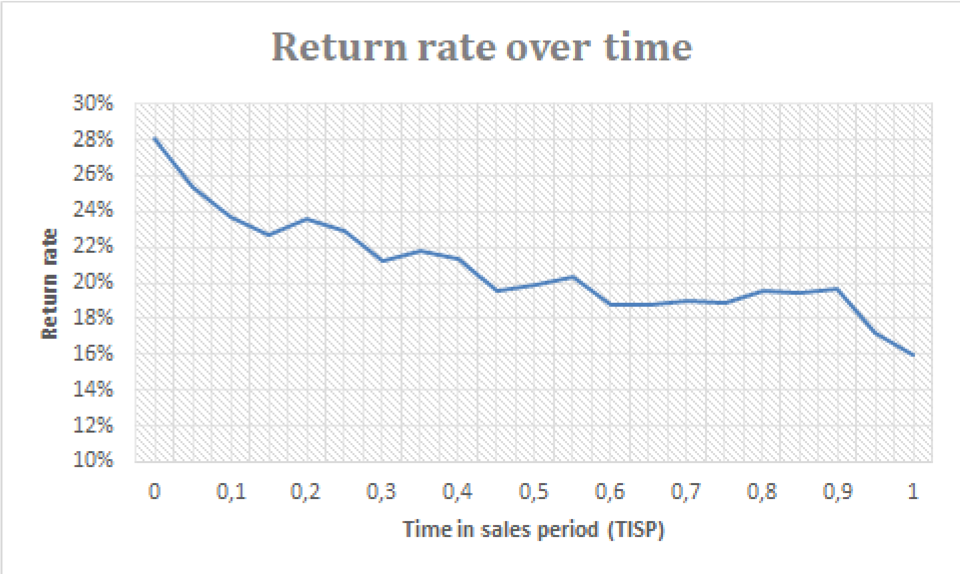

Figure 5.4 The return rate as a function of TISP including all products

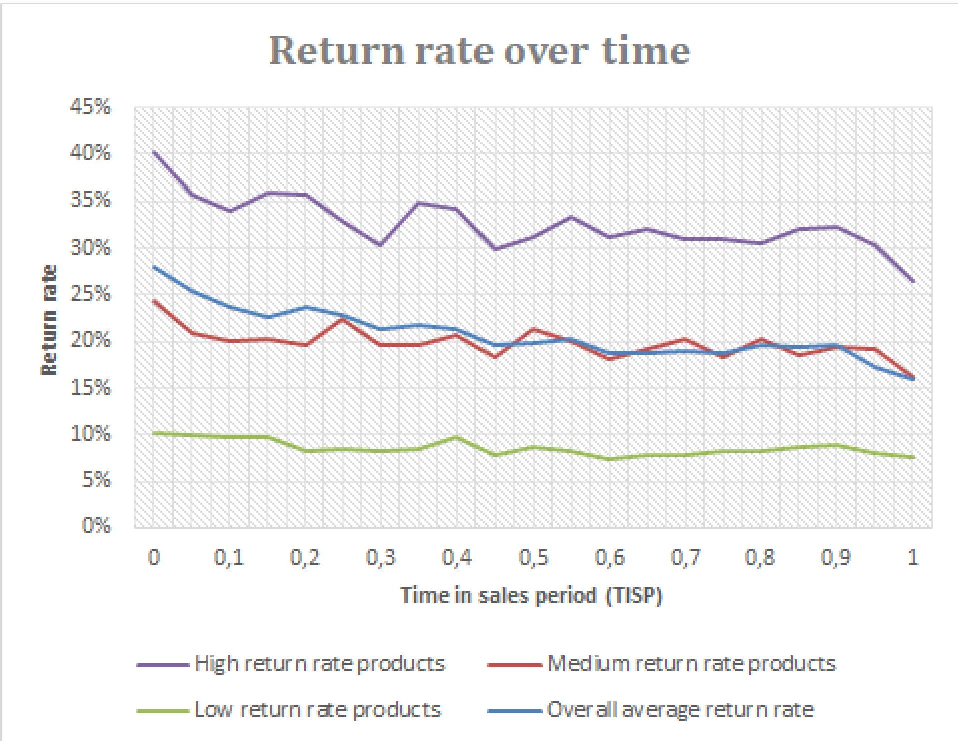

Figure 5.5 The return rate for each category, as well as the total average, as a function of TISP.

From these figures one may conclude that products with high return rates have a larger average decrease in their likelihood of return than products with lower return rates. In order to capture this behavior in the simulation model it was necessary to formulate an equation for this decreasing return rate probability. The relationship for the overall average was used as a starting point when formulating this equation. Using Matlab's curve fitting tool R-squared values were calculated for a variety of different equations. Using these values a third degree polynomial was deemed most suitable. It was considered significantly better than polynomials of first or second degree, while not being unnecessarily complex, thus avoiding over-fitting to the data. Regression using other types of equations as well as polynomials of higher order were also evaluated, but none were determined to provide a significantly better fit than a third-degree polynomial. As a result, Equation 5.2 was formulated:

$$f(RR, TISP) = -\,0.262 * TISP^3 + 0.475 * TISP^2 - 0.317 * TISP + RR \quad (5.2)$$

In this equation, RR is the product-specific return rate and TISP is a value between 0 and 1 describing how deep into its sales period a product is. The equation is presented graphically along with the data it was based on, in Figure 5.6 below.

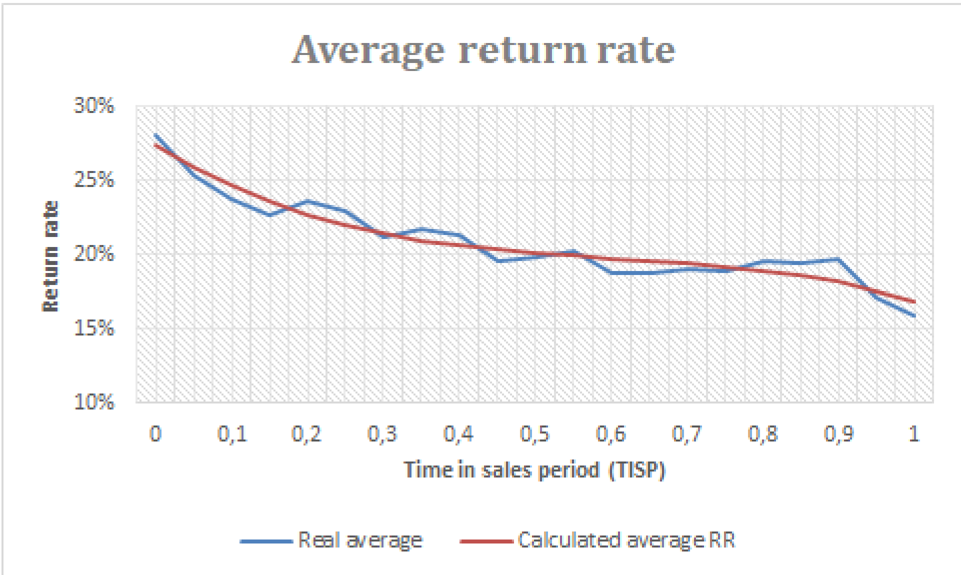

Figure 5.6 Equation representing return rate as a function of TISP, along with the underlying overall return rate data

As this equation would result in an equal decrease in return rate over time regardless of the original return rate value of the product it is being applied to, it would work well for a product with a return rate close to the overall average return rate, but it would work poorly for an outlier product with a very high or very low return rate, in comparison to the overall average. For example, a product with a real return rate close to zero would end up with a negative return rate by the end of its season. Therefore the equation needed to be modified to take into consideration the product-specific return rate when calculating the reduction over time. In order to take this behavior into account Equation 5.2 was modified by dividing the constants for each TISP-factor with the original equation's RR-constant of 0.274, which was based on the average return rate of products in the first TISP bin, and then multiplying it with the product specific RR-value. This means that the equation performs identically as Equation 5.2 for products with the average return rate of 0.274, while products with lower or higher rates are affected to a lesser and greater extend respectively. The resulting Equation 5.3 is presented below.

$$f(RR, TISP) = -0.958 * RR * TISP^3 + 1.736 * RR * TISP^2 - 1.16 * RR * TISP + RR \tag{5.3}$$

The performance of the modified equation was then compared to the original as well as the underlying data the equations were based on. This comparison was done for each of the three return rate categories. These three comparisons can be seen in Figure 5.7, Figure 5.8 and Figure 5.9.

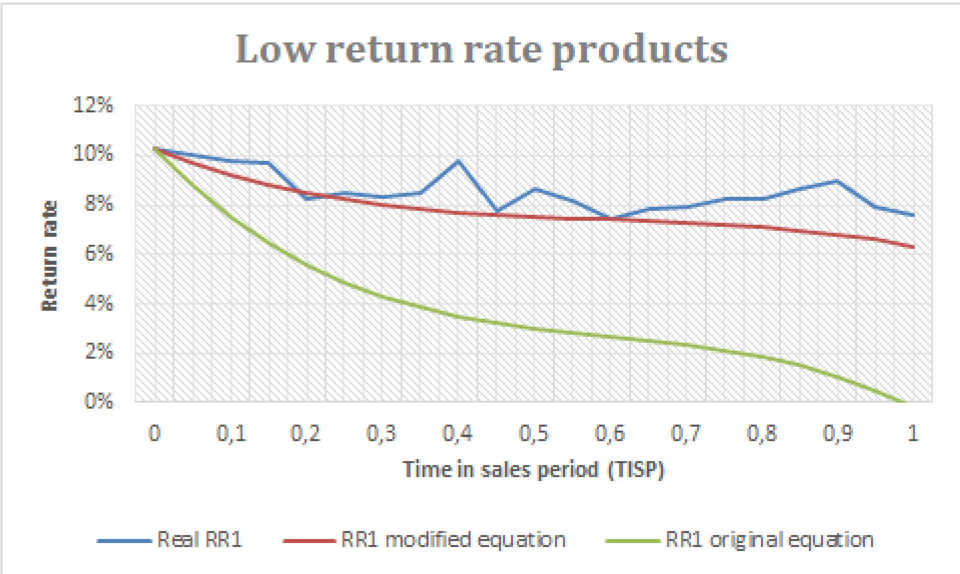

Figure 5.7 Comparison between the real return rate as a function of TISP and the unmodified and modified versions of the equations, for products with low return rate.

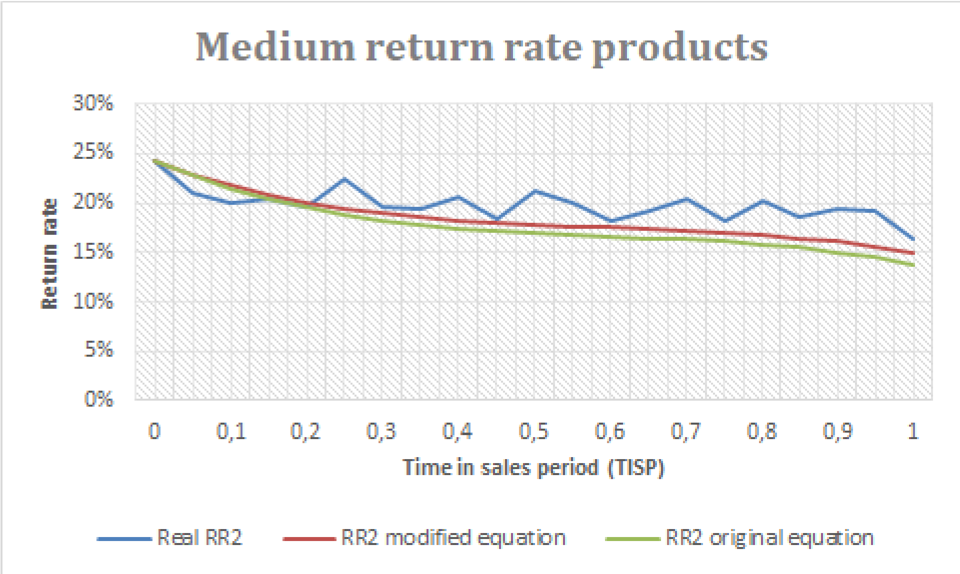

Figure 5.8 Comparison between the real return rate as a function of TISP and the unmodified and modified versions of the equations, for products with medium return rate.

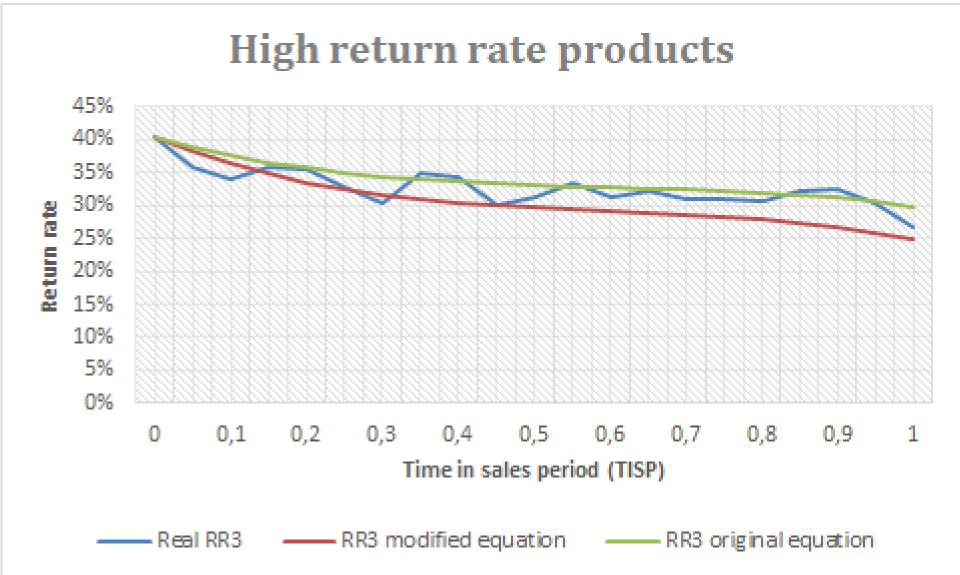

Figure 5.9 Comparison between the real return rate as a function of TISP and the unmodified and modified versions of the equations, for products with high return rate.

As can be observed in these figures, the original equation performs well, as expected, for the medium return rate product category corresponding to those products with return rate close to the overall average. However, in the categories further away from the overall average its performance becomes less accurate, especially when considering products with low initial return rates. When it comes to the modified equation, it performs equally well or better than the original equation for products with medium or high rates and when it comes to products with lower rates it clearly outperforms the original equation.

5.3.3.7 Discount Rate

In order to model discount pricing, a two-step solution was developed. Firstly, the raw data was used to determine the likelihood of a product being discounted at each interval of its season. This led to Equation 5.4 describing the likelihood of a product being discounted, depending on the current TISP:

$$Likelihood\ of\ discount = f(TISP) = 0.4133 * TISP + 0.5067 \quad (5.4)$$

This equation, and the underlying relationship in the data, is presented visually in Figure 5.10 below.

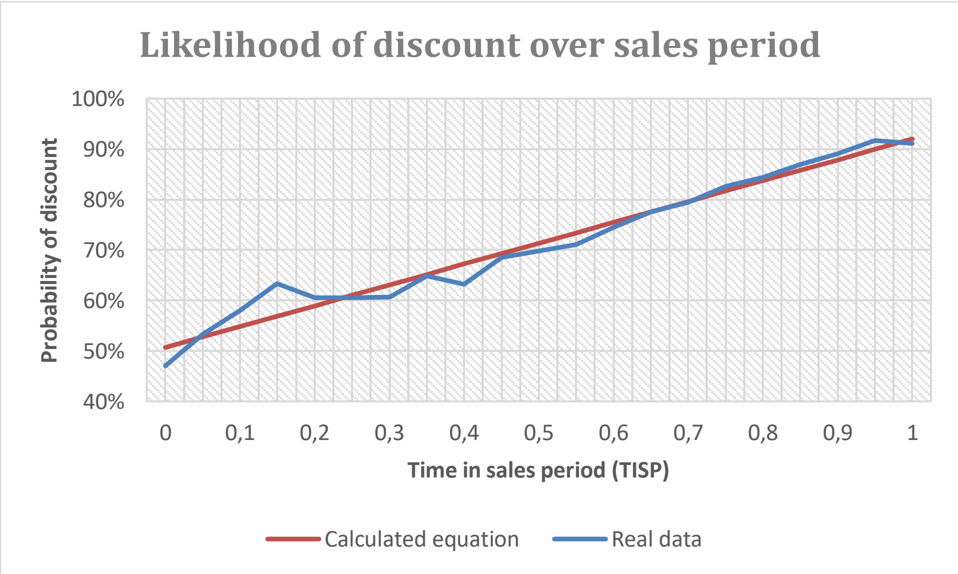

Figure 5.10 The likelihood of products sold being discounted as a function of TISP.

Then the data was used to calculate the average discount rate, considering only those products that were sold at a discount, for each interval of TISP. This led to Equation 5.5 describing how to set discount rates depending on TISP:

$$Discount\ rate = f(TISP) = 0.1203 * TISP + 0.3395 \quad (5.5)$$

A graph of this equation is presented in Figure 5.11 below.

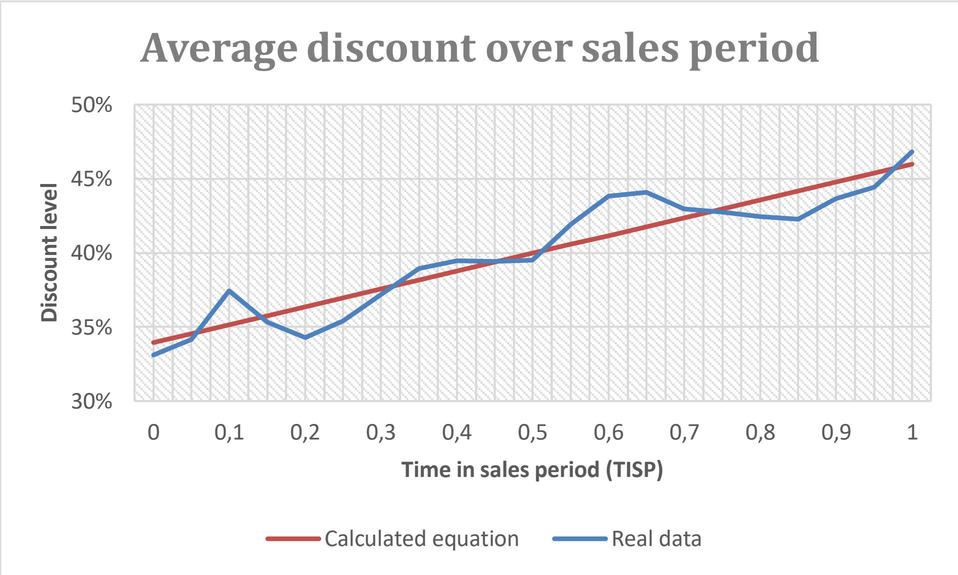

Figure 5.11 The level of discount as a function of TISP.

As using this equation on its own would give a set discount for all products based on their TISP value, the equation was instead used as the input for a triangular distribution of the discount price. Whilst the output of the equation should be considered the mean value for the triangular discount distribution, the triangular distribution requires a lower bound, upper bound and mode as inputs. Therefore, the mode was calculated using Equation 5.6.

$$Mean = \frac{Min + Max + Mode}{3} \xrightarrow{yields}$$
$$Mode = 3 * Mean - Min - Max \tag{5.6}$$

0.1 to 0.75 was determined to be the typical range of values for discount rate based on the raw data with the top and bottom 5% of outlying values removed. This removal was done to avoid anomalies in the data, such as a <1% discount due to a product with a recommended retail price of 400 SEK being sold for 399 SEK, affecting the "real" discount pricing.

5.3.3.8 Disposal Parameters

The disposal rate was estimated to 1.1% using the analyzed data's probability that a returned product was not returned to stock for resale. Disposal cost was set to zero, in accordance with the interview with an anonymous company representative and data showing that almost all products that are deemed unfit for sale by the company are donated and picked up for free by a second-hand shop.

5.3.3.9 Reorder Delay

As there was no way of identifying the time between a product being returned and it being sold once again, this parameter was estimated using time between orders for each product type in the data. When estimating this distribution for the entire data set it was observed that products with a longer sales period generally had a longer time between their orders. In order to take this correlation into account three different distributions were established for the three value ranges of product sales period. The distributions presented in Equation 5.7, 5.8 and 5.9 were determined.

$$Gamma(2, 1.75), for\ sale\ periods\ between\ 21 - 87\ days \tag{5.7}$$

$$Gamma(2.45, 2.1), for\ sale\ periods\ between\ 88 - 141\ days \tag{5.8}$$

$$Gamma(4.99, 1.73), for\ sale\ periods\ between\ 142 - 362\ days \tag{5.9}$$

The distributions along with the data set they were fitted against are presented in Figure 5.12, Figure 5.13 and Figure 5.14.

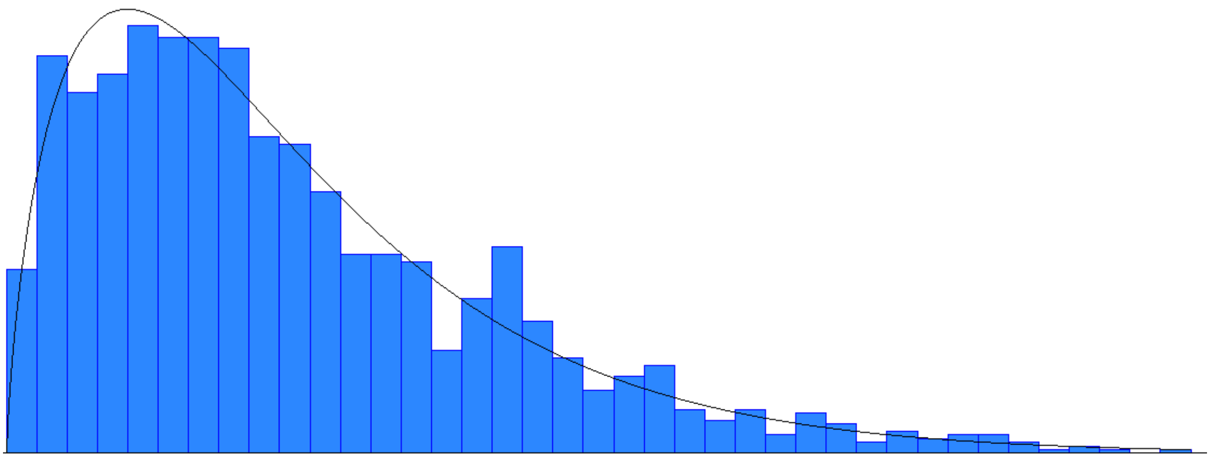

Figure 5.12 The reorder delay distribution for the "High" sales period along with a histogram showing the data it was based on. Gamma(4.99, 1.73)

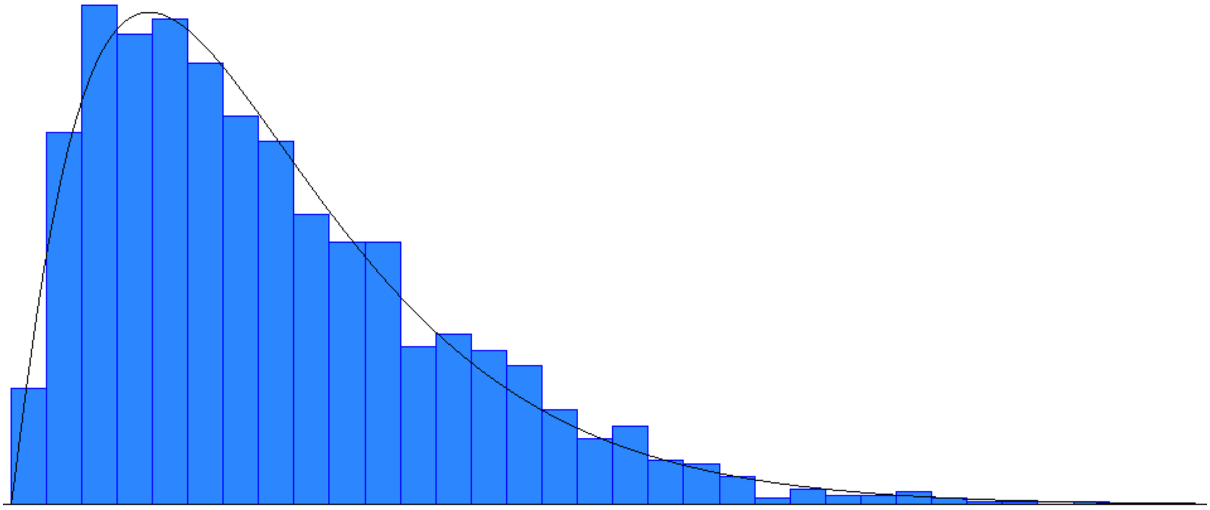

Figure 5.13 The reorder delay distribution for the "Medium" sales period along with a histogram showing the data it was based on. Gamma(2.45, 2.1)

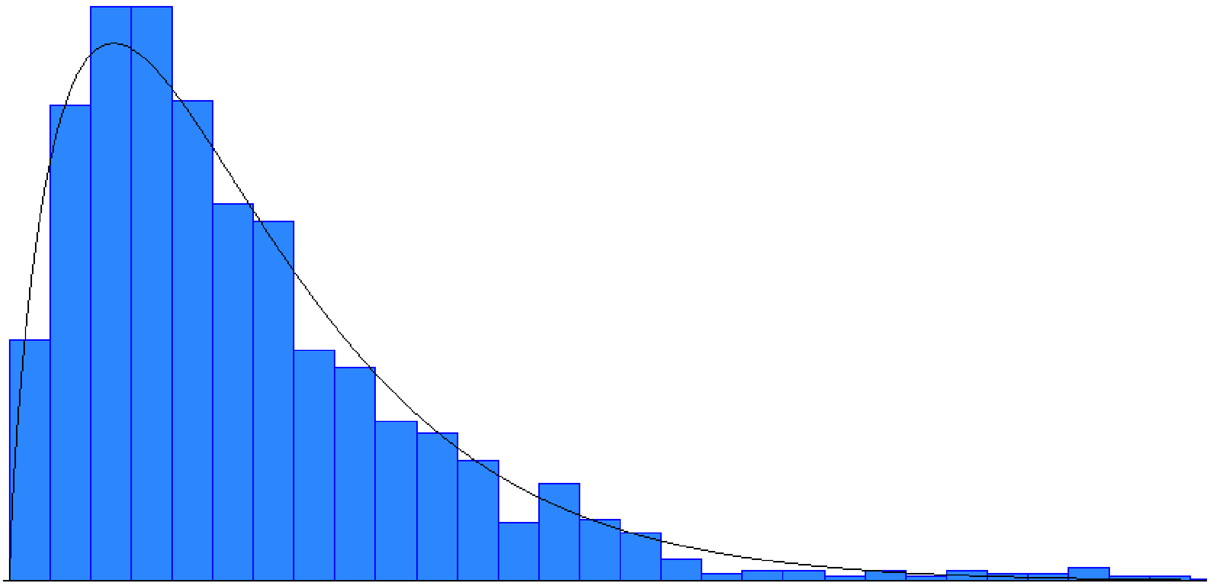

Figure 5.14 The reorder delay distribution for the "Low" sales period along with a histogram showing the data it was based on. Gamma(2, 1.75)

Kolmogorov-Smirnov tests were performed to determine the goodness of fit for these distributions. The tests were all conducted by assuming the alternative hypothesis, H_a, that the collected data came from the Gamma distributions presented. The null hypothesis, H_0, was consequently that the data did not come from these distributions. These tests gave the results presented in Table 5.4 and as seen the null hypothesis was rejected in all of the tests on a 0.05 significance level.

As a result, these distributions were considered appropriate for use as input data for calculating the reorder delay in the simulation model.

Table 5.4 Hypothesis tests for the three distributions for reorder delay.

Sales period length (days)	Distribution	K-S test statistic (D)	Critical value	Null hypothesis rejected?
21 - 87	Gamma(2, 1.75)	0.0277	0.0345	Yes
88 - 141	Gamma(2.45, 2.1)	0.0203	0.0342	Yes
142 - 362	Gamma(4.99, 1.73)	0.0265	0.0345	Yes

5.3.4 **Conceptual Model Validation**

The conceptual model was validated according to the guidelines presented in section 2.5.1. The model was presented and discussed iteratively at several meetings with the project supervisors. Corrections and improvements were made to the model on the concept level, saving project time later on.

5.3.5 **Model Implementation**

In this section a model overview is presented along with model assumptions made.

5.3.5.1 Model Overview

This section outlines the simulation process in logical steps to provide an idea of how the simulation works, and the goal is to describe it on a level that would allow a reader to implement a similar model in any simulation software, although the one used in this project was implemented in Rockwell Arena Simulation Software. The structure of this section will follow the one presented in the conceptual model.

Product Order Creation

The model creates products at a constant rate and randomly assigns them values for sales period length, base price, base cost, return rate and number of items in the order. These values are drawn from distributions based on industry data. An equal number of products is created for each category (1-27).

Order Handling and Transport

The products are then assigned costs for order handling and transport to customer divided by the order bundling factor (since these costs are fixed per order sent by the company). The order bundling factor is drawn directly from the raw data regarding how many items were in each order.

Return Decision

The products then proceed to a decision point where they are either returned or kept by the customer, based on their return rate value. Products that are kept are removed from the system and their profit (final sales price minus total accumulated cost) is added to the total profit of their designated category.

Return Delay and Possible Disposal

If a product is instead returned, it is delayed by an amount drawn from the return delay distribution. It is also assigned costs for return transport and return handling, divided by the return bundling factor. The return bundling factor is drawn directly from the raw data regarding how many items were in each return package. Then it may or may not be disposed of based on the disposal rate. Products disposed of are removed from the system with their sales price set to zero and total cost as-is.

Reorder Delay

In this step, the items that are to be sold again are delayed by a time drawn from the "reorder delay" distribution for the sales period length category the product belongs to.

End Point and Profit Calculation

After reorder delay, the item goes through the same process again, from the "return rate adjustment block". Assuming it is not returned again, it is removed from the system upon a "successful" sale, and its profit is added to its category's total profit.

5.3.5.2 Model Assumptions

Based on the data available a number of assumptions had to be made in order for the model to function. The following assumptions were made:

- As the only way for an item to be disposed of is due to problems related to product quality it is assumed that all other items in stock are sold. This assumption can consequently be expressed as the online fashion retailer having optimal purchasing quantities at all times.
- There is no way to track previously returned products in the data once they are returned to stock, making an analysis on whether or not previously returned products have an increased return probability impossible. As a result, the model assumes that there is no such correlation.

- It is not possible to distinguish between returns sent to the central stock and returns made in physical stores, so all returns are assumed to be sent back to stock.

5.3.6 **Implemented Model Validation**

This step of the simulation process is meant to ensure that the implemented simulation model is valid, and produces the results one would expect of the analogous real-world system. One way to do this is to compare the results to real-world results, which is not possible in this case since the simulation model is designed as a generic online fashion retail supply chain rather than a specific one which the results can be compared to (Law and Kelton, 2003). Similarly, it is not feasible to have a subject matter expert or simulation analyst examine the model and its output as the literature suggests, since there is no real-world analogous model to compare it to (Law and Kelton, 2003). The final aspect of implemented model validation is sensitivity analysis, which is meant to identify key factors in the model which may have major impacts on the results when their values are altered (Law and Kelton, 2003). In this way, the model designers are made aware of which aspects of the model need to be designed with additional care.

5.3.6.1 Sensitivity Analysis

According to the United States Environmental Protection Agency, sensitivity analysis is “the process of determining how changes in the model input values or assumptions (including boundaries and model functional form) affect the model outputs”. (Gaber, 2009)

Whilst the literature would seem to suggest a sensitivity analysis in this case, such an analysis would be focused on varying the input variables one-by-one and determining which effects they have on the output, and identifying potential volatile factors. An example of a volatile factor could be an internal model variable, where a small change in the value of the variable could have a very large effect on the model’s output. However, this type of analysis corresponds almost exactly to the scenario analysis that the model is intended for, which means that a sensitivity analysis in this case would be identical to the scenario analysis. Therefore a sensitivity analysis as such was not deemed relevant in this context.

However, as a result of analyzing the internal functions of the model, certain input distributions developed from real data were replaced by simply using the data directly as model input, in order to reduce potential output discrepancies resulting from differences between the distributions generated and the data they were based on. For example, a return delay distribution was developed at one point, but the decision was later made to use the real data regarding return delay instead of this distribution since this would reduce complexity without affecting the model’s accuracy.

As return rate was a central aspect of the simulation study, while at the same time having a complex relationship with TISP, it was considered crucial to understand how the output return rate from the model compared to the input value developed from data. This was in part done to see how large the multiple-return effect was in the model. The multiple-return effect is defined as the same products being returned more than once, which wasn't possible to capture in the data analyzed since there was no way to know if a product had been returned previously or not. In order to analyze this, simulation scenarios with increasing return rate were run for products with low return rates (0 – 14.7%). The number of products being returned in the model was then tracked to determine how it compared to the input values. The results from this sensitivity analysis is presented in Table 5.5.

Table 5.5 Result from return rate sensitivity analysis

Percental increase of input return rate	Percentage of orders returned in simulation model	Effective increase compared to base scenario
Base scenario	5.38 %	-
5%	5.93%	10.3%
10%	6.20%	15.2%
15%	6.51%	21.1%
20%	7.00%	30.1%
25%	7.47%	38.8%
30%	7.64%	42.0%

These results clearly indicate that there is a multiple-return effect in the model since the actual increase in return rate was around 50% larger than the increase in the return rate input value (if there was no multiple-return effect, the values in the first and third column should be almost identical). This is important to keep in mind in future sections where return rates are increased as part of the scenario analysis.

5.3.7 **Experimental Design**

This part of the simulation study process relates to the way in which experiments/scenarios are designed in the simulation model and how the system is configured. These are key aspects of the study as they directly connect to the output generated as well as the quality of this output.

5.3.7.1 System Configuration

An important part of the experimental design phase is the system configuration, which generally revolves around questions such as "for how long should the simulation run?", "how many replications are necessary?", "does the model in question require a warm-up and/or cool-down period?" and "how should confidence intervals be constructed for parameters of interest?".

As the model created should be viewed as a generalized model of an online fashion return process and analysis would be conducted on product categories described using three parameters rather than real products found in data, the actual simulation time wasn't of primary importance. Instead, the amount of products generated of each category was considered a more critical aspect when setting up the system and the model was designed to end simulation once all products had exited the system. Determining a suitable size of the number of products created of each category was a trade-off between the time it would take to complete each simulation replication and the model generating results with standard deviations small enough to achieve statistical significance. Taking both of these aspects into account, after some trial-and-error analysis, 1500 was deemed an appropriate value.

The next step was to determine how many replications the model should run. Also this aspect was mainly related to ensuring that the generated results would have statistical significance, as a larger number of replications would give a smaller confidence interval and therefore better statistical results. However, the number of replications also greatly increased the time to run simulations and a trade-off had to be made in this case as well. Consequently, a replication test was performed to determine how many replications were necessary to achieve stable results. The value of the model parameter "total profit" (a summation of all 27 product category profits) was compared for runs with different number of replications, ranging from 1 to 100. The parameter value for the run with 100 replications was used as an index when comparing to other runs. After conducting the test, illustrated in Figure 5.15, 15 replications was chosen as an appropriate trade-off between result stability and time for each run.

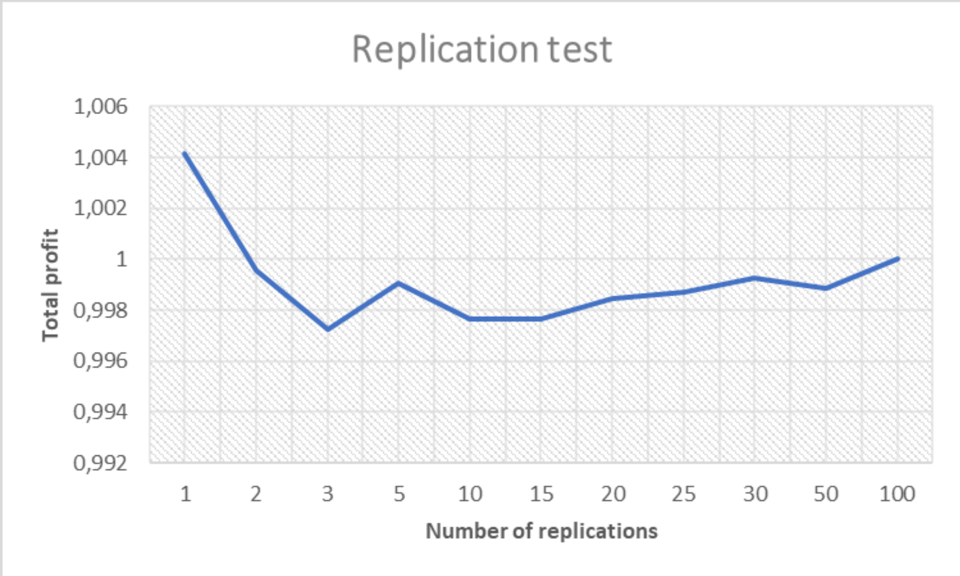

Figure 5.15 Replication test results

Based on the way the model was constructed, there was no need for any warm-up period. However, since it was important that all products exited the system before the simulation was completed, a cool-down period was implemented where no new items were created while the ones still in the system were given time to exit.

Choosing appropriate confidence intervals is another important part of the system configuration that relates to the certainty of results generated from the simulation model. There is no universal value that should be used in all statistical analyses. Instead, the researcher must decide how much uncertainty is acceptable in each specific analysis. An example of this is that a producer of deodorant would want to be able to say with very large confidence, maybe >99.99%, that the product will not be toxic to humans, but at the same time accept a 90% interval that its effect lasts for more than 12 hours. However, a confidence level of 95% is widely used in research and the authors believe that it gives an acceptable level of uncertainty when analyzing the results of this quite complex simulation model. Consequently, this confidence level will be used when analyzing and comparing profitability in the different scenarios.

5.3.7.2 Scenario Analysis

Constructing trustworthy and realistic scenarios was an important step in answering both research questions revolving around investigating the effect of changes in consumer behavior and the length of the return delay, i.e. the time it takes for returns to make their way back to the retailer.

In order to answer RQ1 six scenarios were first generated to explore the effect on profitability of a percental increase of return rate. The idea behind using these scenarios was to investigate how the average profitability changed for each of the product categories compared to the base scenario when increasing the return rate for all products. These results could then be analyzed to see whether or not any changes of statistical significance in the profitability could be observed. In the simulation model this was implemented by multiplying a generated product's return rate by a factor representing the increase. Table 5.6 below illustrate these six scenarios.

Table 5.6 Scenario 1 through 6 with their respective return rate increase.

Scenario	Percental increase of return rate
Scenario 1	5%
Scenario 2	10%
Scenario 3	15%
Scenario 4	20%
Scenario 5	25%
Scenario 6	30%

As this way of increasing return rates led to products with already high rates being much more affected than those with lower rates, it was also considered of interest to investigate whether or not the results would differ when instead increasing by percentage points. This approach would then generate scenarios where the number of expected returns of a product increased equally as much for every product regardless of their initial return rate value. The implementation of this scenario was done by simply adding the percentage point increase to the product's initial return rate value. These additional five scenarios are presented in Table 5.7.

Table 5.7 Scenario 7 through 11 with their respective return rate increase.

Scenario	Percentage point increase of return rate
Scenario 7	2%
Scenario 8	4%
Scenario 9	6%
Scenario 10	8%
Scenario 11	10%

In order to answer RQ2, the effect of increasing and decreasing return delay, some additional scenarios had to be generated. This was done by constructing 12 scenarios with return delay ranging from 70% to 130% of the value in the base scenario. As all generated products were treated the same with regard to return delay, there was no need to also use scenarios where the delay was increased using percentage points or a fixed number of days as was the case when answering RQ1. The results from these scenarios were then compared to the base scenario to see if it was possible to observe any changes of statistical significance in the profitability. The 12 scenarios and their respective change of return delay are presented in Table 5.8.

Table 5.8 Scenario 12 through 23 with their respective change in return delay.

Scenario	Change in return delay
Scenario 12	-30%
Scenario 13	-25%
Scenario 14	-20%
Scenario 15	-15%
Scenario 16	-10%
Scenario 17	-5%
Scenario 18	+5%
Scenario 19	+10%
Scenario 20	+15%
Scenario 21	+20%
Scenario 22	+25%
Scenario 23	+30%

5.3.7.3 Significance Testing

In order to determine whether the results achieved through the simulation study were of statistical significance, a general testing procedure had to be developed. This statistical significance was necessary in order to later on draw conclusion with any certainty from the results presented. As the purpose of the test was to determine if changing the input variables return delay and return rate would render any change in the average total profit over 15 simulation replications, a correlation test was considered suitable. The tests were conducted by assuming the hypothesis, H_a, that there was a significant change in the average profit caused by the change of the input variables. The null hypothesis, H_0, was consequently that there was no such change present. The test was performed by first calculating r, the correlation coefficient, between the input data and the resulting average profit for each product category in all scenarios. This value could then be used in Equation 5.10 to calculate the test statistic, t. This was later used in the 2-tailed t-distribution in Excel to obtain p, the probability value. Finally, the p-value was tested on a 95% confidence level, and could as a result be considered significant if it was smaller than 0.05.

$$t = r * \sqrt{\frac{n-2}{1-r^2}} \tag{5.10}$$

$Where\ t\ is\ the\ test\ statistic, r\ the\ correlation\ coefficient, n$
$the\ sample\ size\ and\ n-2\ the\ degrees\ of\ freedom$

In the cases where significant results were achieved it was also of interest to analyze the correlation effect size, which was obtained by calculating r^2. This procedure was used throughout the simulation results and is presented in the upcoming chapter.

6 Simulation Results

This chapter presents the results from the simulation study described in chapter 5. The presentation of these results will follow the structure of section 5.3.7.2, which means that the base scenario will be presented first, followed by the scenarios with percentage increase of return rate, then the scenarios with percentage point increase in return rate, and finally the scenarios with decreased or increased return delay. Due to the number of product types being analyzed, graphs of the results for each product in each type of scenario will only be presented in the appendix. However, results tables with significance levels and correlation effect size for the difference in mean profit per sold item for each product category will be presented for each type of scenario, and the most significant findings will be highlighted.

6.1 Base Scenario

This scenario was run using the base values for all input variables, calculated as described in chapter 5. This scenario was used as a baseline index for comparing results for each of the product categories in all other scenarios.

6.2 Scenario 1-6

These scenarios represent incremental changes of 5 percent in the return rate for all products. The mean results from 15 replications of the model are shown for each product category in each scenario below. A correlation analysis for each product was performed to identify whether the change in return rate had a significant effect on the results, as interpreted on a 95% confidence level. The effect size was also calculated. These results are presented in Table 6.1, Table 6.2 and Table 6.3 in terms of profit per item sold in SEK for each product category. Graphs illustrating the index change for each product category individually is available in Appendix A.

Table 6.1 Scenario 1-6, product category 1-9.

Scenarios	Prod cat. 1	Prod cat. 2	Prod cat. 3	Prod cat. 4	Prod cat. 5	Prod cat. 6	Prod cat. 7	Prod cat. 8	Prod cat. 9
Sales price range	Low	Low	Low	Low	Low	Low	Low	Low	Low
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	68,93 kr	68,03 kr	70,36 kr	54,33 kr	54,34 kr	54,41 kr	7,81 kr	6,90 kr	8,52 kr
RR +5%	68,00 kr	70,02 kr	68,61 kr	54,04 kr	54,98 kr	53,54 kr	1,18 kr	-0,16 kr	2,26 kr
RR +10%	68,84 kr	69,67 kr	67,74 kr	52,67 kr	51,72 kr	52,06 kr	-2,96 kr	-4,37 kr	-3,73 kr
RR +15%	67,11 kr	67,87 kr	66,46 kr	51,52 kr	50,57 kr	51,68 kr	-8,64 kr	-11,00 kr	-12,61 kr
RR +20%	66,91 kr	68,01 kr	65,72 kr	51,69 kr	50,42 kr	51,50 kr	-17,89 kr	-18,01 kr	-16,56 kr
RR +25%	66,78 kr	66,60 kr	67,33 kr	48,81 kr	48,44 kr	49,89 kr	-20,91 kr	-22,85 kr	-18,94 kr
RR+ 30%	65,78 kr	65,98 kr	67,01 kr	47,17 kr	47,27 kr	46,37 kr	-31,82 kr	-33,11 kr	-28,29 kr
Effect size (R^2)	0,8443	0,5946	0,5483	0,9256	0,9343	0,8758	0,9844	0,9906	0,9832
Significance	0,0034	0,0424	0,0570	0,0005	0,0004	0,0019	0,0000	0,0000	0,0000
Significant effect?	YES	YES	NO	YES	YES	YES	YES	YES	YES

Table 6.2 Scenario 1-6, product category 10-18.

Scenarios	Prod cat. 10	Prod cat. 11	Prod cat. 12	Prod cat. 13	Prod cat. 14	Prod cat. 15	Prod cat. 16	Prod cat. 17	Prod cat. 18
Sales price range	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	206,96 kr	202,96 kr	202,73 kr	182,36 kr	186,02 kr	187,18 kr	126,37 kr	126,02 kr	126,34 kr
RR +5%	201,99 kr	205,78 kr	205,04 kr	184,95 kr	182,54 kr	183,68 kr	121,45 kr	117,47 kr	123,29 kr
RR +10%	203,46 kr	202,62 kr	204,40 kr	183,06 kr	181,69 kr	183,51 kr	114,15 kr	116,71 kr	110,02 kr
RR +15%	204,37 kr	204,53 kr	201,57 kr	181,98 kr	181,27 kr	181,30 kr	108,57 kr	106,63 kr	107,58 kr
RR +20%	201,03 kr	206,75 kr	202,96 kr	177,52 kr	178,92 kr	179,54 kr	100,73 kr	98,16 kr	99,20 kr
RR +25%	202,17 kr	201,17 kr	202,27 kr	178,47 kr	177,66 kr	179,62 kr	92,48 kr	89,44 kr	91,81 kr
RR+ 30%	200,54 kr	202,91 kr	201,78 kr	179,71 kr	178,26 kr	178,25 kr	82,97 kr	84,30 kr	83,57 kr
Effect size (R^2)	0,5540	0,0427	0,3378	0,5850	0,8969	0,9295	0,9908	0,9813	0,9842
Significance	0,0550	0,6568	0,1711	0,0452	0,0012	0,0005	0,0000	0,0000	0,0000
Significant effect?	NO	NO	NO	YES	YES	YES	YES	YES	YES

Table 6.3 Table 6.3. Scenario 1-6, product category 19-27.

Scenarios	Prod cat. 19	Prod cat. 20	Prod cat. 21	Prod cat. 22	Prod cat. 23	Prod cat. 24	Prod cat. 25	Prod cat. 26	Prod cat. 27
Sales price range	High	High	High	High	High	High	High	High	High
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	1 199,91 kr	1 186,50 kr	1 185,88 kr	1 118,27 kr	1 150,96 kr	1 134,89 kr	995,42 kr	991,03 kr	984,39 kr
RR +5%	1 186,53 kr	1 192,94 kr	1 203,56 kr	1 133,47 kr	1 126,83 kr	1 143,37 kr	972,26 kr	982,71 kr	966,36 kr
RR +10%	1 188,14 kr	1 183,70 kr	1 181,33 kr	1 140,62 kr	1 141,33 kr	1 137,84 kr	953,21 kr	974,93 kr	963,47 kr
RR +15%	1 183,99 kr	1 187,04 kr	1 167,91 kr	1 130,36 kr	1 125,04 kr	1 118,38 kr	958,97 kr	949,14 kr	954,38 kr
RR +20%	1 178,08 kr	1 176,69 kr	1 174,48 kr	1 117,69 kr	1 124,91 kr	1 131,02 kr	929,56 kr	941,74 kr	925,09 kr
RR +25%	1 176,57 kr	1 182,35 kr	1 190,46 kr	1 106,60 kr	1 121,03 kr	1 113,02 kr	938,74 kr	919,60 kr	914,25 kr
RR+ 30%	1 174,10 kr	1 187,11 kr	1 171,69 kr	1 116,52 kr	1 113,53 kr	1 112,17 kr	908,34 kr	925,36 kr	903,13 kr
Effect size (R^2)	0,8863	0,1638	0,2237	0,2869	0,7217	0,6898	0,8984	0,9442	0,9641
Significance	0,0015	0,3678	0,2838	0,2153	0,0155	0,0207	0,0012	0,0003	0,0001
Significant effect?	YES	NO	NO	NO	YES	YES	YES	YES	YES

For these scenarios, there were significant results for 20 of 27 product categories.

6.3 Scenario 7-11

These scenarios represent incremental changes of 2 percentage points in the return rate for all products. The mean results from 15 replications of the model are shown for each product category in each scenario below. A correlation analysis for each product was performed to identify whether the change in return rate had a significant effect on the results, as interpreted on a 95% confidence level. These results are presented in Table 6.4, Table 6.5 and Table 6.6 in terms of profit per item sold in

SEK for each product category. Graphs illustrating the index change for each product category individually is available in Appendix A.

Table 6.4 Scenario 7-11, product category 1-9.

Scenarios	Prod cat. 1	Prod cat. 2	Prod cat. 3	Prod cat. 4	Prod cat. 5	Prod cat. 6	Prod cat. 7	Prod cat. 8	Prod cat. 9
Sales price range	Low	Low	Low	Low	Low	Low	Low	Low	Low
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	68,93 kr	68,03 kr	70,36 kr	54,33 kr	54,34 kr	54,41 kr	7,81 kr	6,90 kr	8,52 kr
RR +2%	67,00 kr	66,60 kr	67,61 kr	53,19 kr	52,40 kr	52,08 kr	2,45 kr	3,69 kr	1,75 kr
RR +4%	65,69 kr	65,40 kr	64,69 kr	50,56 kr	49,93 kr	50,00 kr	-0,87 kr	-1,29 kr	-0,46 kr
RR +6%	62,22 kr	62,34 kr	62,92 kr	48,37 kr	48,48 kr	46,91 kr	-4,59 kr	-4,92 kr	-6,98 kr
RR +8%	60,70 kr	61,45 kr	60,43 kr	45,41 kr	45,15 kr	44,22 kr	-8,97 kr	-10,83 kr	-8,45 kr
RR +10%	58,39 kr	56,98 kr	59,27 kr	43,66 kr	41,67 kr	43,84 kr	-14,32 kr	-12,91 kr	-12,34 kr
Effect size (R^2)	0,9877	0,9504	0,9849	0,9898	0,9810	0,9765	0,9944	0,9900	0,9702
Significance	0,0001	0,0009	0,0001	0,0000	0,0001	0,0002	0,0000	0,0000	0,0003
Significant effect?	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6.5 Scenario 7-11, product category 10-18.

Scenarios	Prod cat. 10	Prod cat. 11	Prod cat. 12	Prod cat. 13	Prod cat. 14	Prod cat. 15	Prod cat. 16	Prod cat. 17	Prod cat. 18
Sales price range	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	206,96 kr	202,96 kr	202,73 kr	182,36 kr	186,02 kr	187,18 kr	126,37 kr	126,02 kr	126,34 kr
RR +2%	202,00 kr	201,77 kr	200,46 kr	185,81 kr	183,76 kr	179,40 kr	119,86 kr	121,19 kr	122,11 kr
RR +4%	199,94 kr	199,28 kr	198,84 kr	178,70 kr	180,29 kr	178,45 kr	117,55 kr	113,31 kr	116,01 kr
RR +6%	193,45 kr	194,44 kr	194,64 kr	176,03 kr	176,08 kr	176,78 kr	111,21 kr	110,18 kr	110,86 kr
RR +8%	192,85 kr	193,74 kr	194,12 kr	174,02 kr	174,76 kr	175,00 kr	105,06 kr	103,13 kr	107,61 kr
RR +10%	189,83 kr	189,09 kr	191,16 kr	172,41 kr	172,61 kr	168,73 kr	100,92 kr	102,63 kr	99,59 kr
Effect size (R^2)	0,9613	0,9640	0,9763	0,8392	0,9789	0,9015	0,9899	0,9657	0,9900
Significance	0,0006	0,0005	0,0002	0,0103	0,0002	0,0038	0,0000	0,0004	0,0000
Significant effect?	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 6.6 Scenario 7-11, product category 19-27.

Scenarios	Prod cat. 19	Prod cat. 20	Prod cat. 21	Prod cat. 22	Prod cat. 23	Prod cat. 24	Prod cat. 25	Prod cat. 26	Prod cat. 27
Sales price range	High	High	High	High	High	High	High	High	High
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
Base scenario	1 199,91 kr	1 186,50 kr	1 185,88 kr	1 118,27 kr	1 150,96 kr	1 134,89 kr	995,42 kr	991,03 kr	984,39 kr
RR +2%	1 177,72 kr	1 177,75 kr	1 178,98 kr	1 127,20 kr	1 138,73 kr	1 143,05 kr	977,62 kr	995,31 kr	981,55 kr
RR +4%	1 179,17 kr	1 178,61 kr	1 182,78 kr	1 136,10 kr	1 118,22 kr	1 125,22 kr	961,50 kr	972,93 kr	968,18 kr
RR +6%	1 170,20 kr	1 155,13 kr	1 169,63 kr	1 121,63 kr	1 118,21 kr	1 107,71 kr	967,66 kr	961,00 kr	965,94 kr
RR +8%	1 155,98 kr	1 167,52 kr	1 151,41 kr	1 093,87 kr	1 109,34 kr	1 098,03 kr	957,29 kr	953,65 kr	949,84 kr
RR +10%	1 143,92 kr	1 152,03 kr	1 149,81 kr	1 088,73 kr	1 106,90 kr	1 108,90 kr	947,58 kr	943,89 kr	936,00 kr
Effect size (R^2)	0,9394	0,7671	0,8724	0,5508	0,8957	0,7422	0,8708	0,9352	0,9514
Significance	0,0014	0,0222	0,0064	0,0912	0,0042	0,0274	0,0066	0,0016	0,0009
Significant effect?	YES	YES	YES	NO	YES	YES	YES	YES	YES

In these scenarios, the results were significant for 26 of 27 product categories.

6.4 Scenario 12-23

These scenarios represent incremental changes of 5 percent for the return delay for all products, from a change of -30% to +30%. The mean results from 15 replications of the model are shown for each product category in each scenario below. A correlation analysis for each product was performed to identify whether the change in return rate had a significant effect on the results, as interpreted on a 95% confidence level. These results are presented in Table 6.7, Table 6.8 and Table 6.9 in terms of profit per item sold in SEK for each product category. Graphs illustrating the index change for each product category individually is available in Appendix A. An asterisk indicates a positive effect, i.e. increased return delay led to increased profit, which is contrary to the assumed effect.

Table 6.7 Scenario 12-23, product category 1-9.

Scenarios	Prod cat. 1	Prod cat. 2	Prod cat. 3	Prod cat. 4	Prod cat. 5	Prod cat. 6	Prod cat. 7	Prod cat. 8	Prod cat. 9
Sales price range	Low	Low	Low	Low	Low	Low	Low	Low	Low
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
RD -30%	68,80 kr	69,05 kr	68,26 kr	55,62 kr	54,56 kr	56,38 kr	7,29 kr	6,80 kr	6,55 kr
RD -25%	69,05 kr	69,38 kr	69,25 kr	53,33 kr	54,68 kr	54,68 kr	5,08 kr	6,34 kr	6,57 kr
RD - 20%	69,27 kr	68,92 kr	68,72 kr	54,41 kr	55,45 kr	55,76 kr	6,97 kr	6,04 kr	6,29 kr
RD -15%	68,97 kr	69,47 kr	68,13 kr	55,94 kr	57,13 kr	54,36 kr	8,51 kr	6,43 kr	5,91 kr
RD -10%	69,08 kr	70,08 kr	69,61 kr	54,45 kr	55,32 kr	55,75 kr	6,85 kr	7,65 kr	6,90 kr
RD -5%	68,69 kr	69,40 kr	69,90 kr	56,17 kr	56,25 kr	53,52 kr	4,78 kr	5,84 kr	5,31 kr
Base scenario	68,93 kr	68,03 kr	70,36 kr	54,33 kr	54,34 kr	54,41 kr	7,81 kr	6,90 kr	8,52 kr
RD +5%	67,38 kr	68,79 kr	68,25 kr	55,64 kr	56,16 kr	55,72 kr	8,33 kr	7,18 kr	6,88 kr
RD +10%	69,18 kr	69,61 kr	68,68 kr	54,81 kr	55,80 kr	56,12 kr	5,20 kr	7,80 kr	4,77 kr
RD +15%	70,02 kr	68,37 kr	68,11 kr	54,55 kr	55,54 kr	54,30 kr	7,63 kr	5,60 kr	7,07 kr
RD +20%	67,89 kr	69,22 kr	69,29 kr	55,21 kr	54,49 kr	54,36 kr	6,82 kr	7,57 kr	7,27 kr
RD +25%	68,96 kr	67,70 kr	69,26 kr	55,52 kr	56,99 kr	55,22 kr	6,07 kr	6,40 kr	5,00 kr
RD +30%	67,77 kr	68,58 kr	69,05 kr	54,47 kr	55,02 kr	55,01 kr	5,42 kr	7,45 kr	5,04 kr
Effect size (R^2)	0,0946	0,2283	0,0112*	0,0076*	0,0236*	0,0433	0,0248	0,0778*	0,0579
Significance	0,3066	0,0987	0,7309	0,7770	0,6165	0,4950	0,6070	0,3560	0,4284
Significant effect?	NO	NO	NO	NO	NO	NO	NO	NO	NO

Table 6.8 Scenario 12-23, product category 10-18.

Scenarios	Prod cat. 10	Prod cat. 11	Prod cat. 12	Prod cat. 13	Prod cat. 14	Prod cat. 15	Prod cat. 16	Prod cat. 17	Prod cat. 18
Sales price range	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
RD -30%	200,93 kr	202,36 kr	204,46 kr	185,41 kr	186,97 kr	188,08 kr	127,80 kr	123,56 kr	123,14 kr
RD -25%	202,53 kr	202,83 kr	206,51 kr	188,03 kr	185,36 kr	185,69 kr	126,56 kr	124,17 kr	126,90 kr
RD - 20%	203,57 kr	201,97 kr	202,74 kr	185,61 kr	184,99 kr	183,95 kr	125,99 kr	123,49 kr	124,20 kr
RD -15%	205,96 kr	204,03 kr	205,70 kr	184,82 kr	185,78 kr	186,46 kr	126,45 kr	126,27 kr	122,77 kr
RD -10%	203,69 kr	205,10 kr	202,70 kr	184,44 kr	186,34 kr	185,87 kr	124,46 kr	126,84 kr	123,55 kr
RD -5%	203,53 kr	205,63 kr	204,81 kr	183,29 kr	186,91 kr	185,83 kr	127,11 kr	125,00 kr	122,86 kr
Base scenario	206,96 kr	202,96 kr	202,73 kr	182,36 kr	186,02 kr	187,18 kr	126,37 kr	126,02 kr	126,34 kr
RD +5%	203,61 kr	206,03 kr	202,57 kr	183,35 kr	186,66 kr	188,12 kr	125,32 kr	124,37 kr	125,60 kr
RD +10%	204,58 kr	202,86 kr	204,63 kr	183,42 kr	186,80 kr	183,26 kr	124,25 kr	124,95 kr	124,25 kr
RD +15%	203,67 kr	205,14 kr	206,09 kr	186,19 kr	188,45 kr	185,66 kr	125,19 kr	125,28 kr	126,07 kr
RD +20%	201,22 kr	205,60 kr	205,68 kr	184,65 kr	185,92 kr	185,38 kr	125,02 kr	126,89 kr	123,75 kr
RD +25%	204,74 kr	202,72 kr	204,39 kr	185,92 kr	185,77 kr	185,55 kr	124,90 kr	122,62 kr	128,87 kr
RD +30%	204,53 kr	204,31 kr	205,38 kr	184,33 kr	183,94 kr	186,29 kr	125,63 kr	124,74 kr	125,21 kr
Effect size (R^2)	0,0546*	0,1419*	0,0210*	0,0706	0,0054	0,0292	0,4011	0,0081*	0,1652*
Significance	0,4421	0,2046	0,6369	0,3801	0,8115	0,5770	0,0201	0,7696	0,1682
Significant effect?	NO	NO	NO	NO	NO	NO	YES	NO	NO

Table 6.9 Scenario 12-23, product category 19-27.

Scenarios	Prod cat. 19	Prod cat. 20	Prod cat. 21	Prod cat. 22	Prod cat. 23	Prod cat. 24	Prod cat. 25	Prod cat. 26	Prod cat. 27
Sales price range	High	High	High	High	High	High	High	High	High
Return rate range	Low	Low	Low	Medium	Medium	Medium	High	High	High
Sales price range	Low	Medium	High	Low	Medium	High	Low	Medium	High
RD -30%	1 197,97 kr	1 193,30 kr	1 195,31 kr	1 139,68 kr	1 125,35 kr	1 137,78 kr	1 000,74 kr	981,43 kr	990,62 kr
RD -25%	1 208,03 kr	1 180,81 kr	1 190,11 kr	1 136,70 kr	1 120,25 kr	1 150,33 kr	1 000,65 kr	984,84 kr	995,98 kr
RD - 20%	1 192,65 kr	1 181,38 kr	1 195,86 kr	1 130,61 kr	1 128,20 kr	1 139,22 kr	1 001,08 kr	1 005,10 kr	999,86 kr
RD -15%	1 189,75 kr	1 179,98 kr	1 194,48 kr	1 133,78 kr	1 125,67 kr	1 146,63 kr	1 001,61 kr	990,35 kr	987,67 kr
RD -10%	1 181,95 kr	1 190,96 kr	1 193,93 kr	1 131,49 kr	1 137,56 kr	1 128,50 kr	980,62 kr	993,17 kr	991,28 kr
RD -5%	1 172,58 kr	1 188,40 kr	1 196,98 kr	1 129,70 kr	1 124,58 kr	1 146,93 kr	1 000,48 kr	1 006,93 kr	991,10 kr
Base scenario	1 199,91 kr	1 186,50 kr	1 185,88 kr	1 118,27 kr	1 150,96 kr	1 134,89 kr	995,42 kr	991,03 kr	984,39 kr
RD +5%	1 167,71 kr	1 192,65 kr	1 178,43 kr	1 133,19 kr	1 129,06 kr	1 144,57 kr	1 000,62 kr	995,79 kr	997,51 kr
RD +10%	1 178,52 kr	1 182,80 kr	1 185,60 kr	1 129,82 kr	1 126,27 kr	1 150,49 kr	989,62 kr	994,49 kr	989,79 kr
RD +15%	1 187,31 kr	1 186,81 kr	1 191,30 kr	1 136,89 kr	1 137,05 kr	1 145,26 kr	981,47 kr	1 001,19 kr	1 015,04 kr
RD +20%	1 197,83 kr	1 190,75 kr	1 184,15 kr	1 137,69 kr	1 149,03 kr	1 159,53 kr	1 005,86 kr	1 006,25 kr	975,34 kr
RD +25%	1 203,32 kr	1 195,27 kr	1 180,64 kr	1 133,09 kr	1 139,50 kr	1 136,42 kr	1 008,59 kr	994,35 kr	996,49 kr
RD +30%	1 202,54 kr	1 188,17 kr	1 184,88 kr	1 147,78 kr	1 152,77 kr	1 135,98 kr	1 001,94 kr	995,10 kr	996,26 kr
Effect size (R^2)	0,0001*	0,1368*	0,4907	0,0463*	0,4893*	0,0098*	0,0035*	0,1865*	0,0030*
Significance	0,9753	0,2136	0,0077	0,4804	0,0078	0,7476	0,8484	0,1406	0,8581
Significant effect?	NO	NO	YES	NO	YES	NO	NO	NO	NO

These scenarios only yielded statistically significant effects on the profits of three product categories. However, even in these cases the effect size is quite small, and for one of these cases the effect is actually positive, i.e. increased return delay led to increased profit.

7 Analysis and Discussion

In this chapter the project's results are analyzed and the implications for theory and practice are debated. The limitations of the study are also discussed, as well as the various sources of error in the data analysis and simulation.

7.1 Analysis of Initial Data Study and Results

This part of the chapter covers the results of the initial data analysis performed in Chapter 4. The research areas examined here, in order, include retail borrowing and associated return behavior, the effects of TISP and discount rate on return rate, the effect of product sales price on return rate and multiple size ordering return behavior.

7.1.1 **Retail Borrowing Return Behavior**

Three hypotheses were formulated and examined as a way of identifying retail borrowing behavior in the data received and as seen in chapter 4.2, only one of these tests generated results in accordance with the hypothesis presented.

As for hypothesis 1, that dresses in general had a longer return delay than other products, there was no indication of this phenomenon in the data. An issue with this approach was that the return delay calculated from data also consisted of transportation time, since there was no way to separate these from each other. Another problem was that the behavior examined, if it exists, most likely would be quite rare. Consequently, it is unlikely that it would have a significant impact on the average return delay and using this method to prove its occurrence might be difficult.

The second hypothesis stated that dresses should have a larger proportions of returns with stains than other products. However, the hypothesis test indicated the opposite, that this proportion was actually smaller for dresses. Unfortunately this approach had several issues making it difficult to draw any certain conclusions from it. The one that likely had the largest effect on the results was that customers were responsible for informing that a product had stains on it when stating their reason for returning a product. This fact presents several problems. Firstly, almost all returned products were returned with the reason “did not meet expectations”, which was the first alternative presented. Even excluding the fact that many customers likely just tick the first box presented, this return reason is quite vague. One could easily imagine that customers returning a product they received with stains on it would characterize this as something which did not meet their expectations. A second, even more, problematic part of this information coming directly from customers is that in order to trust the results presented, one would also have to consider the customer’s information as completely trustworthy. This would require that a customer returning a product they intentionally retail borrowed and accidently put a stain on, would have to say that the fact that the product had a stain on it was the reason for the return. It is somewhat difficult to imagine that customers would behave in this way, as it seems more likely that the condition of their return is put under more scrutiny than if they use another return reason.

In order to properly examine this behavior it would have been very useful to have information available regarding the returns department’s comments on the condition of returned products. This data would have been much more trustworthy and a better foundation to construct an analysis than the consumer information that was received.

The third hypothesis was that items returned with stains were more likely to be retail borrowed than other items and as a result should have a longer average return delay than other returns. This analysis actually resulted in significant results, which confirmed that clothes returned with stains did in fact have a longer average return delay. This was somewhat surprising considering the results from hypothesis two, but could nonetheless be an indication of retail borrowing behavior. However, the issues related to the second hypothesis test also apply in this case and one should be cautious before drawing any major conclusions from these results.

However, as literature suggest that retail borrowing is an existing behavior it is still considered of interest to present and discuss some suggestions for how retailers can combat the issue. The first, maybe most intuitive, response could be to try and solve this problem by introducing harsher policies, or rather implement more scrutiny when screening returns in order to find these retail borrowed products. This is also in line with some of the literature regarding gatekeeping presented in 3.2.1.

An issue with this approach is of course that such an implementation likely is rather expensive and could cost more than it would save. This could potentially be handled by targeting the screening efforts towards those products that are most likely to be retail borrowed, although that would require a thorough analysis of which products to target, potentially also somewhat expensive. Despite these negative aspects of this gatekeeping approach, it is still possible that retailers can find a way to balance the increased screening-related cost with reduced costs related to retail borrowing to achieve a positive outcome, making this worthy of consideration for industry professionals.

A second possibility is to use an approach based on avoidance, as presented in 3.2.2 to make it more difficult for those retail borrowing to achieve the other part of their intentions, that is to actually use the product being “borrowed”. There are examples of products that cannot be returned once they have been used, underwear may be the most common example of such products. Going this far in terms of all products would naturally not be advisable, as trying products on at home to make sure they fit and look right is a key part of ordering clothes online. However, it should be possible to find a middle way to address the issue at hand.

One proposal is to introduce some sort of label to those articles that are more likely to be retail borrowed that customers can’t remove if they are to return the product. The purpose of said label is to make it more difficult for customers to then wear it in public without removing it. Exactly how such a label should make it difficult to wear in public is up for debate, but two suggestions are that it either makes a strong visual impression that customers rather would avoid, or that it makes the product uncomfortable to wear for a longer period of time. However, if retailers choose to implement one of these solutions, or something similar, it is vital that it’s constructed in a way that doesn’t affect customers not intending to retail borrow in an explicit negative way. Should this be the case, it is quite possible that this results in a backlash with larger negative effects for the retailer than the positive ones that were gained. Nonetheless, retailers that find a way to implement a label-solution that reduces the risk of retail borrowing behavior while at the same time not affecting other customers could find this quite profitable.

The third suggestion to handle this issue takes an entirely different approach. Despite it being easy to view retail borrowing behavior as customers fraudulently taking advantage of generous return policies from retailers, it is impossible to disregard the fact that it exists also indicates that there is a demand for this kind of service. As a result, retailers could also look at this as an opportunity to take advantage of. If retailers successfully implement a solution were customers can borrow clothes that they only intend to use once and then send them back to the retailer, given the clothes are in acceptable condition, it is possible that they can turn a negative phenomenon which is difficult to manage into something positive and potentially profitable. This alternative approach was discussed briefly with the industry representative that was interviewed as a part of this study, who found it intriguing and worth looking further into. However, it may not be in the retailers’ interest to offer such a service as it will also compete with their main target, which is selling clothes. In spite of this fact, the authors believe it is an interesting topic to examine more thoroughly and gain more knowledge on the potential of such an approach.

The fourth and final proposal is to introduce harsher policies for categories or specific products where retail borrowing is common. By doing so retailers could target products deemed most problematic in regards to this while not affecting other, less troublesome, products. The perhaps easiest way to construct such a return policy is to not offer free returns for those products identified, as doing so would ensure such behavior also resulted in a cost for customers. Implementing this dynamic return policy would however not be entirely straightforward, mainly for two reasons. First of all, to successfully carry out a switch to a dynamic return policy would require a great deal from a consumer communication aspect. It would have to be made very explicit to customers what the different policies looked like and what products or product categories they covered. Failing to address this properly could have huge negative effects with bad customer reviews and general PR, which would likely outweigh the positive effects of the new policy. Secondly, the implementation of a dynamic return policy would affect many customers not contributing to this problem in the first place. Most consumers do not retail borrow and could feel that this kind of policy only results in an extra cost in those instances where they feel the need to return a product they have purchased. As the industry is highly competitive, this in itself could cause customers to decide to purchase their clothes from a different retailer, who offers a more generous return policy. Although retailers could see benefits from a more dynamic return policy it will be important to keep both of these aspects in mind when implementing it, as it likely will not be successful otherwise.

7.1.2 **Product Return Rate Relationship with TISP and Discount Rate**

The hypothesis for this analysis was that return rate would be higher at the start of a product's sales period, i.e. near the product's launch. One major reason for the formulation of this hypothesis is that products were assumed to be less likely to be discounted when they have just been launched, compared to later in their life cycle when the retailer wants to sell the product out in order to make room for the next product launch. It was also assumed that customers are less likely to return products if the purchase was made at a discounted price. Because of these assumptions, the data analysis was performed in several steps.

7.1.2.1 Product Return Rate as a Function of TISP

The first step was to divide sold items according to when they were sold within the product's sales period and compare the return rate at each point in time. As in Figure 4.1, the results showed that return rate decreased from 28% to 16% along the sales period. A correlation analysis showed that 82.1% of the variability can be explained by TISP, which equates to a strong correlation. The next step was to identify the underlying factors behind this relationship.

7.1.2.2 TISP Effect on Discount Likelihood and Discount Rate

The hypothesis assumed that the primary reason for customers to return less later in the sales period was that TISP was also correlated with increased discount rate, meaning that the same product was relatively cheaper later in the sales period. In order to test this assumption, it was first necessary to examine the relationship between TISP and discount rate. Both the likelihood of items being discounted, as well as the discount rate in percentage points for discounted items were measured. The average likelihood of discount increased from 47% at the start of a product's sales period to 91% at the end. The average discount rate for discounted items sold increased from 33% to 47%. Correlation analysis indicated that 96.8% and 88.4% of variation, respectively, could be attributed to TISP. Discount likelihood and average discount rate could thus be said to be very strongly correlated with TISP. Both of these results are considered fairly expected, as it seems logical that products' discount rate increases as the season progresses, since this would be when the retailer wants to make sure that all items in stock are sold before the next season's clothes are introduced.

7.1.2.3 Return Rate as a Function of Discount Rate

In this step the goal was to determine how return rate is affected by discount rate. Products were divided into bins in accordance with their discount rate in percentage terms. Discount rate was strongly correlated with decreased return rate, as products with no discount had a 25% average return rate and products with the highest level of discounts had 5%. Correlation analysis showed that 78.5% of variability in return rate could be explained by discount rate. Also this correlation result was anticipated, as the authors hypothesized that discount rate would be the factor most responsible for the pattern identified. However, the effect of discount rate was expected to be even larger than what was observed, especially since the correlation between return rate and TISP was larger than 78.5%. This indicates that there likely exists other factors contributing to the declining return rate over time.

Since this effect is so large it is believed of interest to discuss how this information could be useful for retailers. As the result indicates that discounting products has a significant effect on the customer's return decision it is possible that retailers can use this to their advantage. One way of doing this could be that retailers deliberately over-price products only as a way to then "discount" them to the intended sales price. Theoretically, the results presented indicate that such a pricing-technique could result in decreasing returns of these products, although the results presented regarding the effect of sales price on return rate somewhat reduces the effect. However, in order to state anything with great certainty a much deeper analysis is required.

7.1.2.4 TISP Effect on Return Rate Excluding Discounted Products

The final step of this part of the data analysis was to determine if there was an effect of TISP on return rate even without including discounted products. This analysis would confirm whether or not any conclusion can be drawn regarding if discounts are the sole reason that TISP is correlated with decreased return rate.

The analysis showed that there is still a strong negative effect even if only items sold at full price are included. Correlation analysis gave an R-squared value of 0.817, corresponding to a strong correlation. Therefore it is possible to conclude that there must be more factors involved than just discount rate, affecting the customer's decision to return depending on whether the item is sold early or late in its sales period.

A possible explanation for why this consumer return behavior is so clearly visible in the data analyzed is that it is a simple case of supply and demand. At the start of any given season (generally summer, fall, winter and spring) there will most likely be a large variety of similar clothes available for consumers. One can imagine that this abundance of choices for customers to compare between makes them more likely to end up dissatisfied with their purchase and ultimately deciding to return it and buy one of the other similar products they were interested in. As the season then progresses, the supply continuously decreases and as a result so does also the number of possible choices for customers. With a smaller number of products to choose from it is possible that customers later on in the season "settle" for the product they purchased, deem it "good enough" and decide not to return it, while they maybe would have returned had they purchased it earlier in the season.

Another possible explanation discussed that might be a minor underlying factor for this return rate pattern is repeat customers of specific products, i.e. people that purchase an additional pair of something they have already bought once before. The reasoning behind this explanation is that a customer that re-purchases a product would be very unlikely to return it considering the fact that the customer already has an identical product that one would have to assume he/she is satisfied with. However, as this consumer behavior most likely would be quite uncommon for many types of clothing articles it seems unlikely that this effect, if it exists, would be a major contributor to the decreasing return pattern that has been observed.

A final explanation proposal is that some customers may have been weighing their options for a purchase for some time and finally decide on a product late in the sales period. This implies a more informed and well thought-out purchasing decision, reducing the likelihood of being unsatisfied with the purchase, compared to a more impulsive purchase.

7.1.3 **Impact of Sales Price on Return Rate**

The hypothesis regarding sales price and return rate assumed that increased sales price was correlated with higher return rate. This was based on theory and assumptions regarding consumer behavior. The first assumption is that fashion customers who are unsure about whether or not they are satisfied with their purchase and whether they will be satisfied in the long run, may opt to return if the product is more expensive, since the financial risk related to having wasted money on an undesirable product is higher. Secondly, cheaper products tend to be more basic, common products such as socks or simple t-shirts, which are less difficult to judge online as opposed to in real life, when compared to more expensive product types which may have a unique design or more specific fitting requirements. A third reason, as suggested by literature, is that some fashion consumers order and return later as they realize they made a purchase they feel they cannot afford, or because they want to spend the money on something else. It seems likely that this type of return behavior would be more closely associated with higher-priced products.

The products were divided into 25 price ranges and average return rate was calculated for each bin. The results showed that there was an overall weak correlation between higher sales price and increased return rate, with an R-squared value of 0.212. However, if the analysis was limited to the first 10 bins, i.e. sales price between 0 and 1000 SEK, there was a strong correlation between higher price and increased return rate, with an R-squared of 0.854. This means that there is a clear effect between the most cheap, basic products where the average return rate is as low as 5%, and moderately expensive products where the average return rate is close to 25%. There is no significant effect on return rate between prices of 1000 and over. However, the data for higher-priced products is somewhat limited in the sample size, since these products are not sold in nearly the same volumes as cheaper products.

The data seems to indicate that there is a clear difference in return rate when comparing the lowest price category of products to medium-priced products. However, since the data does not include reliable return reason reporting, it is difficult to determine the most important underlying reasons for more expensive products having higher return rates, although there are several theories presented in the hypothesis formulation. As for strategies to reduce returns, product based policies are an option, where limits for returning could be stricter for expensive products. However, if this would effectively be a step back from current, more lenient policies for a company, customers may have a sharp negative reaction, at least in the short term. It might also be confusing for customers if return policies are not the same for all products.

7.1.4 **Multiple Size Ordering and Return Behavior**

The hypothesis regarding this area arose from return behavior suggested by literature where fashion customers purchase multiple sizes of the same product in order to try them on at home, then returning those items that do not fit. The goal was simply to find if the data indicated the occurrence of multiple size ordering and return behavior, and this was done by calculating the percentage of orders which contained this type of return behavior. Results showed that 2.26% of orders overall included at least one occurrence of multiple size ordering and return. As for only those orders where at least one product was returned, 12.9% of those orders included at least one instance of this type of return.

There is a caveat to mention regarding the method used. Some of these returns could have arisen from e.. orders of two items of the same product but different sizes, that were meant for two people, where one of them was not satisfied with the product. However, this is most likely quite rare, and would not comprise such a high percentage of total orders and returns. The data thus seems to confirm that the aforementioned type of return behavior is quite prevalent. The authors were quite surprised to learn that such a high proportion of fashion returns are essentially premeditated returns, arising from the situation where the customer tries on products in their home.

One way for companies to manage and reduce this type of return behavior would be to improve the information regarding fitting on their web page, for example by providing more images of the product being worn, perhaps by models with different body types, or providing information about whether the product is typically a tight or loose fit compared to other products with the same nominal size and fit. Some fashion e-tailers are already working with these types of solutions to reduce returns. There is still potentially a challenge in terms of convincing customers who are used to trying on different sizes, to order only one item at a time and returning it if it does not fit, rather than guaranteeing returns by ordering more items than they intend to keep.

Another improvement potential that may not be as widely used within the industry is to provide information about how a product fits compared to other products that the customer has purchased previously. This would provide customers with more personalized information and thus making them feel secure enough about their choice of size not to order multiple sizes. Consequently, this could help companies in combating multiple size ordering behavior. One could also imagine a scenario where this strategy is developed further to include the same information from other customers with similar characteristics. This would require extensive data collection on customers in order to match them into different "size-categories", but considering that e-commerce is a heavily data-driven industry it is possible that many larger e-tailing companies already have the data required to explore such a solution.

As a slight decrease in customer return may not be deemed profitable enough to develop such a solution, it is important to also mention what additional benefits it may generate. One such benefit could be that the same information is used to further increase the effectiveness of target advertising. By grouping customers into different categories it is possible to identify customers that have similar purchasing patterns, and target them with ads of products that customers from the same category have purchased. Going back to the fact that e-commerce is a data-driven industry it is possible that many companies already use similar tactics when creating target advertising, although perhaps not as ambitious as proposed here. Given that this is the case, the step towards also including a size fitting tool into this data algorithm would not be as large a step as it first may seem.

A final suggestion that could address this issue is through implementing harsher policies. By identifying within which product categories multiple size ordering behavior is most common it could be possible to construct return policies where these categories are targeted as a way to reduce said behavior. This could be similar to the solution presented for retail borrowing, where the identified products or categories were given return policies that did not include free returns. The issues related to this implementation are the same as presented in regards to retail borrowing and should not be ignored when considering switching to a dynamic policy. Nonetheless, it is once again important to state that should the dynamic return policy be successfully implemented and well communicated towards customers it could be quite profitable for retailers.

7.2 Analysis of Simulation Results

This section covers the results from chapter 6, obtained from the simulation model scenarios described in chapter 5. The scenario types covered include return rate percental increase, return rate percentage point increase and return delay reduction and increase.

7.2.1 **Impact of Increased Return Rate (percental)**

When increasing return rate in steps of 5%, from 5% to 30%, there was a significant negative effect on profit for 20 out of 27 product categories when comparing results across the six scenarios as well as the base scenario. For the remaining seven product categories, there was a negative effect, but not large enough to be statistically significant. These results indicate that there is a clear overall negative connection between percentage return rate increase and profit, which is in line with expectations.

Based on the observed effect size, the effect is largest for product categories 7-9 and 16-18, which are all products with high return rate and low (7-9) or medium (16-18) sales price. In accordance with the expectations presented in section 5.3.7.2, products with high return rate are disproportionately affected in terms of profit in scenarios that use percental increase. Furthermore, when looking at actual profit per item sold, there is an extreme effect for products with a high return rate but low price. This is in line with expectations that products with low base sales price will be heavily affected by fixed costs associated with returns, such as transport costs. Meanwhile, there is no statistically significant effect for any of the product categories with a medium or high sales price and low return rate (categories 10-12 and 20-22). These results indicate that percentage point increase is most likely a more useful method of measuring the effects of increasing return rate, since it should alleviate most of the described issues.

7.2.2 **Impact of Increased Return Rate (percentage point)**

When instead increasing return rate using percentage points in steps of 2, from 2% to 10%, a significant decrease in profit was observed in 26 out of 27 product categories. For the one category that did not generate statistical significance it was observed that the effect also in this case was negative. In combination, this clearly indicates that a percentage point increase results in increasing cost for retailers and decreasing profit. This result was of course expected but it is of interest to analyze which product categories were affected the most. The effect size was very large, above 0.99, for category 7, 8 and 18, which is in line with what was presented in the previous section. However, the fact that all categories within the low sales price range (1-9) had an effect size above 0.95 is striking when comparing to scenarios 1-6, as this clearly indicates the effect of a percentage point increase. As stated earlier, the reason for conducting scenario 7-12 was that the authors didn't believe that the percental increase properly illustrated how a general change in consumer behavior would affect products with lower return rates. Hence, these results are an indication of the profitability related effects retailers could expect as a purchasing behavior where customers order clothes online and use their homes as a fitting room becomes more common and accepted. Considering for instance that product category 1, with the low range in all parameters, has a decreased profit of 15% when comparing the base scenario to a 10 percentage point increase in return rate further illustrates this effect. Consequently, should consumer behavior continue to move towards what was just described, as the authors hypothesize, it will be important for retailers to find a way to face this challenge.

Many of the suggestions presented in the analysis of chapter 4 will not be as easily applicable in this case, since some of those methods rely on the fact that the return was a result of customers having insufficient information about the product. If all customers instead move towards a purchasing pattern where they order a shirt with the intent to try it at home and only keep it if they are completely satisfied (as they would have in-store), it is difficult to see that an increased amount of information regarding products would have a significant effect on the number of shirts being returned. When this kind of shopping behavior becomes more common, where ordering a product online is viewed more as "window-shopping" than an actual purchase by the general consumer, companies will instead have to develop new strategies to deal with such a new e-commerce landscape. A strategy that has been discussed in previous sections is dynamic return policies, and this could potentially be a way to combat this issue. Using dynamic policies, retailers could target those products most affected by this "buy-to-try" behavior and use differentiated policies to lessen its effect. This would likely involve decisions such as only having free returns on products that can remain profitable despite increasing returns. However, the problems with implementing this strategy remains and it could potentially be difficult to stay competitive in the industry if such measures are taken.

Another way of looking at this is from the ordering perspective. It is quite common for retailers to offer free shipping, but some have implemented policies where customers pay for shipping if the total order value is below a certain amount. It is possible that such an approach also could be used to deal with the "buy-to-try" behavior, or at least lessen its profitability related effect. If implementing this policy can make consumers order at least two or three products, the cost of shipping will be split between these items and the profit margin for each item will increase. The same logic of course goes for the return transport, although that depends on how many items the customer decides to keep. Even if sustainability related factors are not part of this thesis' scope, it is also important to note that such multi-ordering behavior is clearly beneficial in that aspect, as it reduces the necessary transport. However, an issue with this strategy is that the limit for getting free shipping often is set at a total order value, which still makes it possible for consumers to make single order purchases. This is in many ways logical as items with higher sales prices generally have higher nominal profit margins, making them less affected by shipping costs. Meanwhile, these products also have a higher average return rate and should returns in general continue to increase it is possible that also they are affected to a larger extent. As a result, it could be interesting to instead use a limit where customers instead have to reach a certain number of items before the shipping becomes free, or perhaps even a combination of the two. Even if this really does not deal with the underlying problem, the increasing returns, it does still help retailers to reduce its effect.

Many suggestions presented up to this point have discussed the issue of increasing returns and consumer behavior from a perspective of avoidance, gatekeeping and policy changes. However, another important aspect to mention is how this will affect retailers supply chain processes and in which areas it is possible that most resources should be invested to increase efficiency and effectiveness.

Returns management is of course a part of the supply chain that will be heavily affected by an increasing amount of returns. It is likely that returns will become more common but that the number of items per return continues to be small. This would result in a large increase in return deliveries and could cause problems when receiving them. This will be important to have in mind when designing warehouses and returns management facilities since a poor layout could result in major future returns handling issues.

Another important aspect of this is the restocking of items. As products are expected to "need" a larger number of loops in the supply chain before finally being sold to a customer, it will be vital to make sure that products are available for sale as quickly as possible after being returned. One way for retailers to increase their chances of being successful in regard to this, is to ensure that they have full visibility of products in the later parts of the supply chain. Implementing systems that allows them to know in advance if returns are incoming will give a competitive edge towards competitors that do not have this ability, as they will be able to plan ahead and know what products marketing should push and perhaps even sell products currently out of stock prior to the incoming return. One way of constructing such a system would be that customers looking to return a product would have to pre-register this return. This could have some service related issues, as it makes it slightly more difficult for customers to return, but if implemented successfully the advantages should outweigh the disadvantages.

It is also possible to imagine retailers taking the reselling of returns even further. By having complete visibility of the supply chain it could be possible to sell and deliver a product being returned to a new customer without first having it restocked. This would probably require some sort of repackaging facility ensuring that the product is delivered in acceptable condition to the next customer and also a system that decides whether a return should be sent to a new customer or go back in stock. By doing this retailers could reduce transportation costs, return handling cost and increase the rate in which returns are resold, potentially resulting in increased profits. One could also argue that an implementation like this would have positive environmental effects as transportation is reduced.

A final suggestion which could be interesting for retailers to investigate further is an omni-channel approach to customer returns, i.e. where returns can be made either by sending the shipment back to the warehouse or in a physical store. It is possible that allowing online purchases to also be returned in-store could give retailers the opportunity to resell products faster than if only allowing online returns. Even if the retailer wants to have the channels separated, i.e. only selling returned online products online and returned store items in-store, the possibility to consolidate return shipments from stores in itself could render cost-savings. Another benefit could be that customers returning in-store are more likely to purchase additional products instead of only returning the item they are bringing with them, which of course would be a positive outcome for the retailer compared to an online return. However, an omni-channel solution presents the obvious restriction that the retailer is required to have an online store as well as a physical one, which many retailers do not have. Nonetheless, further investigation on the effects of omni-channel returns would be interesting for retailers that have this opportunity.

7.2.3 **Impact of Varying Return Delay**

Compared to the scenario analysis involving return rate, varying the return delay in steps of 5%, from -30% to +30%, produced much more ambiguous results. The effect was only statistically significant for 3 of the 27 categories (16, 21 and 23), and for one of those, category 23, the effect was actually positive, meaning that according to the results, increasing the return delay would actually improve profit per item sold. Since this idea goes against all assumptions regarding how return delay should affect profits based on how the model was conceptually designed, this seems to indicate a "false positive", i.e. a result caused by random chance which is accidentally determined to be statistically significant. However, even if a 99% significance level was used instead of the typical 95%, the two remaining significant product categories would still include category 23. This indicates that the model in its current form does not accurately represent the real effects of return delay, and that any effects observable in this experiment are largely the result of random chance. Possible causes include weaknesses related to the definition of sales period within the study, which is the parameter that is most closely associated with return delay since, in theory, a long return delay should cause returned items with shorter "prime selling seasons" to be sold at significantly lower prices. It would have been useful to have a better way of classifying products into those with a small window of time for generating sales, and those that could remain popular with customers over a longer period of time, rather than simply estimating this value based on when 90% of a certain product's inventory was sold. Particularly, as mentioned previously, for many of the products that sold out in very short time, they would probably have sold more if their inventory had not been so limited. So instead of them having a short window of opportunity for generating sales like our model implies, in reality they were limited by available supply rather than demand.

However, since the results were inconclusive for more or less all product categories, it seems unlikely that a better definition of sales period on its own would have generated useful results for the return delay experiment. One major reason why return delay may have a limited effect is that according to the model, and indicated by data, return rate decreases further into the sales period, which offsets the increase in discounts. Another possible cause is that the model completely disregards issues related to stock-keeping levels. For example, based on interview information, if an online fashion company is rapidly selling out of a popular new item, it may decide to replenish stock with another same-sized batch from the supplier just a few days after the product is launched. If it then turns out that 60% of customers return the product, the company will suddenly end up with 160% of the stock they had at the product launch, in addition to whatever is left of the original batch. While this example may be extreme, it is a possibility that the model doesn't take into account at all regarding products with short sales windows.

Another possibility is of course that return delay simply is not that important of a factor related to fashion e-tailer profits, and that smaller, more realistic changes between -30% to +30% are not enough to generate statistically significant profit effects. Whilst the authors believe that the model performs reasonably well at capturing the discount effects of when a product is sold, since the relationship is based on large amounts of recent sales data, the effects of return delay on their own may not be large enough to produce significant effects. What is certain is that no accurate conclusions regarding the effects of return delay can be drawn from this experiment, as a more accurate model, and probably a more advanced method of measuring the effects of return delay, incorporating more factors, would be necessary.

8 Conclusions

This chapter describes the contributions of the project findings for theory and practice and presents suggestions from the authors regarding future research within the field.

8.1 Key Findings

This section presents the findings for each of the five research questions posed in chapter 1.

8.1.1 **Research Question 1**

The first research question was formulated in the following way:

"How are different product categories affected in terms of profitability by increasing return rates?"

In order to answer this question a simulation model representing a generalized fashion e-tailing return process was developed. A simulation study was then performed where the average profit was compared between a base scenario and scenarios with increased return rates for 27 different product categories. An analysis of the following results then concluded that categories with high return rates and low to medium sales prices were affected the most in terms of decreasing profitability in these scenarios. Furthermore, the analysis indicated that increasing return rates in general have a significant negative effect on profitability. As discussed more in-depth in 7.2.2, a continuous increase of returns will force retailers to adopt and implement new policies and/or strategies to ensure future profitability in this highly competitive market, particularly as different product categories are affected to different degrees.

8.1.2 **Research Question 2**

The second research question was formulated thusly:

"How are different product categories affected in terms of profitability by increasing or decreasing return delay?"

The same method as in the case of RQ1 was used for answering this question. However, in the case of varying return delay, the results were determined to be inconclusive. No conclusion could be drawn regarding how different product categories are affected in different return delay scenarios. As discussed in section 7.2.3, it is possible that a more detailed model or a different approach entirely is required in order to properly answer this question, or it is possible that realistic variation in the return delay does not affect profitability of product categories to a degree that is statistically significant considering the sales volumes in the data used in this study.

8.1.3 **Research Question 3**

The third research question was formulated as:

"How are return rate, discount rate and time in sales period connected?"

and

"How is return rate affected by sales price?"

The approach used to answer these questions was to conduct a data analysis on data received from industry practitioners, where different statistical analyses were performed to gain insight into how these parameters affected return rate. As discussed more in depth in 7.1.2 these analyses resulted in several interesting results and confirmed the initial hypothesis that both discount rate and sales price seem to have a substantial effect on whether or not products are returned. Products with higher sales prices generally had larger return rates and increasing discount further into the sales period lead to decreasing returns. However, the analyses also indicated a strong negative correlation between time in sales period (TISP) and return rate. This effect was more surprising and although some possible explanations were presented it is considered of interest to analyze further.

8.1.4 **Research Question 4**

The fourth research question was formulated thusly:

"Is it possible to find data to indicate the occurrence of "retail borrowing" behavior?"

The first approach used to find evidence of the existence of retail borrowing behavior was to examine if dresses had a longer average return delay than other product types. The reasoning behind this was that dresses, in particular party dresses, have been referred to as an example of a product type that is particularly at risk when it comes to retail borrowing. However, there was no indication in the data that this was the case. Most likely, due to the limited data available and retail borrowing probably being a fairly rare phenomenon, any occurrence would not have caused enough of an increase in the average return delay for dresses compared to other product types to achieve statistical significance. The results may have been different if it was possible to specifically identify party dresses in the data.

The second approach was to see if dresses were more likely to be returned with the return reason stated as being stains, tears or other signs of use. This approach actually indicated that dresses were less likely to be returned due to signs of damage or use. The main issue with this approach, as discussed in section 7.1.1, is that customers were themselves responsible for choosing the return reason, and an overwhelming majority chose the generic first option, "did not meet expectations", for all product categories. Therefore the data for other responses to this question was very limited and unlikely to produce usable results. In order for this approach to be more successful, the company providing data may need to record statistics regarding which returns show signs of use by the customer beyond a mere try-on. As in the first case, it would also be helpful to be able to specifically identify party dresses.

The third approach did not consider product categories but only the specified return reason for returned items. The hypothesis in this case was that items returned due to signs of use might have a longer return delay, possibly arising at least in part due to retail borrowing. This did turn out to be the case, as there was a statistically significant difference where products returned due to signs of use on average had 21.2 days of return delay compared with 12.9 days for all other returns. It is necessary to consider the data limitations regarding return reasons as described earlier, but this discrepancy may still be an indication that retail borrowing does occur at significant levels.

8.1.5 **Research Question 5**

The fifth research question was formulated thusly:

"To what extent does the data indicate the occurrence of multiple size ordering?"

The method used to answer this question was to use filtering to identify those orders that contained multiple sizes of the same product, where at least one of those items was returned. 2.26% of all orders, and 12.9% of orders containing returns, consisted of orders associated with multiple size ordering and return behavior. As presented in 7.1.4, the authors were surprised to find such a large proportion of orders associated with this specific type of return behavior and believe that companies should strongly consider taking steps to measure and contain it, if they have not already done so. This is one form of returning where improving the online shopping experience and the information available may have a significant effect in terms of reducing the number of unnecessary returns, without any negative side effects for the customer.

8.2 Contribution to Industry

As return rates increase, retailers in the online fashion industry can expect to face challenges both in terms of dwindling profitability and strained supply chain processes. Those companies most adaptable in this new e-commerce landscape will be able to gain a competitive advantage, but will at the same time be required to search for new solutions and strategies to solve the upcoming challenges.

The authors hope that this study can provide industry representatives with some knowledge regarding how product characteristics affect profitability as well as what factors affect return rate, and then apply this to their own specific products and draw further conclusions. The thesis also presents a number of returns mitigation techniques that could prove useful to practitioners, although some of them may already be implemented to some extent. Hopefully they will then be able to use these insights to better prepare for and handle an increasing amount of returns.

8.3 Contribution to Theory

Most other research within this field has taken the "customer approach" and tried to explain and prevent returns from a customer-based perspective. This study on the other hand, has been an attempt to approach the same question from a product characteristics perspective. The authors believe that this has provided some insight to the current body of knowledge on how different product specific characteristics can affect profitability if the trend of increasing consumer returns continues. Additionally, the authors hope that the study can spark an interest among researchers in this alternative perspective to analyze returns, resulting in more large-scale quantitative research within this under-researched field.

8.4 Limitations and Future Research

One of the main limitations that constrains the model's usefulness is that returns are only modeled from a passive perspective, in the sense that all information about the occurrence of returns comes from recorded data of past returns. There is nothing in the model regarding reasons for returning, since these are more based in human psychology, which is much more difficult to measure and model accurately. Indeed, much of the research in the field of consumer returns has been focused on identifying reasons for returning, and whilst some progress has been made, there is not yet any comprehensive framework regarding this subject, particularly not of the quantitative sort. This study to a minor extent attempted to contribute to this field by analyzing data related to retail borrowing and multiple size ordering return behavior. However, what would be exciting is to see a more ambitious simulation model in a future attempt to incorporate reasons for customer returns into the simulation logic. This could potentially be a future way to perform cost-benefit analysis regarding avoidance or gatekeeping methods that focus on specific forms of return behavior.

Another underlying reason for many of the significant limitations in this study was the decision to construct a generalized model of the fashion e-tailing return process, rather than one designed around the real-world process of a specific company. The ultimate decision to construct a generalized model was mostly taken due to time constraints relating to the increased complexity of the real-world system and not yet having access to industry contacts until the later stages of the study. The most significant limitation regarding the generalized model relates to the fact that only the data from one company, in one market (Sweden), with a specific set of EU regulation regarding online consumer returns was used. This means that many details regarding returns data for another company might be completely different, especially if that company operates on a different market. Therefore the model may be viewed more as a proof-of-concept rather than an accurate forecasting tool.

Another meaningful way to expand the scope of this study would be to investigate an omni-channel retail supply chain, where returns can take place either online or in brick-and-mortar stores. In fact, this was the case for the supply chain where the data for this study was gathered from, but as mentioned earlier time constraints meant that such a model could not be constructed within this paper's scope. It would be valuable to compare differences in return patterns between the channels, as well as identify which benefits can be identified when it comes to brick-and-mortar returns where return delay may be shorter, the customer is responsible for the initial return transport to the store, and where any transports to a distribution center could be consolidated by the company. There may also be unforeseen costs related to brick-and-mortar returns which would be interesting to uncover.

An idea that was previously mentioned to investigate retail borrowing in more detail would be to perform a study in cooperation with a fashion retailer where the company makes sure to record statistics regarding any signs of use beyond a try-on by the customer, particularly for product categories such as party dresses which have been suggested as particularly exposed to retail borrowing in the past. It would be valuable to see large-scale statistics for how common retail borrowing is.

As sales period seemed to have a very small or almost non-existing effect on profitability in the model created, it would be of interest to look at alternative ways to define this parameter. The authors believe it to be unlikely that the sales period length in reality has such a minor effect, and therefore find it necessary to conduct further investigation in order to better understand how it interacts with other parameters.

The results from the simulation study also indicated that there were no significant cost-related effects of increasing and decreasing return delay. This initially appears unlikely as longer return delays should increase the likelihood that products are sold on discount. Meanwhile, the paper also suggests that the likelihood of customers returning products decreases as discount rates increase. In the simulation model constructed these two relationships appear to cancel each other out, and authors believe further research into the dynamics of this interaction will be necessary in order to create a refined model of the e-tailing return process.

Another useful insight believed to need further research is the relationship between TISP and return rate. This paper indicates the existence of a strong negative correlation between the two parameters even when excluding products on sale. Although this paper does provide hypotheses on why this is, further investigation is needed in order to determine whether or not these hypotheses hold up.

A final proposal in terms of future research is to conduct deeper analyses into how discount affects return rate. Data indicates that a discount in itself could have a strong negative effect on consumer's return rate decision, which retailers potentially can use to their advantage. However, additional studies, preferably in collaboration with industry, are required to provide further insight into this relationship. A more specific research suggestion is to conduct an experiment where customers are divided into two groups; one where the products' initial sales price are set with current standards and one where prices initially are higher and then almost immediately discounted to the same price as the first group. It would be interesting to see if such an experiment would generate significant differences between the two groups. Of course, if such an experiment was performed in a real market environment, it would need to be carefully refined in order to avoid ethical, legal and public relations issues.

References

Al-Yateem, N. (2012) ‘The effect of interview recording on quality of data obtained: a methodological reflection’, Nurse Researcher, 19(4), pp. 31-35.

Arshed, N. and Danson, M. (2015). ‘The Literature Review’, Research Methods for Business and Management: A Guide to Writing Your Dissertation, pp. 31-49

Avittathur, B. and Biswas, I. (2017) ‘A note on limited clearance sale inventory model’ International Journal of Production Economics, Volume 193, November 2017, Pages 647-653

Banks, J. (2010), ‘Discrete-event system simulation’, Pearson Education, Upper Saddle River, N.J., USA

Bell, J. (2010) ‘Doing Your Research Project’, McGraw-Hill Education

Bernon, M.,Upperton, J., Bastl, M. and Cullen, J. (2013) ‘An exploration of supply chain integration in the retail product returns process’, International Journal of Physical Distribution & Logistics Management, 43(7), pp. 586-608’

Bobko, P. (2001) ‘Correlation and regression: Applications for industrial organizational psychology and management’ (2nd ed.), Thousand Oaks, CA: Sage Publications

Bower, A.B. and Maxham III, J.G. (2012) ‘Return shipping policies of online retailers: Normative assumptions and the long-term consequences of fee and free returns’, Journal of Marketing, Volume 76, pp. 110-124

Brain, M. (2000) ‘How E-commerce Works’, Retrieved October 12, 2018, from https://money.howstuffworks.com/ecommerce.htm

Caro, F. and Gallien, J. (2012) ‘Clearance pricing optimization for a fast-fashion retailer’, Operations Research, 60(6), pp. 1404–1422

Cohen, A. M. (2011) ‘Fast Fashion: Tale of Two Markets’, FUTURIST, 45(5), pp. 12–13

Conradie, W. et al. (2017) ‘Toward an Epistemic-Logical Theory of Categorization’, Electronic Proceedings in Theoretical Computer Science, pp. 167-186

Croxton, K.L., Garcia-Dastugue, S.J., Lambert, D.M. and Rogers, D.S. (2001) ‘The supply chain management processes’, International Journal of Logistics Management, 12(2), pp. 13-36 de Leeuw, S., Minguela-Rata, B., Sabet, E., Boter, J. and Sigurðardóttir R. (2016)

’Trade-offs in managing commercial consumer returns for online apparel retail’, International Journal of Operations & Production Management, 36 (6), pp.710-731

Friedman, V. (2017) ‘The New Meaning of Fast Fashion’, Retrieved October 14, 2018, from https://www.nytimes.com/2017/04/20/fashion/farfetch-gucci-designer-delivery.html

Gaber, N. et al.(2009) ‘Guidance on the Development, Evaluation, and Application of Environmental Models’, retrieved at: https://www.epa.gov/sites/production/files/2015-04/documents/cred_guidance_0309.pdf

Gallo, A. (2015) ‘A Refresher on Regression Analysis’, Harvard Business Review, Retrieved April 9, 2019, from https://hbr.org/2015/11/a-refresher-on-regression-analysis

Gardner, J. T. and Cooper, M. C. (2003) ‘Strategic supply chain mapping approaches’, Journal of Business Logistics, 24(2), pp. 37-64

Hellström, D., Hjort, K., Karlsson, S. and Oghazi, P. (2017) ’Konsumentreturer i digital handel’, Handelsrådet, 2017(5)

Hjort, K. (2013) ‘On Aligning Returns Management with the E-commerce Strategy to Increase Effectiveness’, Göteborg: Chalmers University of Technology

Hjort, K., and Lantz, B. (2012) ‘(R)e-tail borrowing of party dresses: an experimental study’, International Journal of Retail & Distribution Management, 40(12), pp. 997-1012

Hjort, K., and Lantz, B. (2016), ‘The impact of returns policies on profitability: A fashion e-commerce case’, Journal of Business Research, 69(11), pp. 4980–4985

J.A. Petersen and V. Kumar (2010) ‘Can product returns make you money?’, MIT Sloan Management Review, 51, pp. 85-89

Janakiraman, N., Syrdal, H. A., and Freling, R. (2015). ‘The effect of return policy leniency on consumer purchase and return decisions: A meta-analytic review’, Journal of Retailing, 92(2), pp. 226-235

Jennings, G. R. (2005) ‘Interviewing: a focus on qualitative techniques’, Tourism Research Methods: Integrating Theory with Practice

Jonker, J., and Pennink, B. (2010) ‘The Essence of Research Methodology’, Springer-Verlag Berlin Heidelberg

Konsumentverket. (2018) ’Om kunden ångrar distansköpet’, Retrieved March 18, 2019, from https://www.konsumentverket.se/for-foretag/konsumentratt-for-foretagare/om-kunden-angrar-sitt-kop/

Kosow, H. and Gaßner, R. (2008) ‘Methods of future and scenario analysis’, German development institute, ISBN 978-3-88985-375-2

Kuhrana, A. (2018) ‘Advantages and Disadvantages of Ecommerce’, Retrieved October 12, 2018, from https://www.thebalancesmb.com/ecommerce-pros-and-cons-1141609

Lambert, D. M. (2004), ‘The eight essential supply chain management processes’, Supply Chain Management Review, 8(6), pp. 18-26

Law, A. M. (2003) ‘How to conduct a successful simulation study’, Proceedings of the 2003 Winter Simulation Conference, pp. 66-70, Piscataway, NJ, USA

Law, A. M. and Kelton, W. D. (2000) ‘Simulation Modeling and Analysis’, McGraw-Hill, New York, NY, USA

Lingard, L. (2018) ‘Writing an effective literature review’, Perspectives on Medical Education, 7(1), pp. 47–49

Lummus, R. R, Vokurka, R. J. and Krumwiede, D. (2008), ‘Supply chain integration and organizational success’, SAM Advanced Management Journal, 73(1), pp. 56-63

Mentzer, J. T., Dewitt, W., Keebler, J. S., Soonhoong, M., Nix, N. W., Smith, C. D. and Zacharia, Z. G. (2001), ‘Defining supply chain management’, Journal of Business Logistics, 22(2), pp. 1-25

Mietzner, D. and Reger, G. (2005) ‘Advantages and disadvantages of scenario approaches for strategic foresight’, International Journal of Technology Intelligence and Planning, 1(2), pp. 220–239

Nenni, M. E., Giustiniano, L. and Pirolo, L. (2013) ‘Demand Forecasting in the Fashion Industry: A Review’, International Journal of Engineering Business Management, 5(37)

Novikov, A. and Novikov, D. (2013) ‘Research Methodology’, London: CRC Press

Orendorff, A. (2018) ‘The State of the Ecommerce Fashion Industry: Statistics, Trends & Strategy’, Retrieved October 18, 2018, from https://www.shopify.com/enterprise/ecommerce-fashion-industry

PostNord. (2018a) ‘e-barometern 2017 årsrapport’, Retrieved October 13, 2018, from https://www.iis.se/docs/e-barometern-arsrapport-2017.pdf

PostNord (2018b). ’e-barometern Q2. PostNord i samarbete med Svensk Digital Handel och HUI Research’, Retrieved October 13 2018, from http://pages.postnord.com/rs/184-XFT-949/images/e-barometern-q2-2018.pdf

Powers, T. and Jack, E. (2013) ‘The Influence of Cognitive Dissonance on Retail Product Returns’, Psychology & Marketing, 30(8)

Rogers, D. S., Croxton, K. L., Garcia-Dastugue, S. J. and Lambert, D. M. (2002) ‘The returns management process’, International Journal of Logistics Management, 13(2), pp. 1-18

Röllecke, F. J., Huchzermeier, A. and Schröder, D. (2018) ‘Returning Customers: The Hidden Strategic Opportunity of Returns Management’, California Management Review, 60(2), pp. 176–203

S.K. Mukhopadhyay and R. Setaputra, (2007) ‘A dynamic model for optimal design quality and return policies’, European Journal of Operational Research, 180, pp. 1144-1154

Saarijärvi, H., Sutinen, U. and Harris, L. C. (2017) ‘Uncovering consumers’ returning behaviour: a study of fashion e-commerce’, The International Review of Retail, Distribution and Consumer Research, 27(3), pp. 284-299

Simard, R. and L’Ecuyer, P. (2011), ‘Computing the two-sided Kolmogorov-Smirnov distribution’, Journal of Statistical Software, 39(11), pp. 1–18

Statista. (2018) ‘eCommerce Report 2018 – Fashion’, Retrieved October 18, 2018, from https://www.statista.com/outlook/244/100/fashion/worldwide

Statista. (n.d.) [Homepage on online fashion market description]. Retrieved October 13, 2018, from https://www.statista.com/outlook/244/100/fashion/worldwide

Wachter, K. and Vitell, S. (2012) ‘Exploring Consumer Orientation Toward Returns: Unethical Dimensions’, Business Ethics: A European Review, 21(1)

Wagner, N. (n.d.) ‘How Does eCommerce Reduce Business Transaction Costs?’, Retrieved October 12, 2018, from https://yourbusiness.azcentral.com/ecommerce-reduce-business-transaction-costs-23855.html

Welch, B. L. (1938) ‘The significance of the difference between two means when the population variances are unequal’, Biometrika, 29, pp. 350-362.

Wikipedia. (2018) ‘Kolmogorov–Smirnov test’ Retrieved January 13, 2018, from https://en.wikipedia.org/wiki/Kolmogorov%E2%80%93Smirnov_test#/media/File:KS2_Example.png

Wilson, M. and Sapsford, R. (2006) ‘Asking questions’, In Sapsford, R., and Jupp, V. *Data collection and analysis*. London: SAGE Publications Ltd

Winkler, N. (2018) ‘Ecommerce Returns: Policy, Rates, Best Practices & Statistics’, 2018 Holiday Edition, Retrieved October 26, 2018, from https://www.shopify.com/enterprise/ecommerce-returns

Zhang, J. Onal, S. and Das, S. (2017) ‘Price differentiated channel switching in a fixed period fast fashion supply chain’, International Journal of Production Economics, 193, pp. 31–39

Appendix A

A.1 Interview Guide

Reaprissättning och kampanjer

1. Hur ser beslutsprocessen ut när man väljer att sätta en produkt på rea?
    a. Finns det riktlinjer för hur djup rean är?
2. Hur vanligt förekommande är kampanjer av olika slag? (rabatter på hela köp, 3 för 2, medlemspriser, kampanj på specifika kategorier etc.)

Kassering av produkter

3. Vad händer med de returnerade produkter som inte anses vara i tillräckligt bra skick för att återgå i lager?
    a. Säljs de vidare? Finns i så fall data kring försäljningspris?
    b. Vad är kostnaden för att kassera produkter?

Reorder delay

4. Finns det något sätt att uppskatta hur lång tid det tar för returnerade produkter att säljas igen? Fördelning?
    a. Finns det data som visar denna tid?

Produktsäsonger

5. Vilka olika typer av "säsonger" finns det för produkterna i sortimentet? Vissa menar att t.ex. Zara har uppemot 20 "säsonger" per år, hur ser ni på det? Är det något som blir vanligare?
    a. Hur lång skulle du uppskatta att de kortaste säsongerna är?

Returstrategier

6. Vilka strategier jobbar ni med för att minska returer och ev. även försöka få kunder att returnera produkter snabbare?

a. Vilka strategier har ni använt tidigare? Finns det skillnader?
    i. Har ni använt er av strategier där produkter behandlas olika? (exempelvis att kunder betalar returfrakt på produkter som oftare returneras)
b. Finns det något som har visat sig vara särskilt effektivt?
c. Hur upplever ni att returfrekvensen eller den tid det tar till att returerna kommer tillbaka har förändrats de senaste åren?

7. Hur tänker ni när det kommer till policys gällande frakt och returer?
    a. Får kunder returföljesedel med ordern eller måste man registrera den först?
        i. Hur skulle ni ställa er till att erbjuda ytterligare rabatt till kunder som funderar på att returnera för att undvika returen?
    b. Hur upplever ni att det fungerar med att tillåta returer i både butik och via ombud?
        i. Vilka svårigheter finns det kring systemkoordination? Hur väl integrerat är det mellan e-handel och fysiska butiker?
8. Hur arbetar ni med kontroll av inkommande returer?
    a. Stickprov? Samtliga kontrolleras?
9. Hur vanligt upplever ni att det är med beteende likt retail borrowing?
    a. Skiljer det sig mellan produktkategorier?
    b. Vilka strategier ni för att motverka sådant beteende?
10. Hur vanligt förekommande är det att samma kund beställer flera storlekar av samma vara för att sedan returnera de som inte passar?
    a. Skiljer det sig mellan kategorier?
    b. Vilka strategier arbetar ni med för att minska den typen av beteende?

Appendix B Results from Simulation Study

This appendix contains individual results for each product category from the simulation study. The results are presented in index form where 1 illustrates the base scenario.

B.1 Percental Increase of Return Rate

This section contains the results for each product category from simulation scenarios 1 through 6 and are presented in Figure B1 to B27.

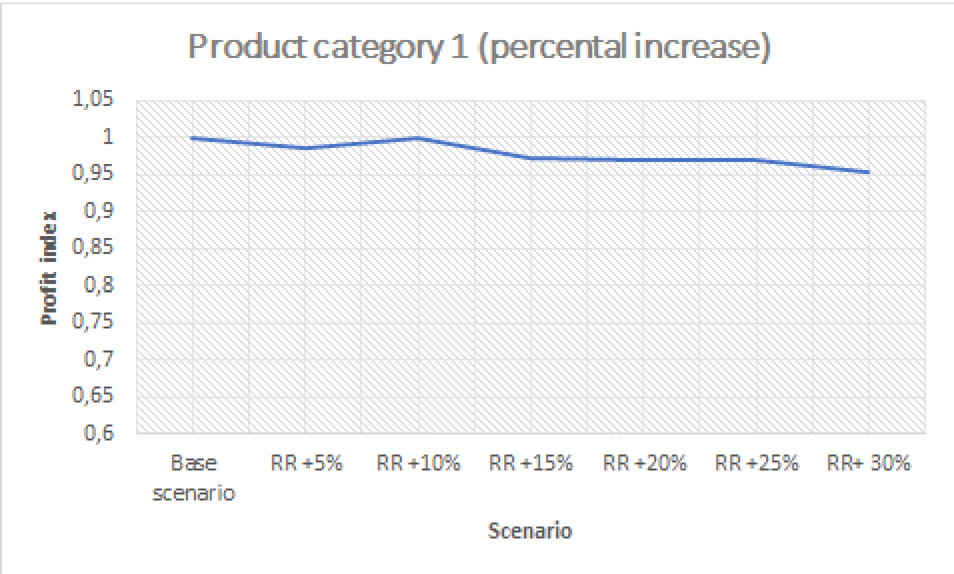

Figure B. 1 Profit index change for product category 1.

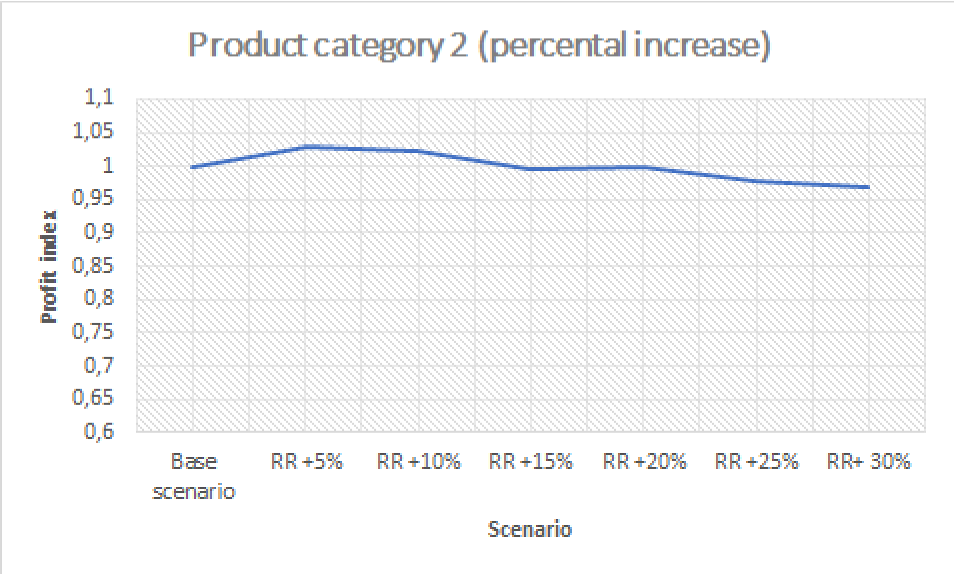

Figure B.2. Profit index change for product category 2.

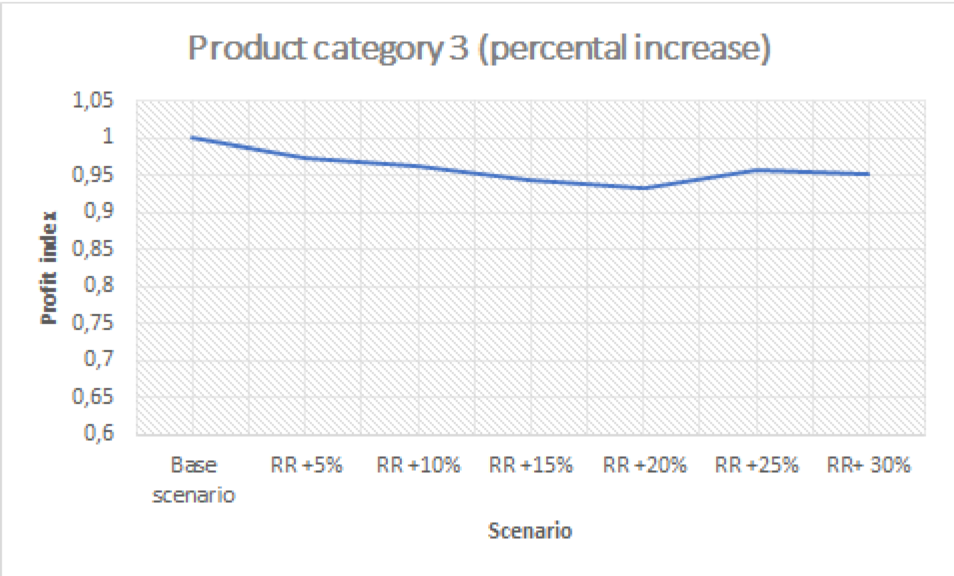

Figure B.3. Profit index change for product category 3.

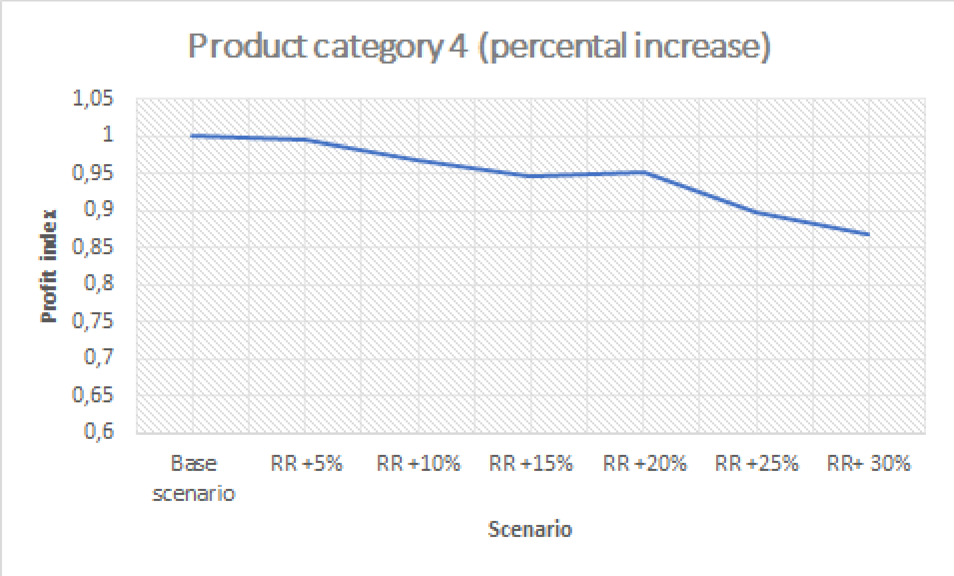

Figure B.4. Profit index change for product category 4.

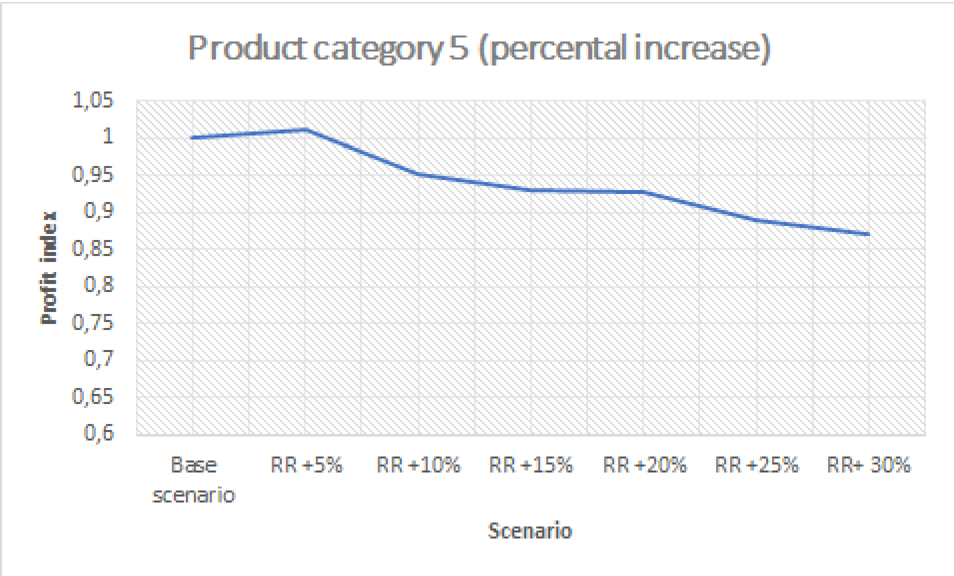

Figure B.5. Profit index change for product category 5.

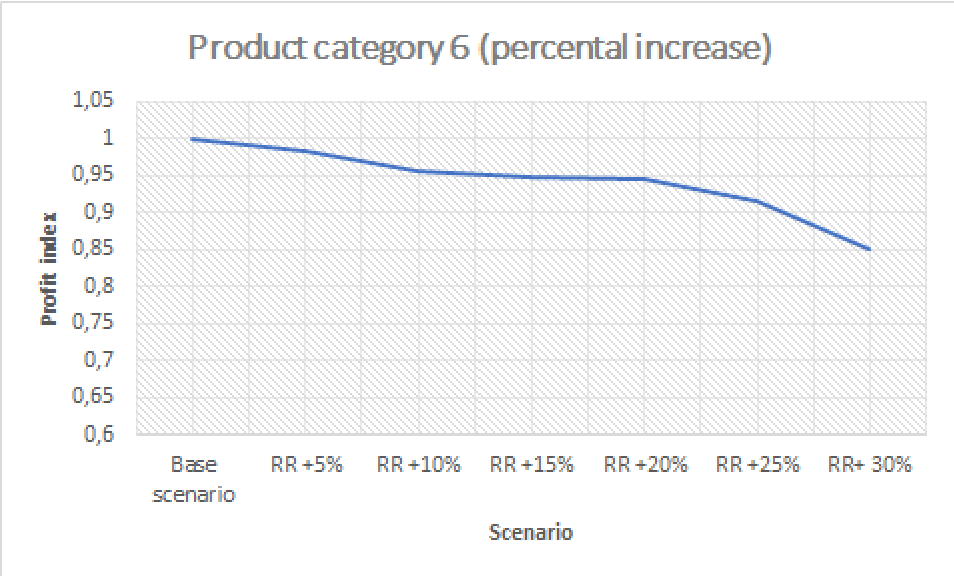

Figure B.6. Profit index change for product category 6.

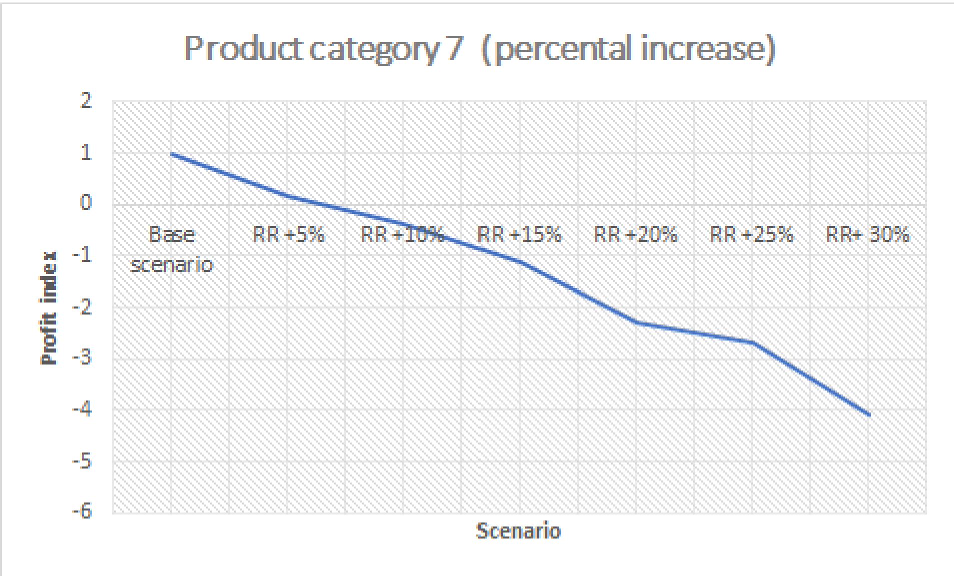

Figure B.7. Profit index change for product category 7.

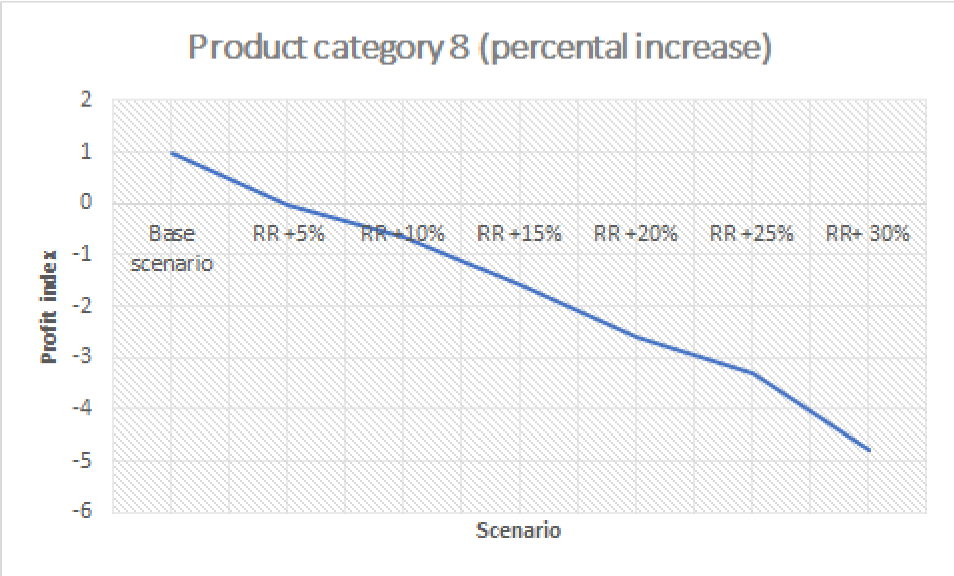

Figure B.8. Profit index change for product category 8.

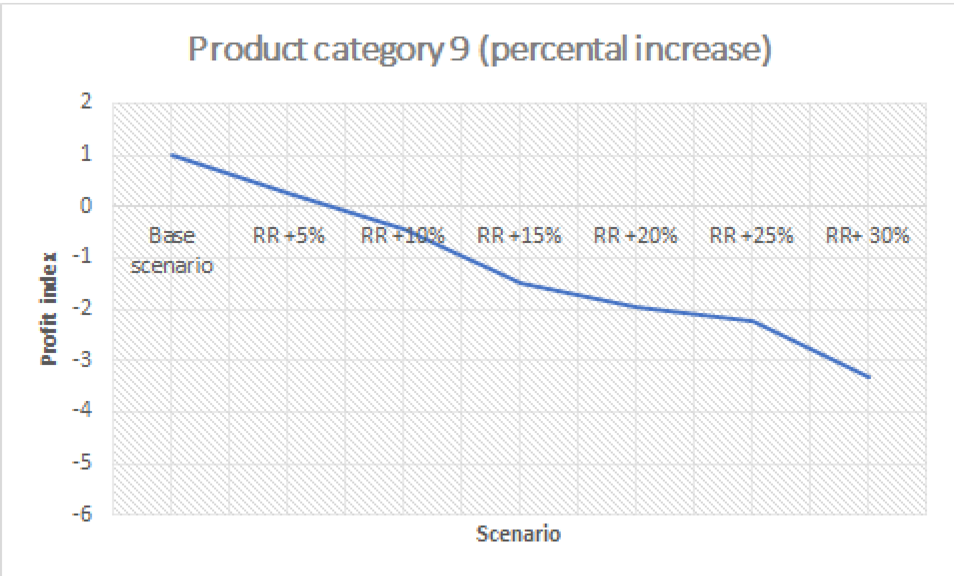

Figure B.9. Profit index change for product category 9.

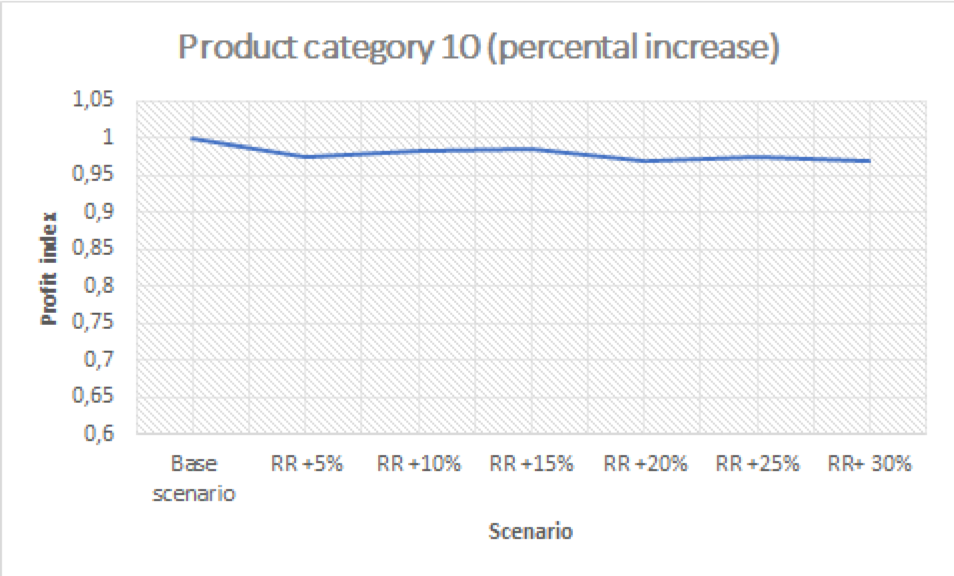

Figure B.10. Profit index change for product category 10.

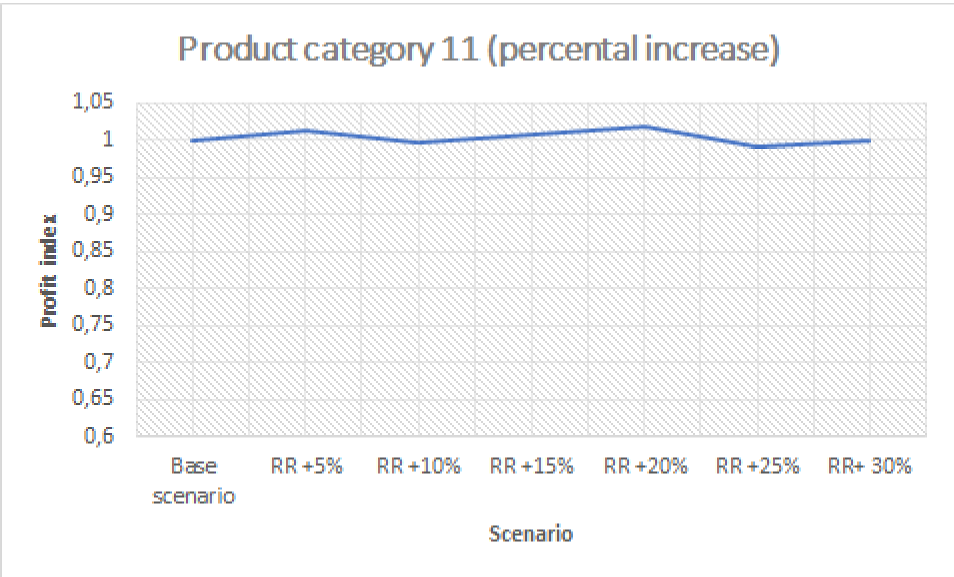

Figure B.11. Profit index change for product category 11.

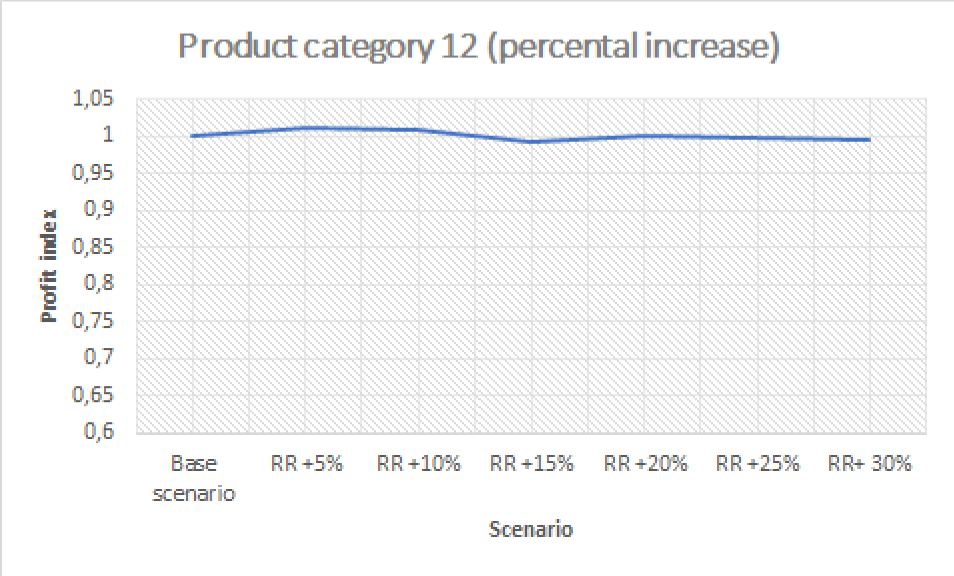

Figure B.12. Profit index change for product category 12.

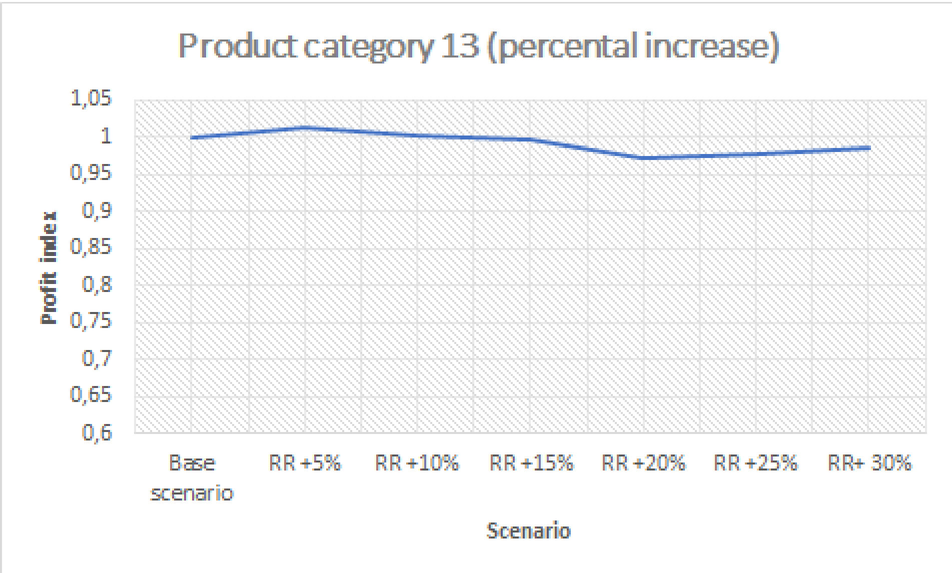

Figure B.13. Profit index change for product category 13.

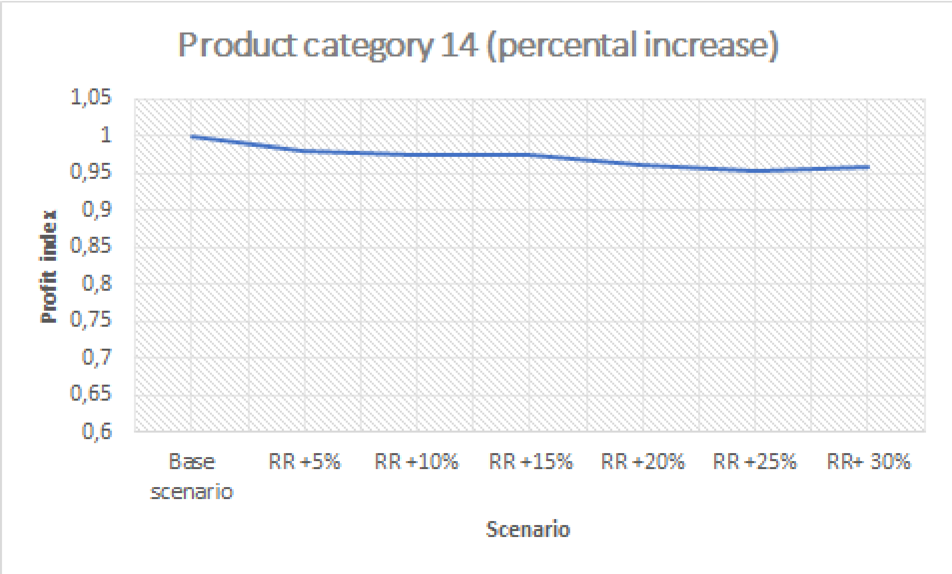

Figure B.14. Profit index change for product category 14.

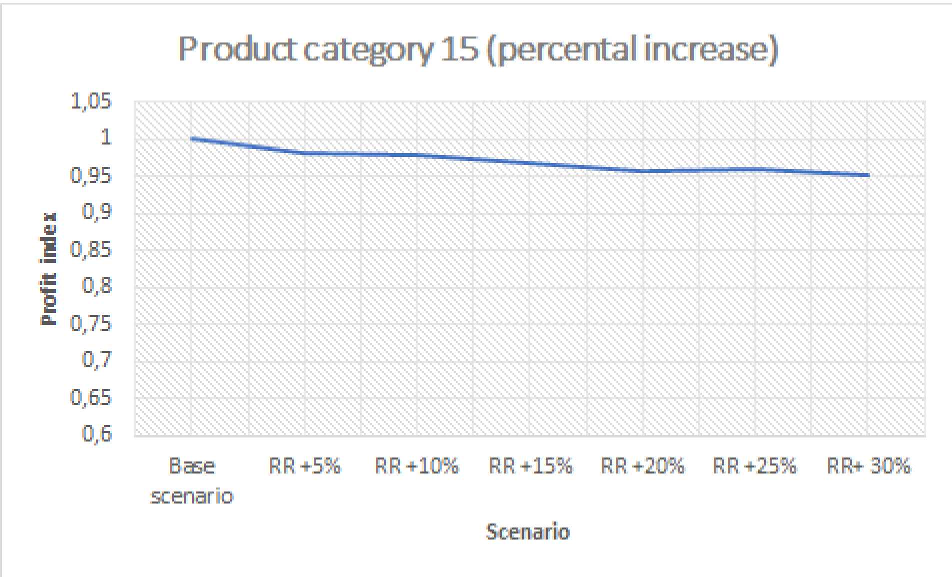

Figure B.15. Profit index change for product category 15.

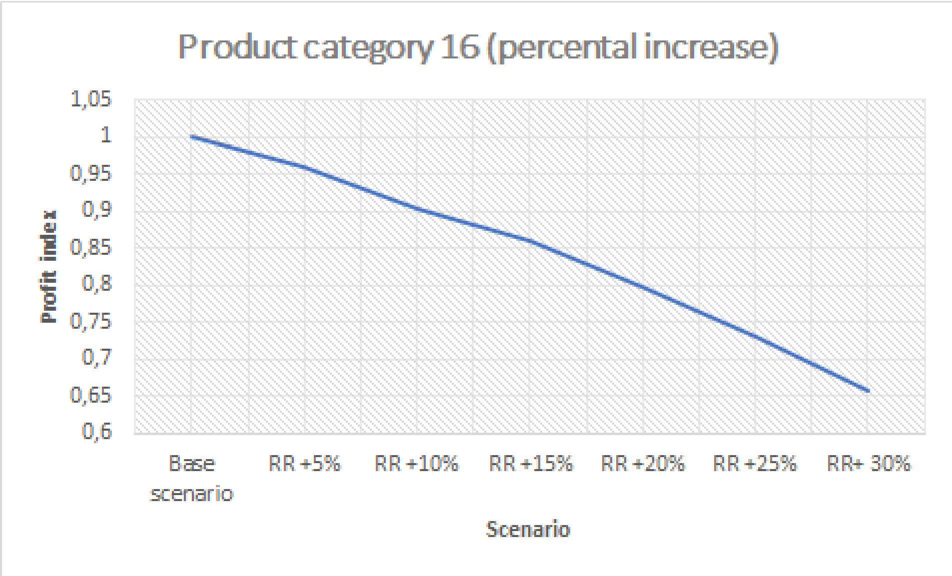

Figure B.16. Profit index change for product category 16.

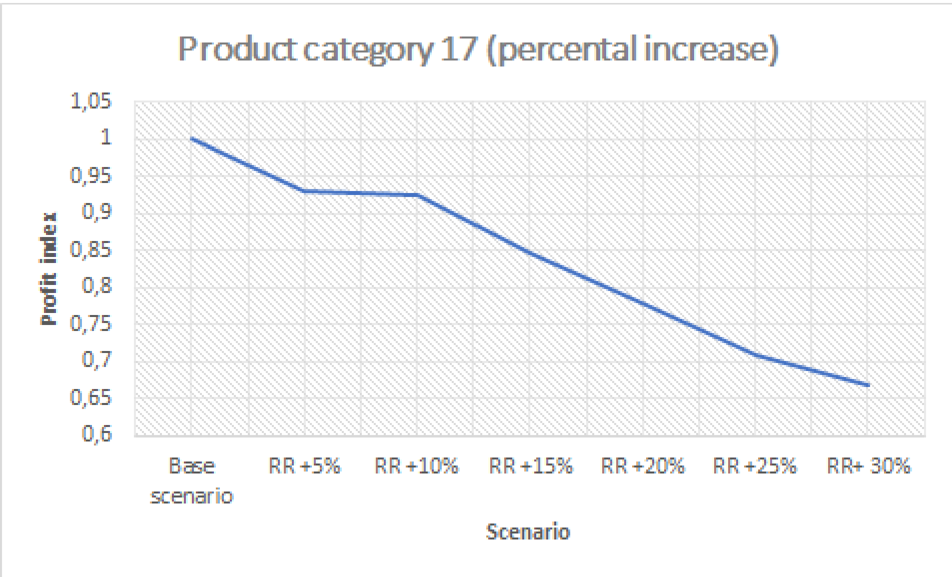

Figure B.17. Profit index change for product category 17.

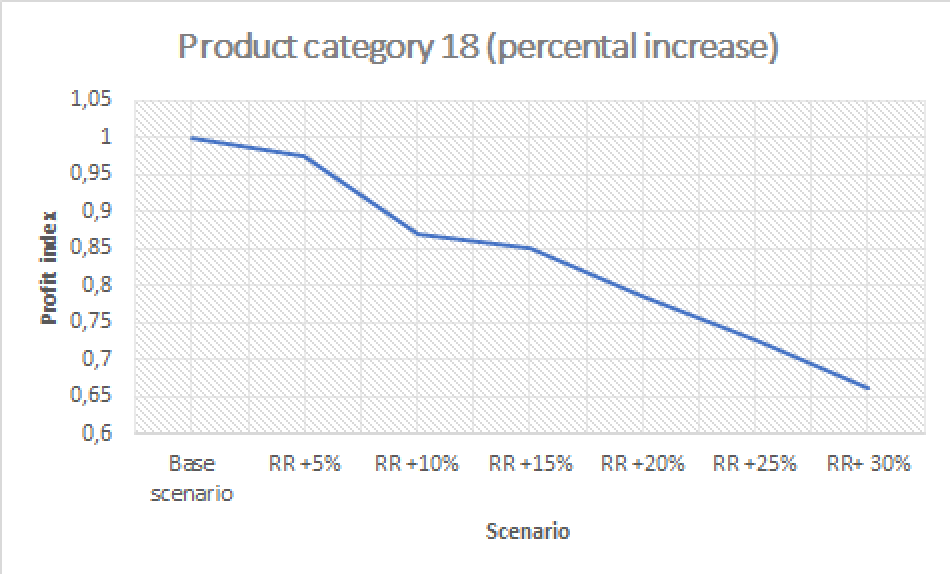

Figure B.18. Profit index change for product category 18.

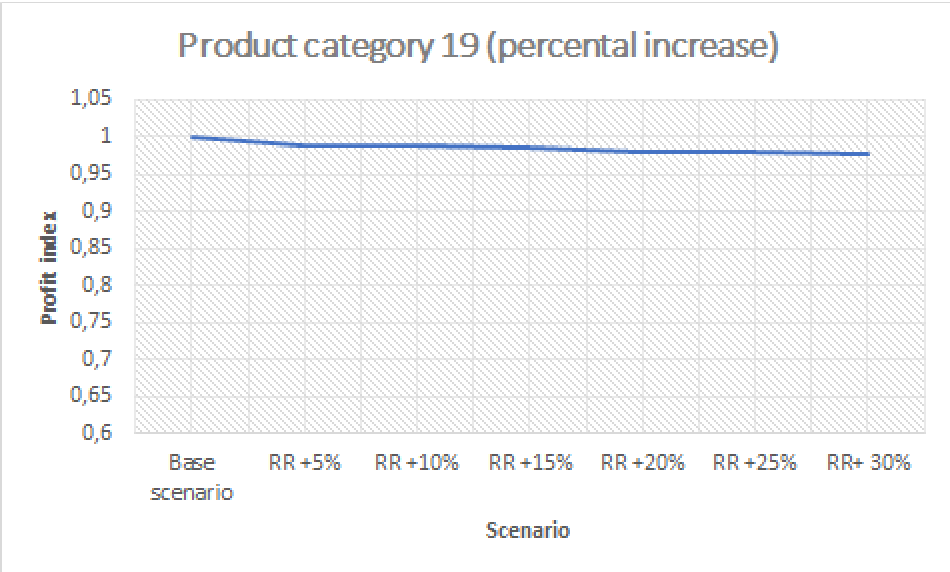

Figure B.19. Profit index change for product category 19.

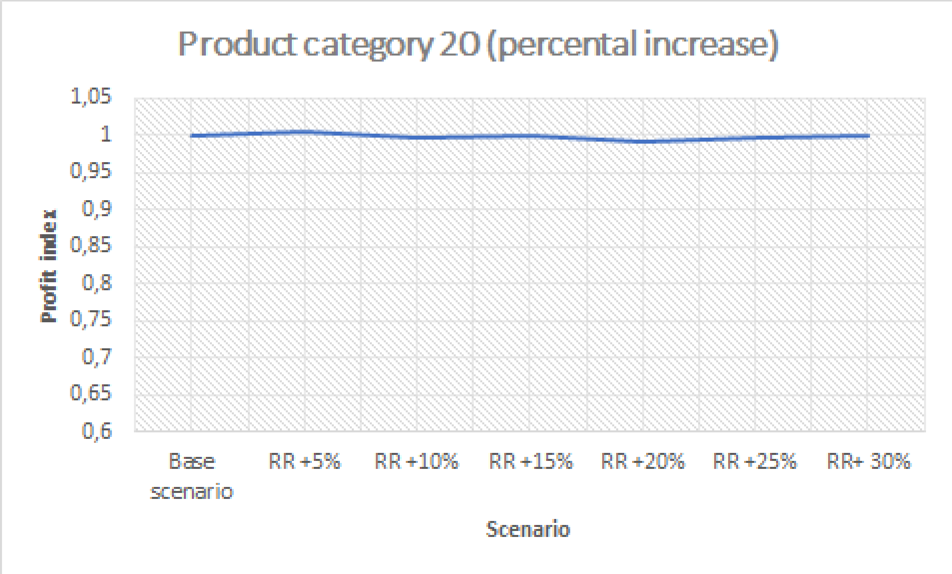

Figure B.20. Profit index change for product category 20.

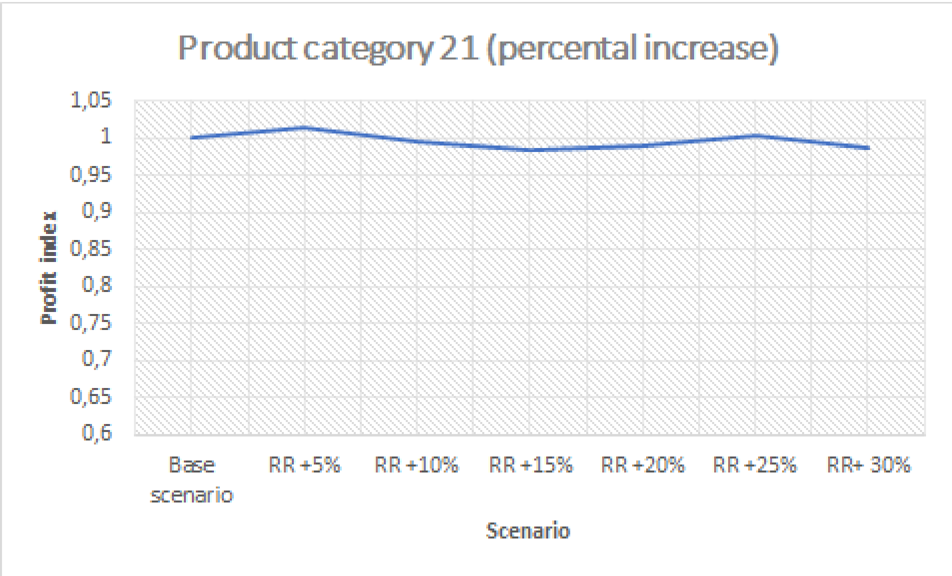

Figure B.21. Profit index change for product category 21.

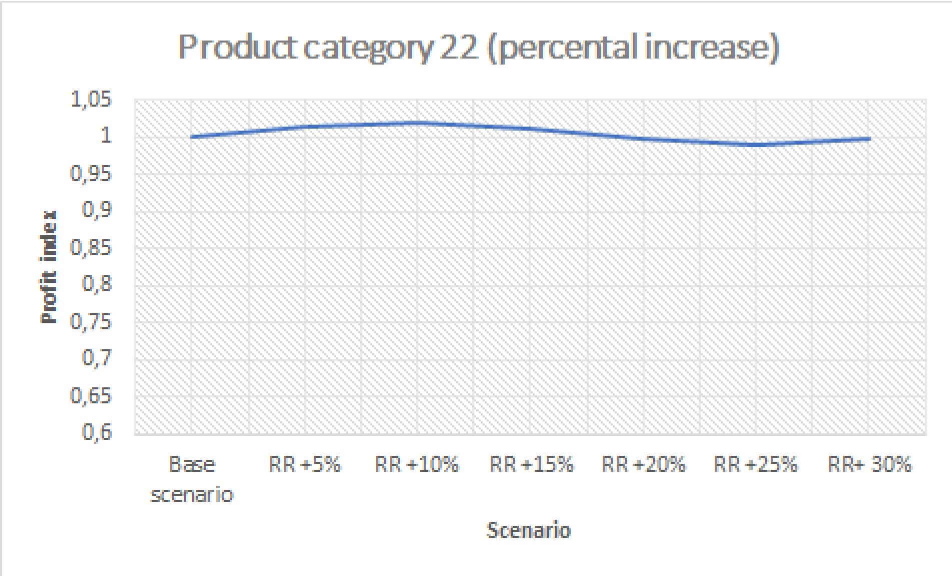

Figure B.22. Profit index change for product category 22.

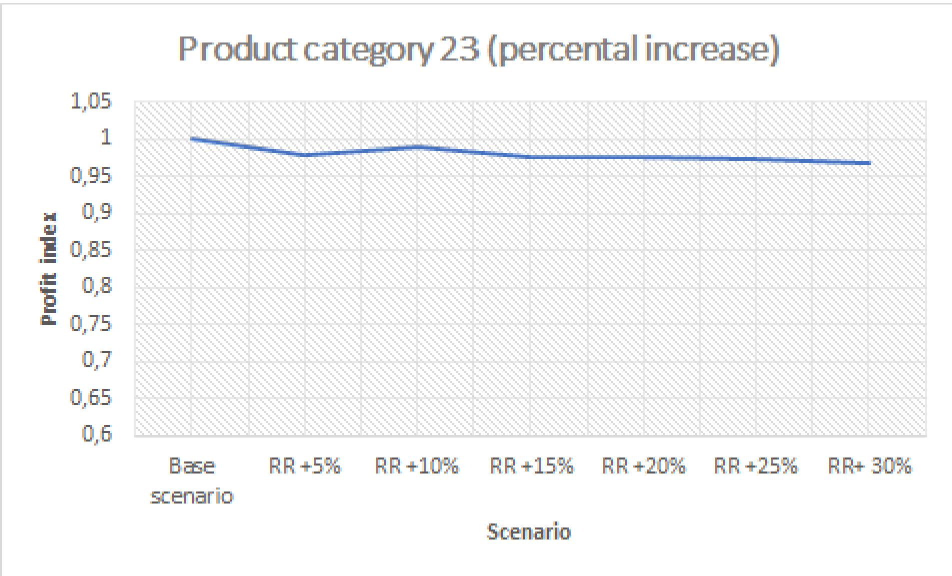

Figure B.23. Profit index change for product category 23.

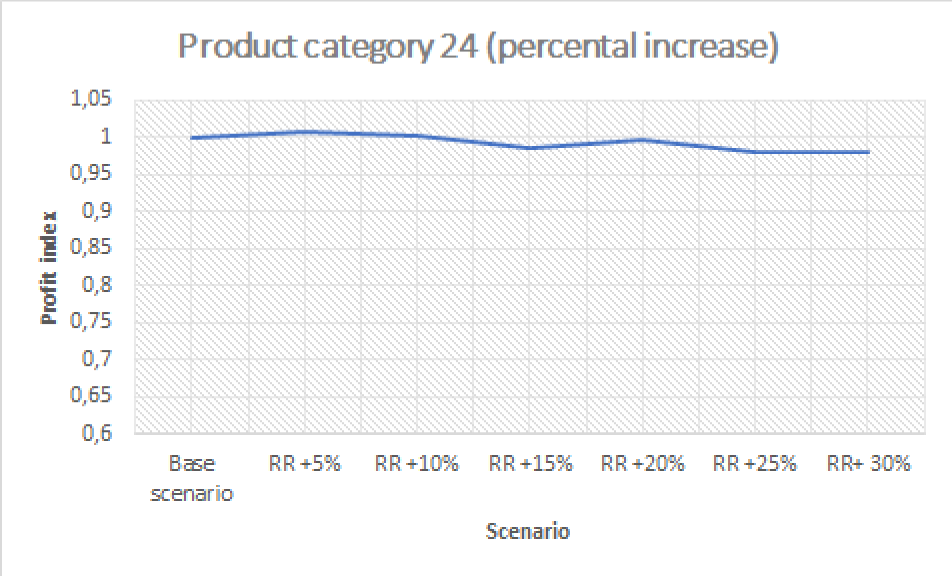

Figure B.24. Profit index change for product category 24.

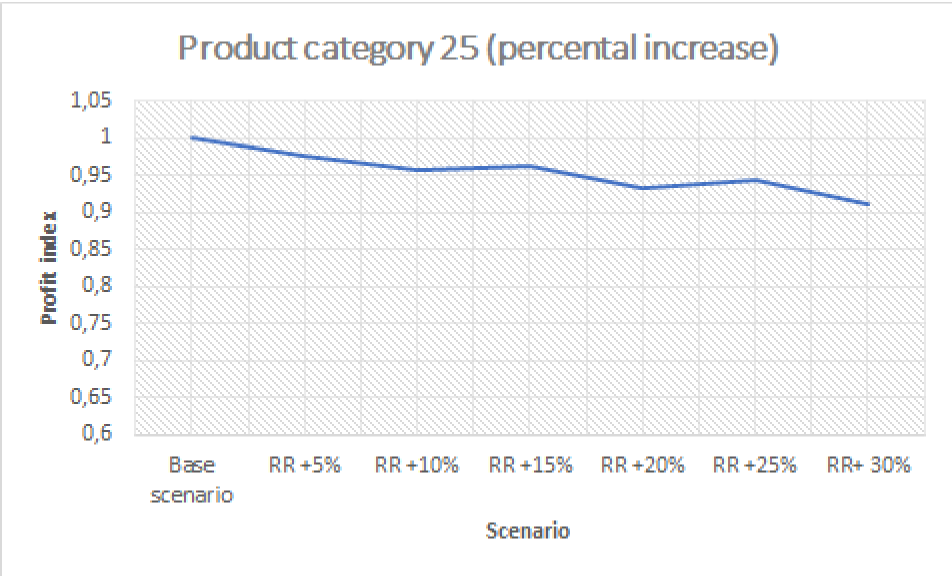

Figure B.25. Profit index change for product category 25.

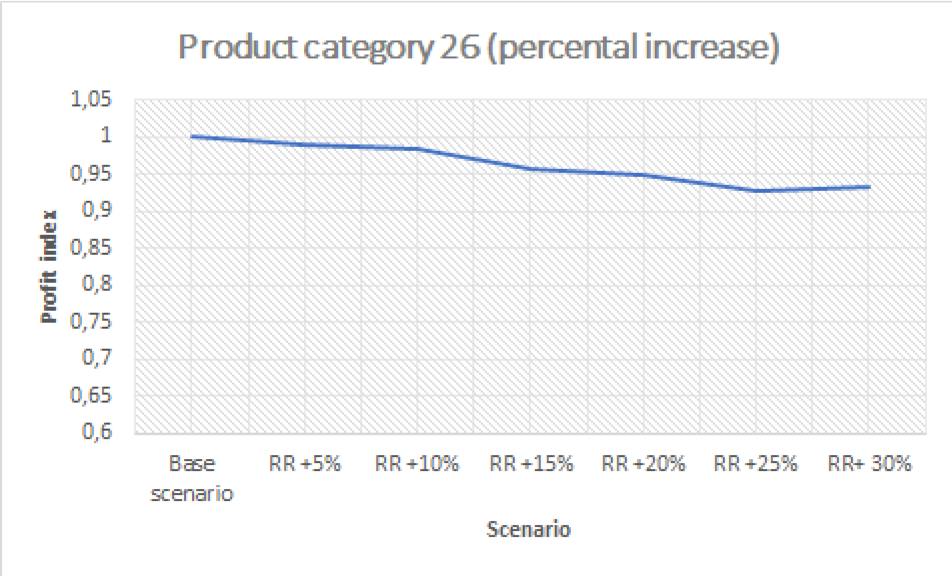

Figure B.26. Profit index change for product category 26.

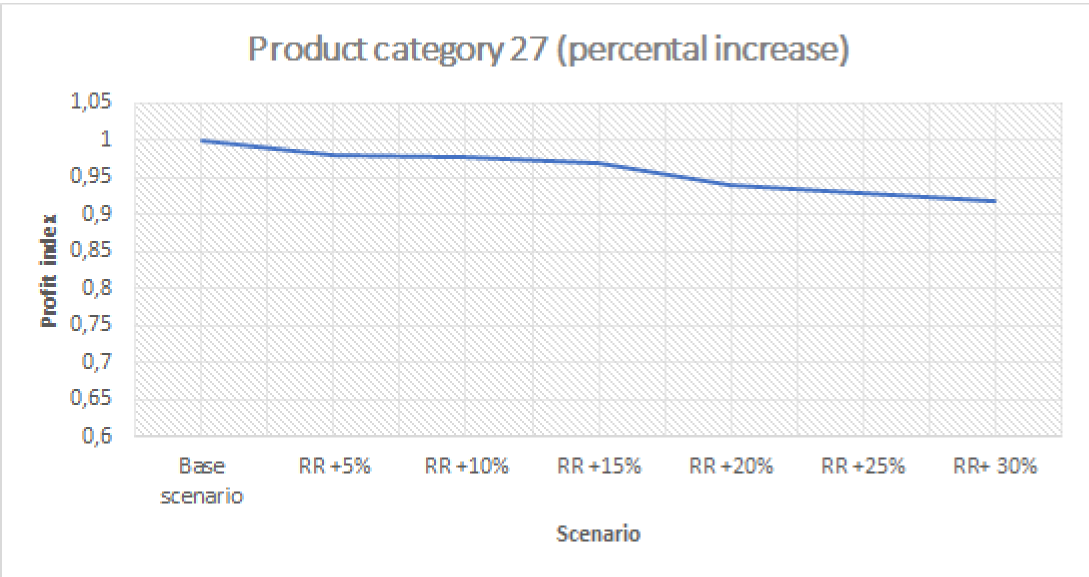

Figure B.27. Profit index change for product category 27.

B.2 Percentage Point Increase of Return Rate

This section contains the results for each product category from simulation scenarios 7 through 11 and are presented in Figure B28 to B54.

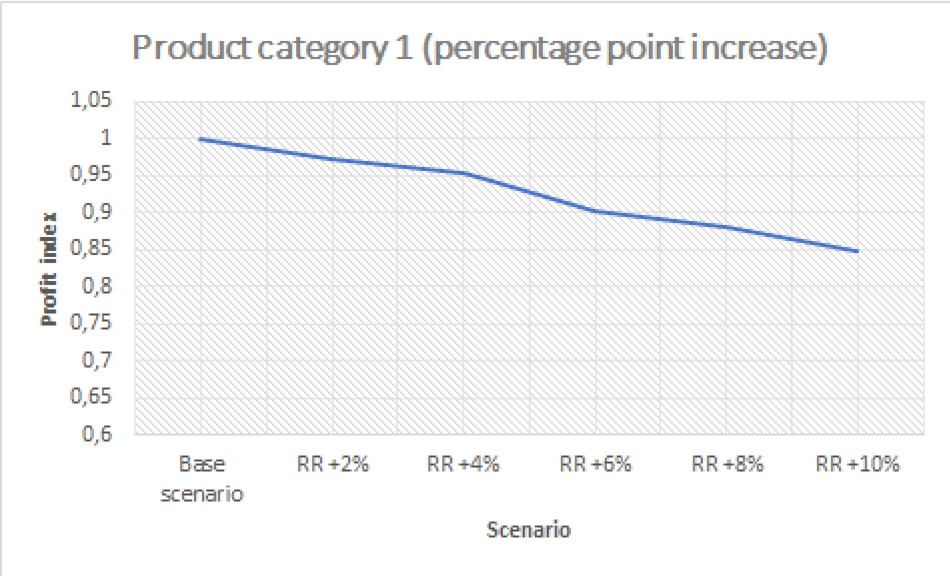

Figure B.28. Profit index change for product category 1.

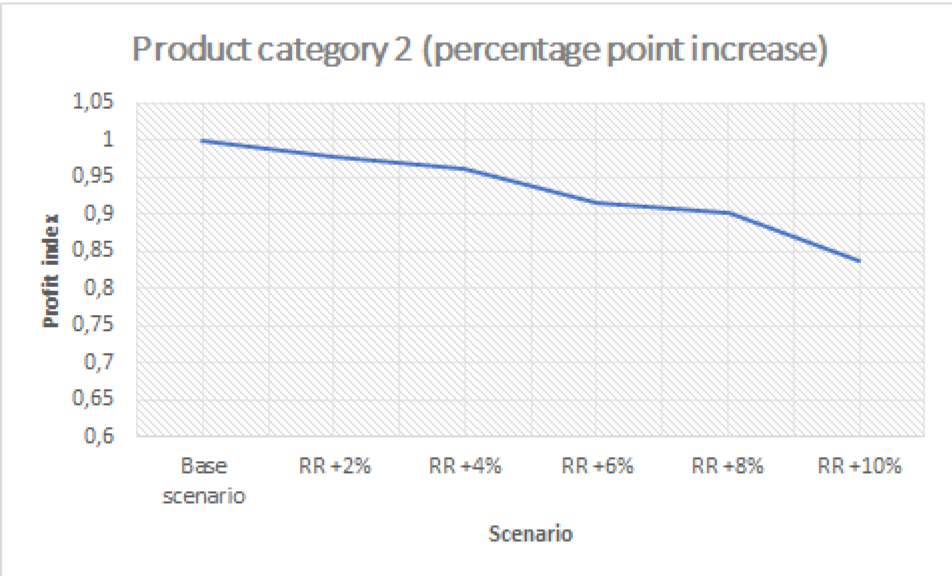

Figure B.29. Profit index change for product category 2.

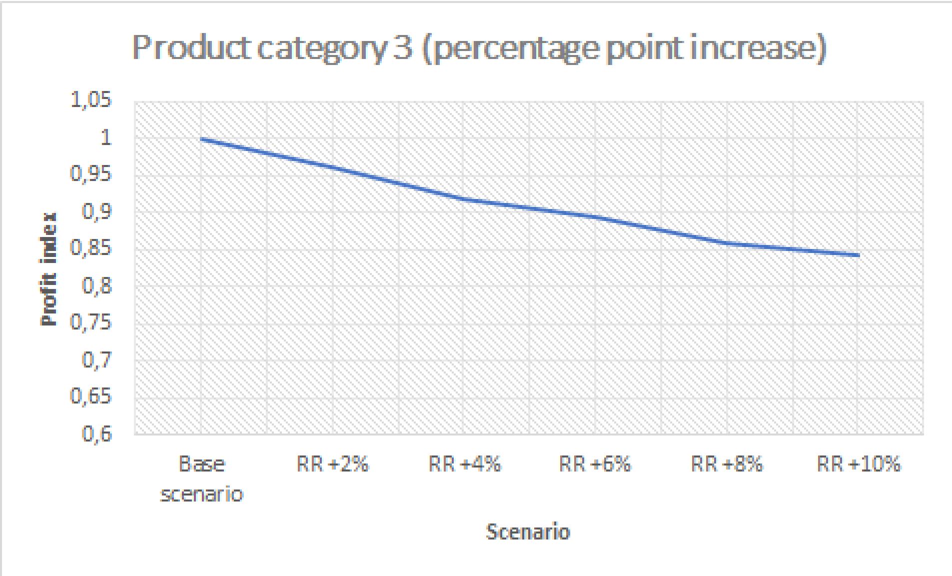

Figure B.30. Profit index change for product category 3.

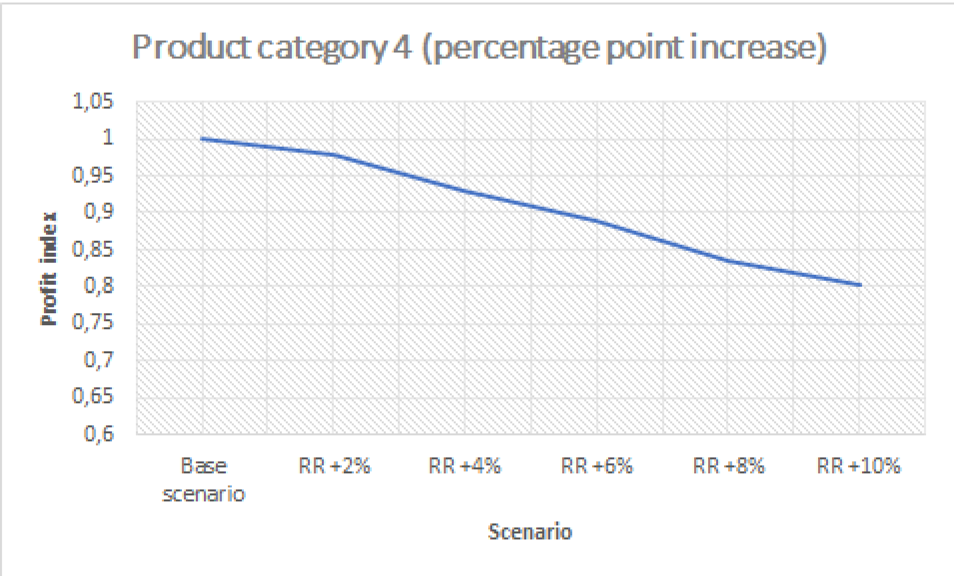

Figure B.31. Profit index change for product category 4.

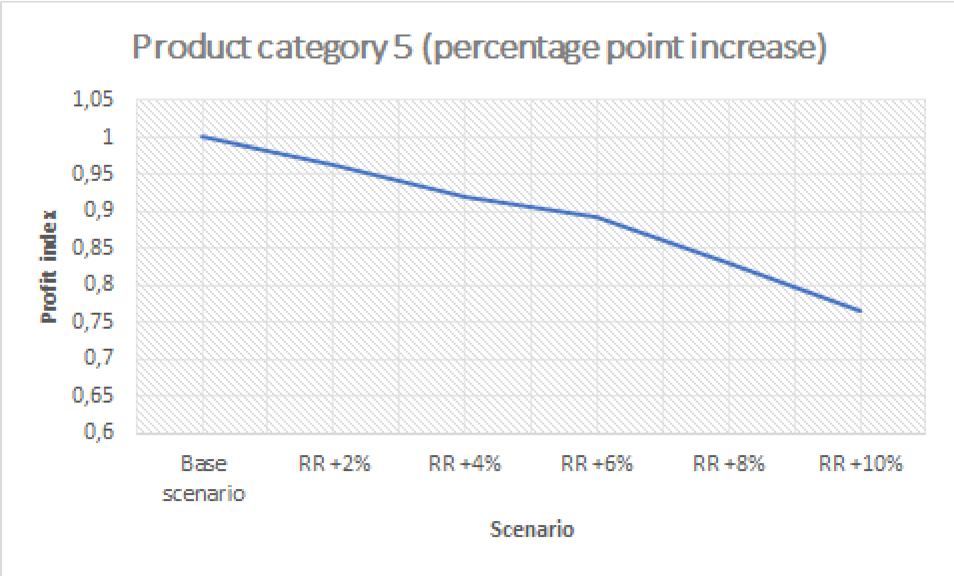

Figure B.32. Profit index change for product category 5.

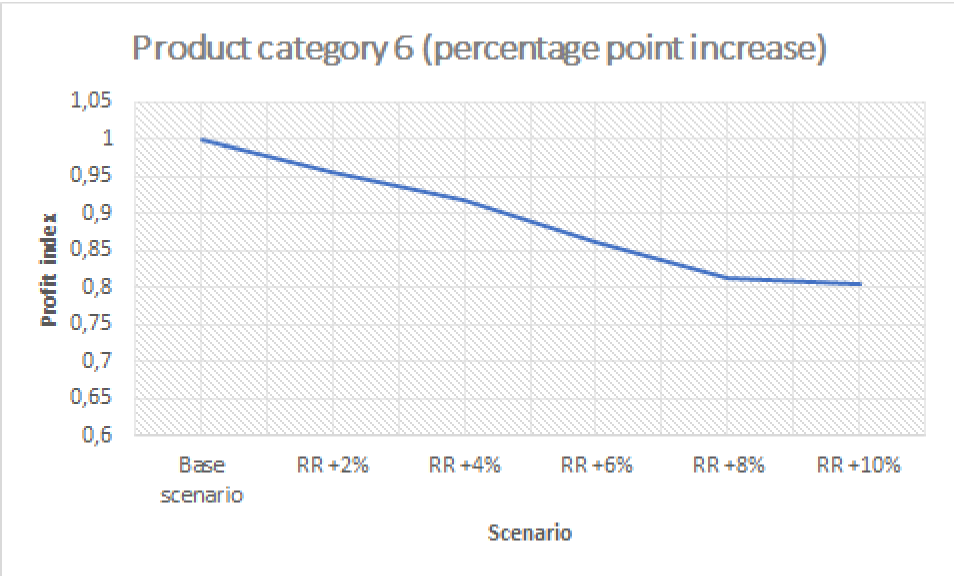

Figure B.33. Profit index change for product category 6.

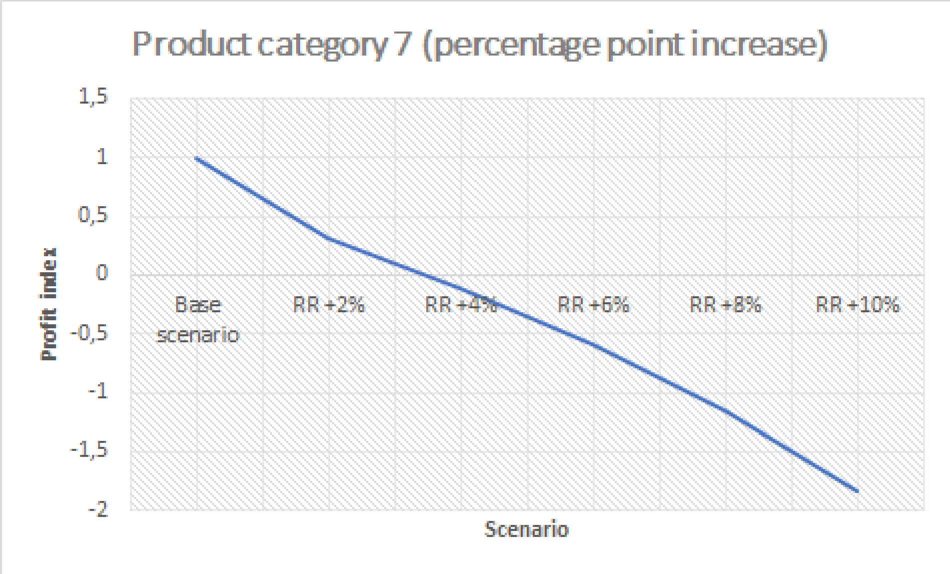

Figure B.34. Profit index change for product category 7.

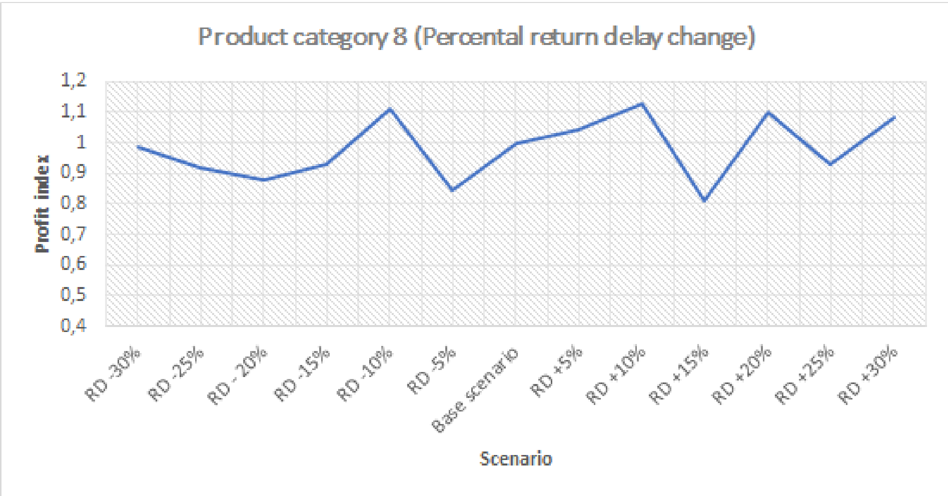

Figure B.35. Profit index change for product category 8.

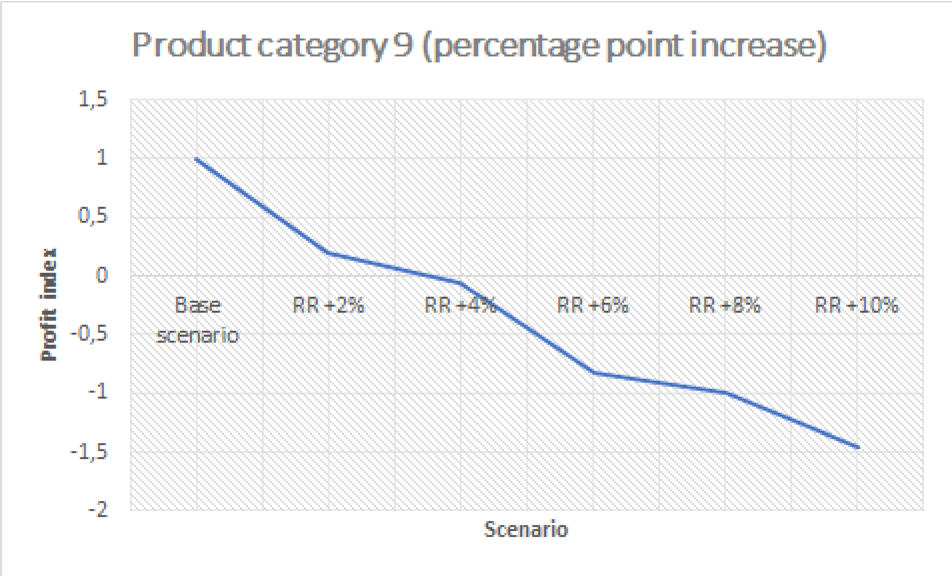

Figure B.36. Profit index change for product category 9.

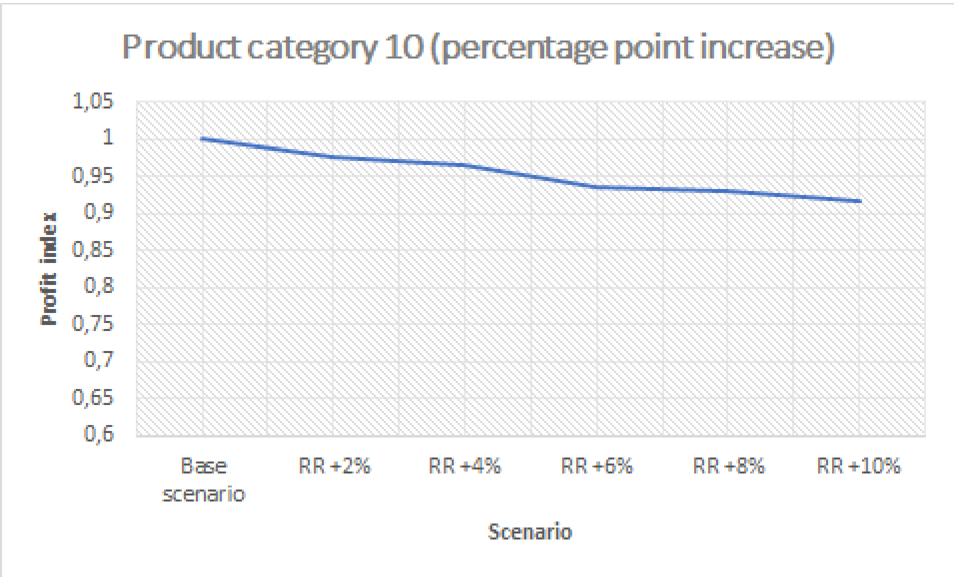

Figure B.37. Profit index change for product category 10.

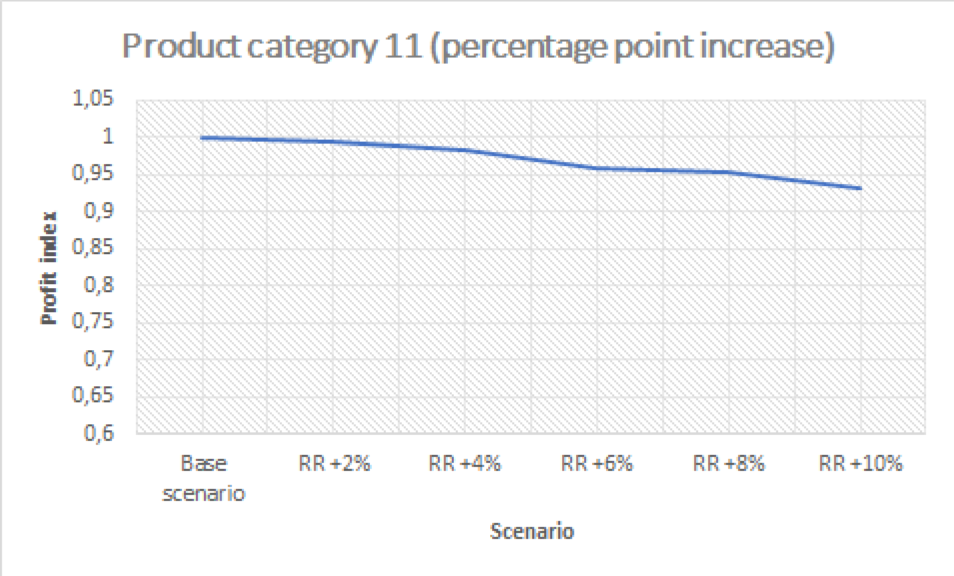

Figure B.38. Profit index change for product category 11.

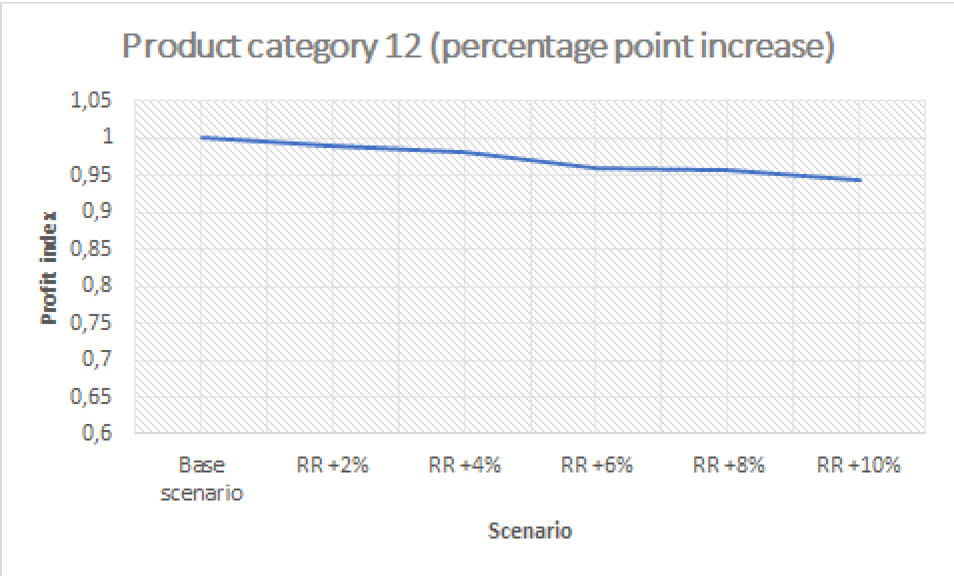

Figure B.39. Profit index change for product category 12.

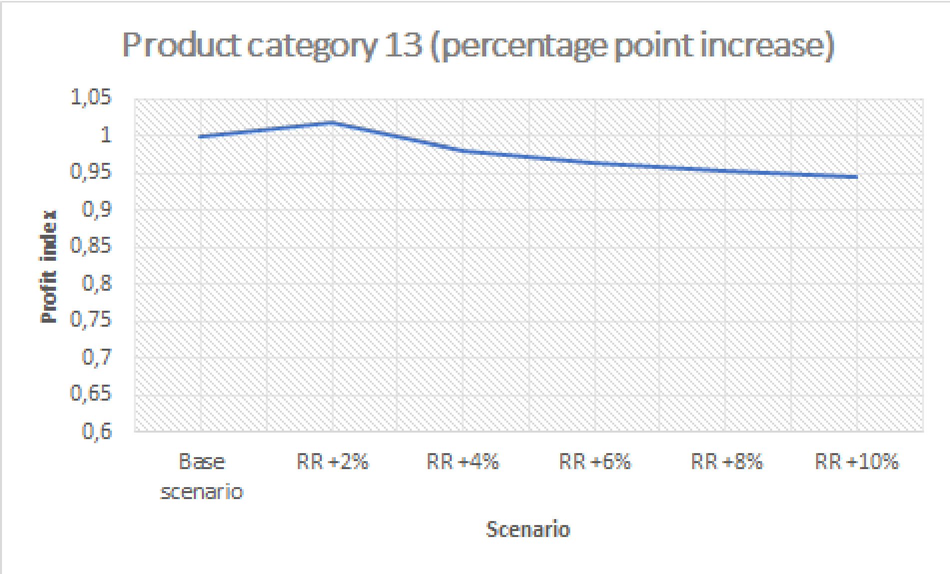

Figure B.40. Profit index change for product category 13.

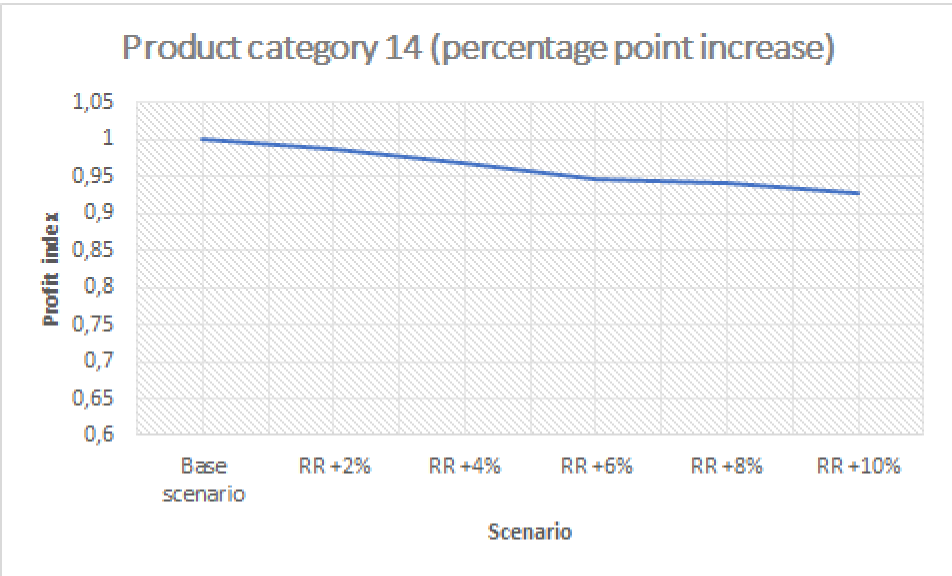

Figure B.41. Profit index change for product category 14.

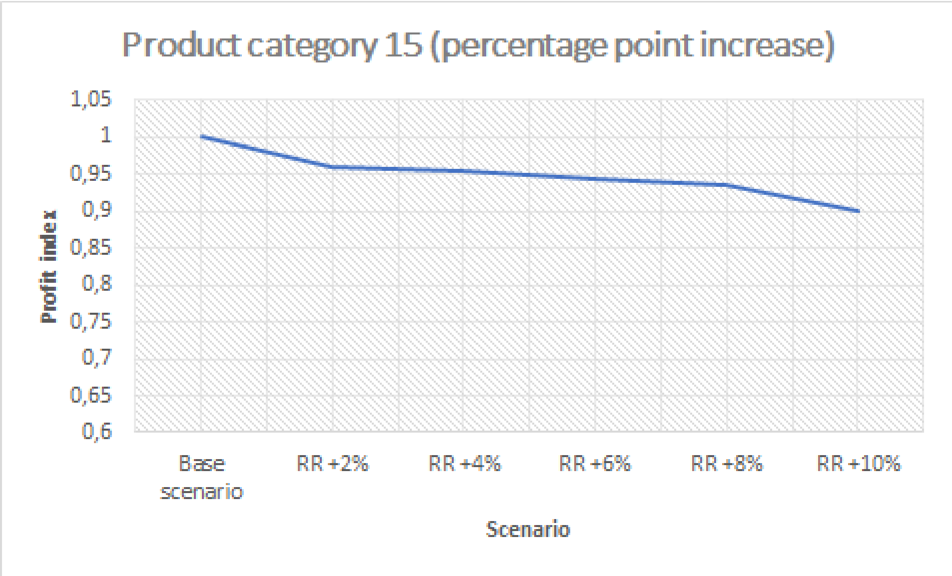

Figure B.42. Profit index change for product category 15.

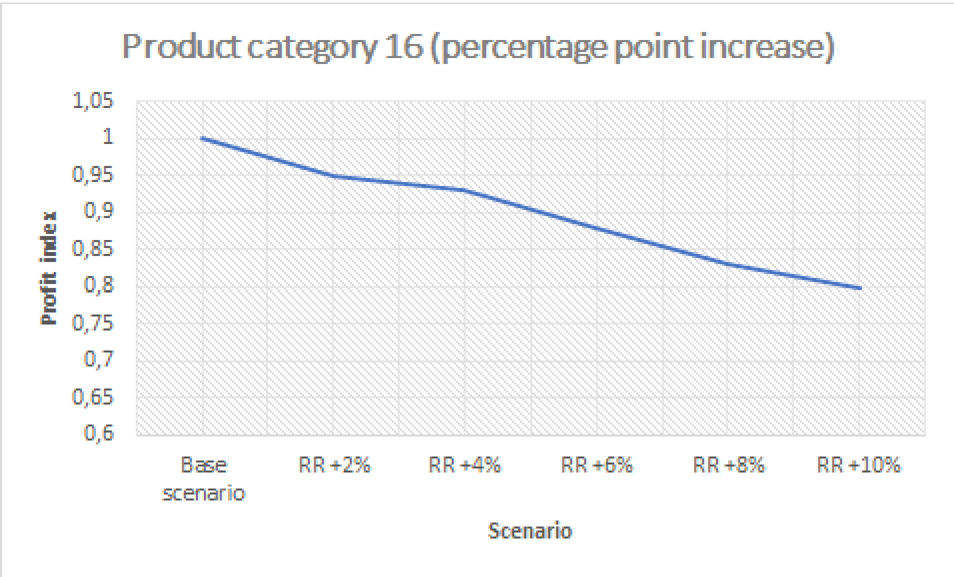

Figure B.43. Profit index change for product category 16.

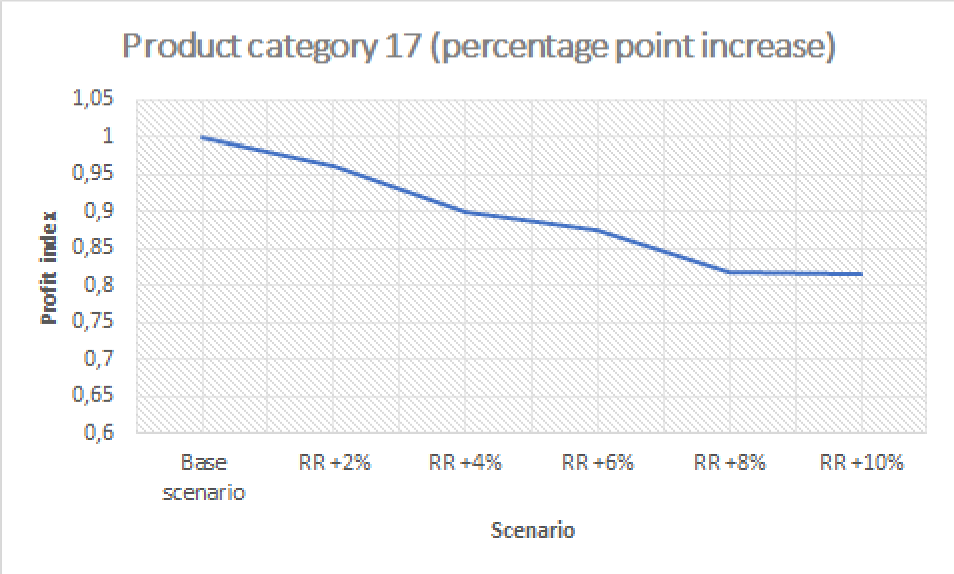

Figure B.44. Profit index change for product category 17.

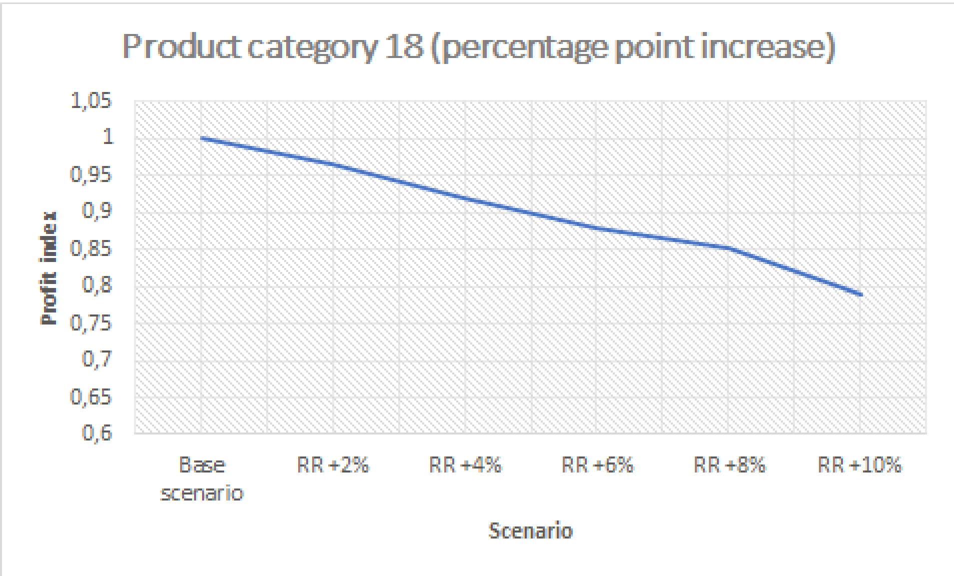

Figure B.45. Profit index change for product category 18.

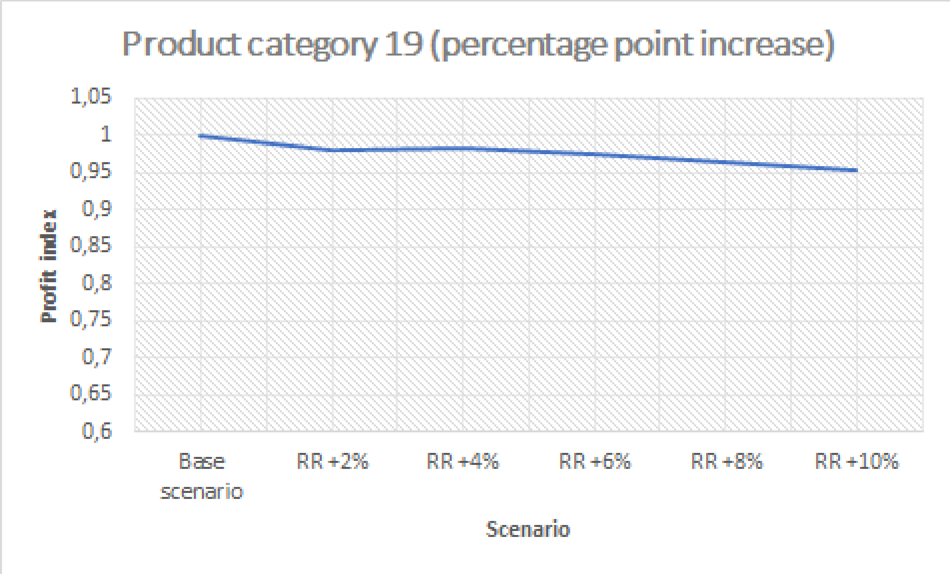

Figure B.46. Profit index change for product category 19.

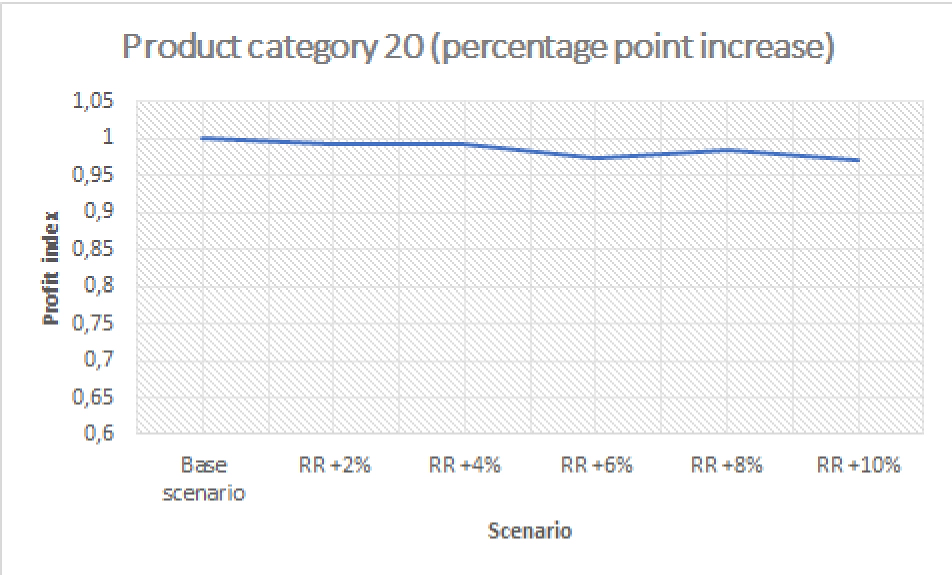

Figure B.47. Profit index change for product category 20.

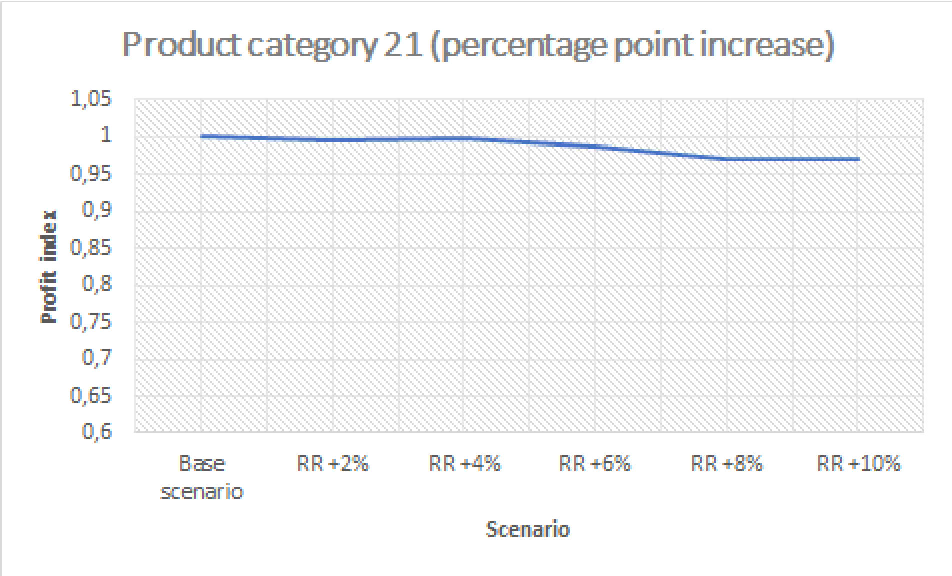

Figure B.48. Profit index change for product category 21.

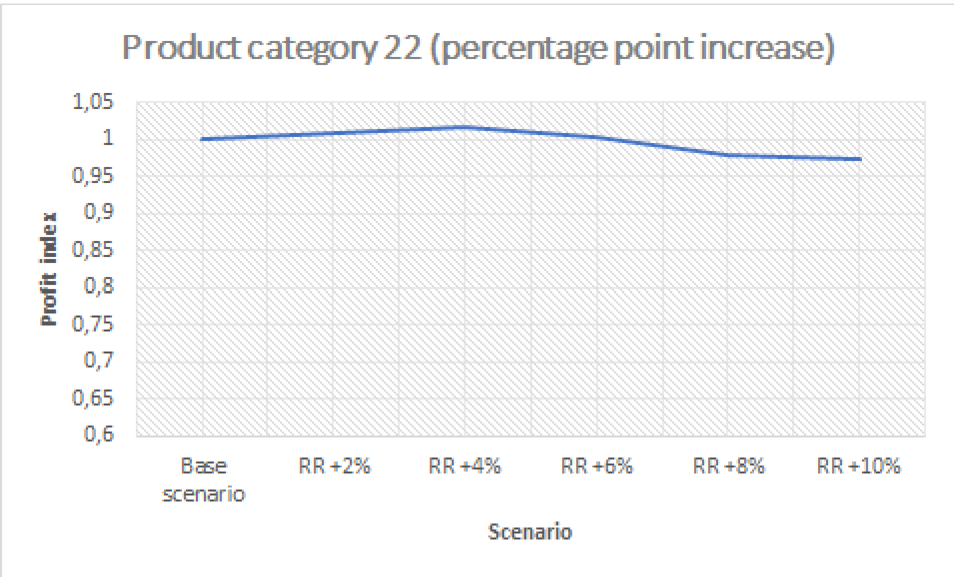

Figure B.49. Profit index change for product category 22.

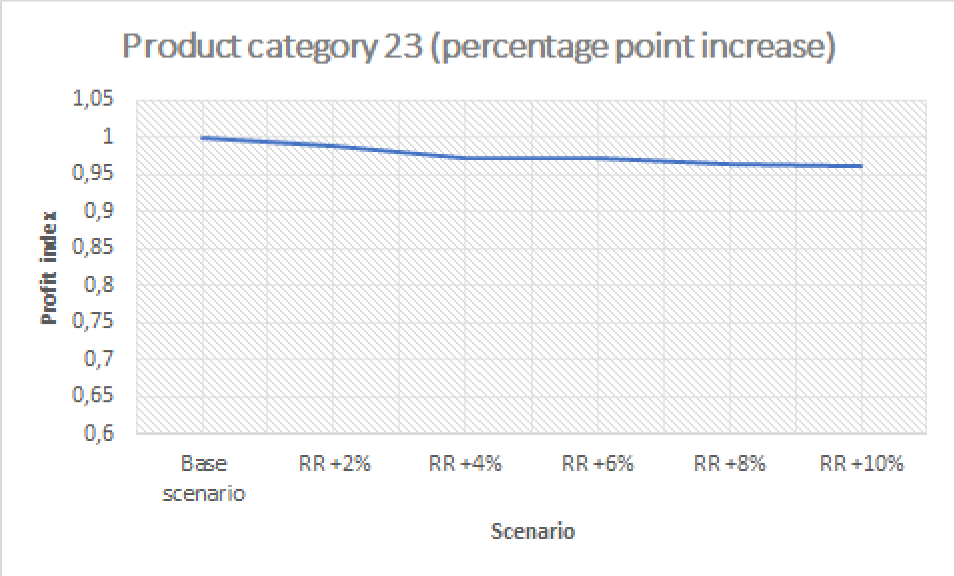

Figure B.50. Profit index change for product category 23.

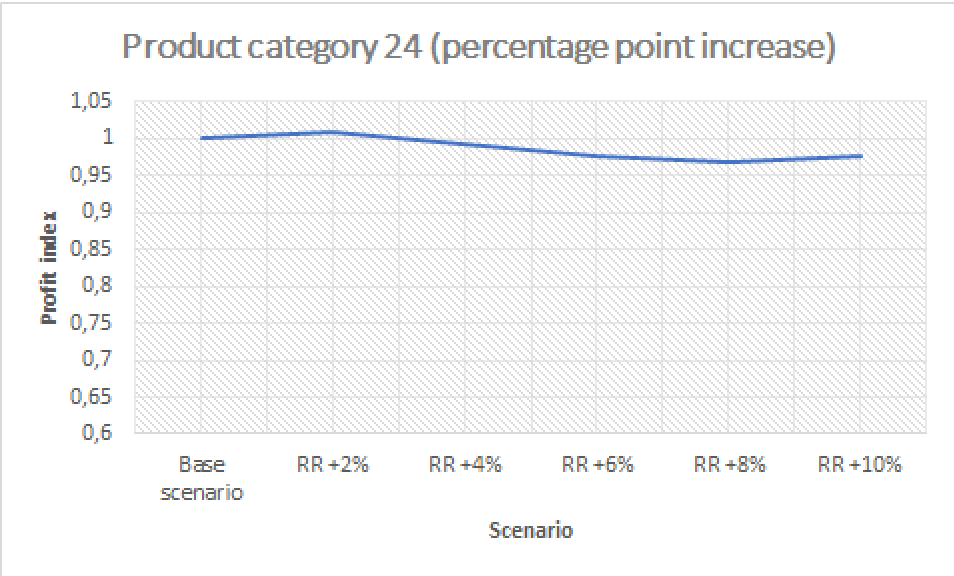

Figure B.51. Profit index change for product category 24.

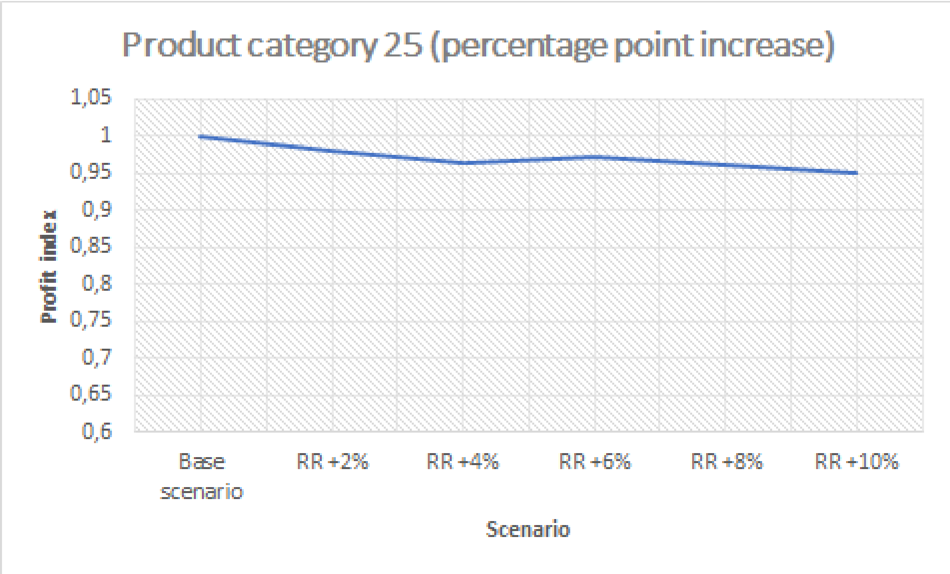

Figure B.52. Profit index change for product category 25.

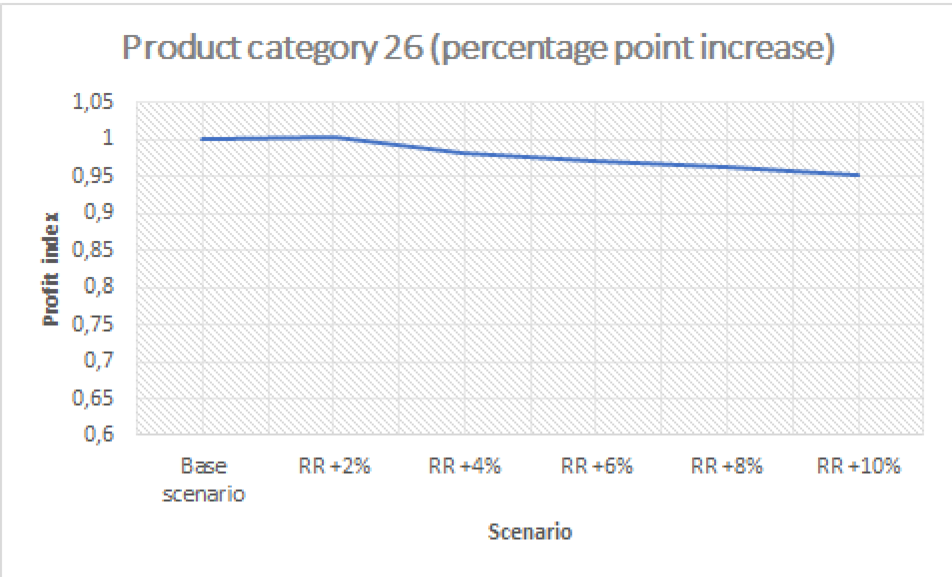

Figure B.53. Profit index change for product category 26.

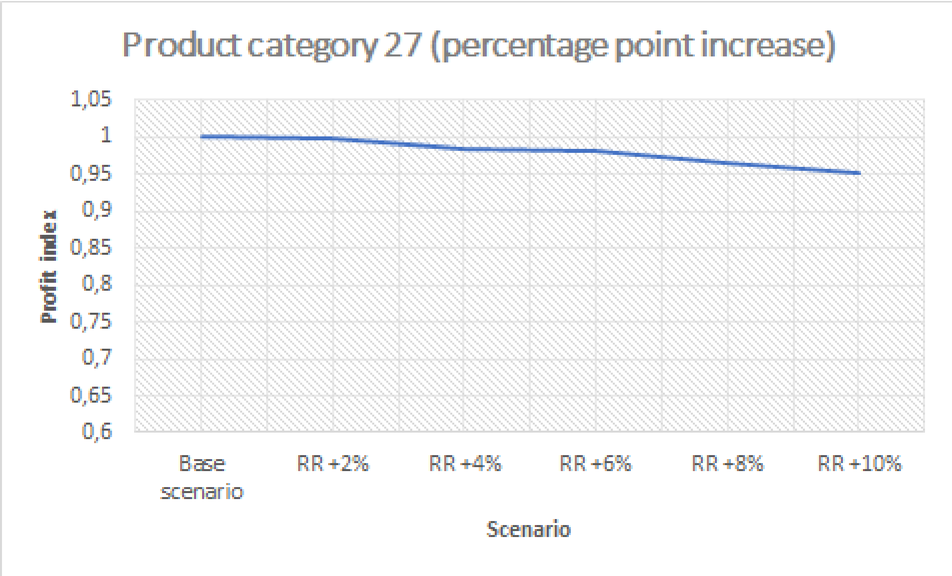

Figure B.54. Profit index change for product category 27.

B.3 Percental Change in Return Delay

This section contains the results for each product category from simulation scenarios 12 through 23 and are presented in Figure B55 to B81.

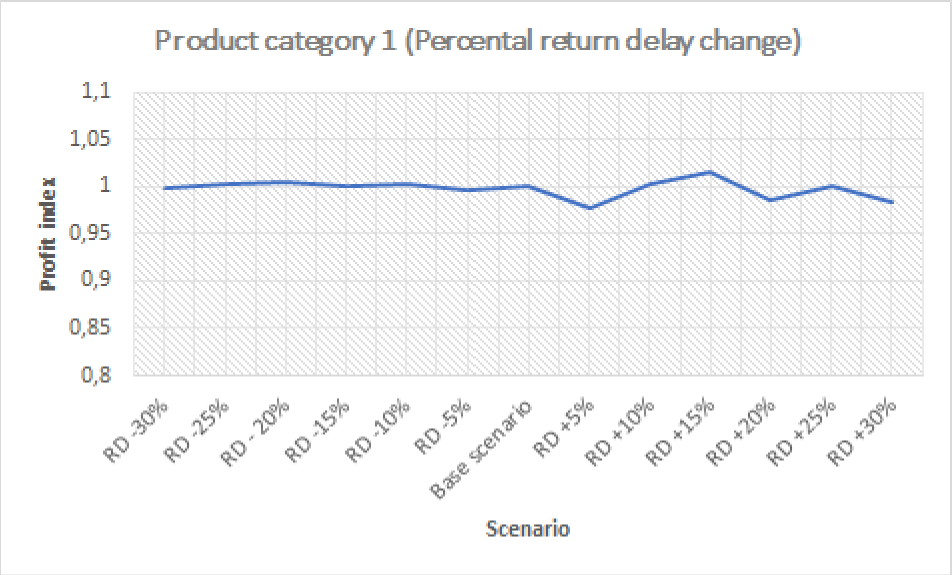

Figure B.55. Profit index change for product category 1.

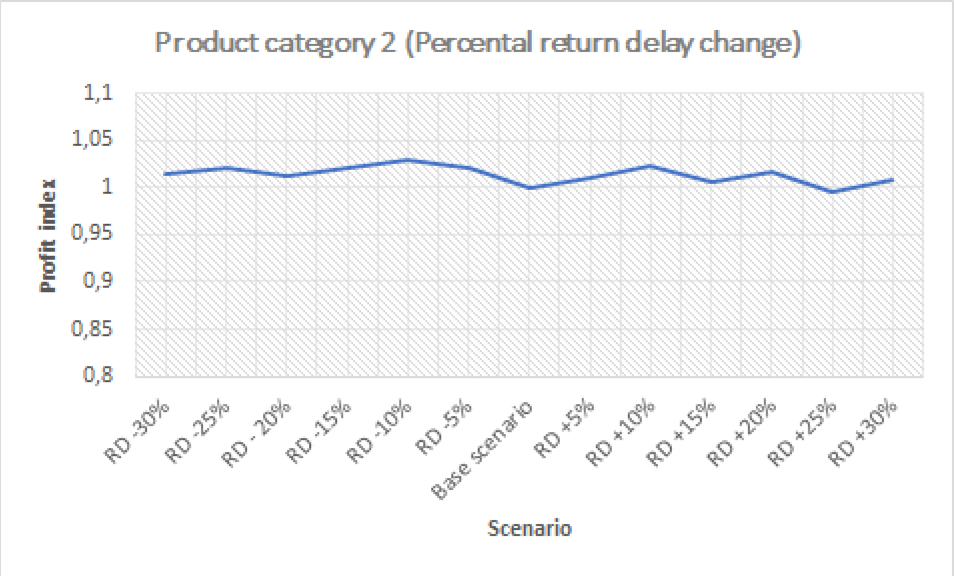

Figure B.56. Profit index change for product category 2.

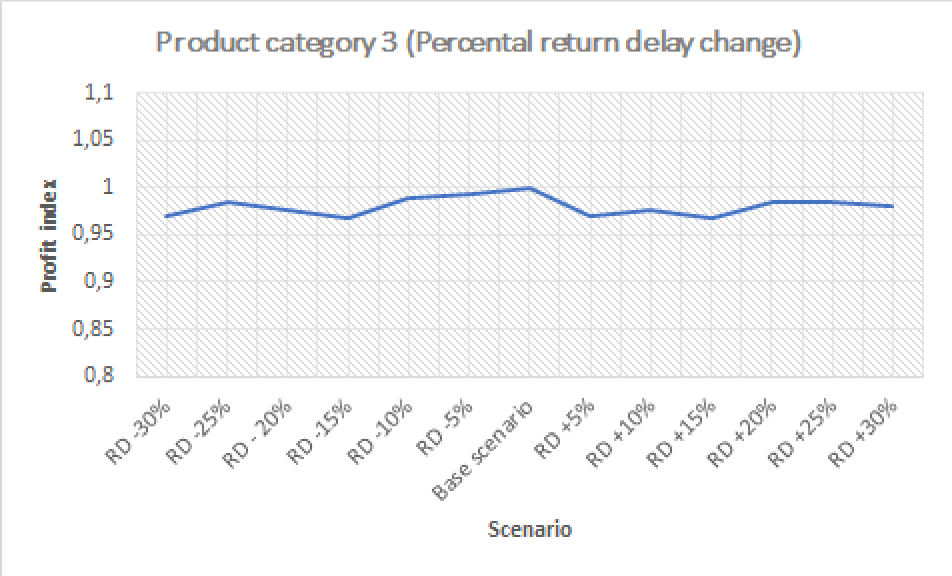

Figure B.57. Profit index change for product category 3.

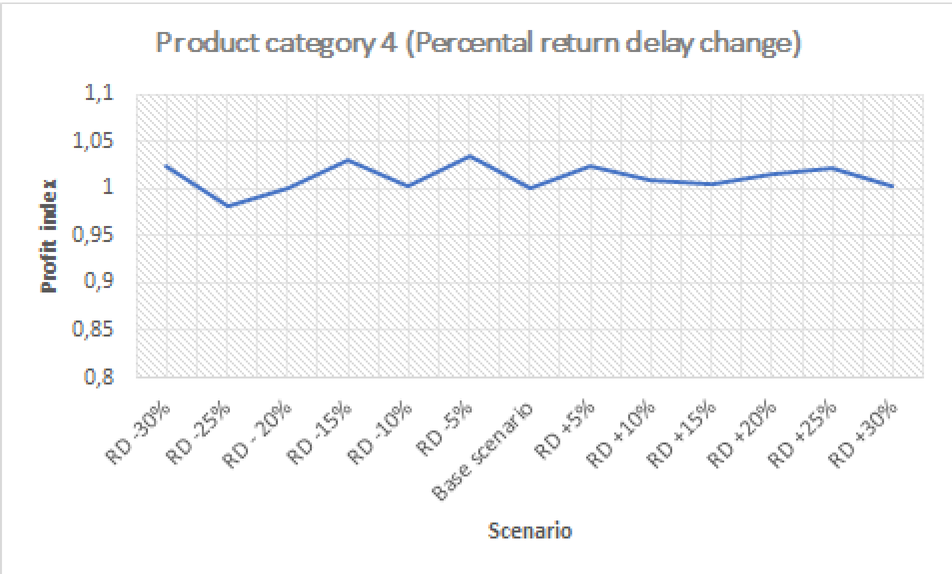

Figure B.58. Profit index change for product category 4.

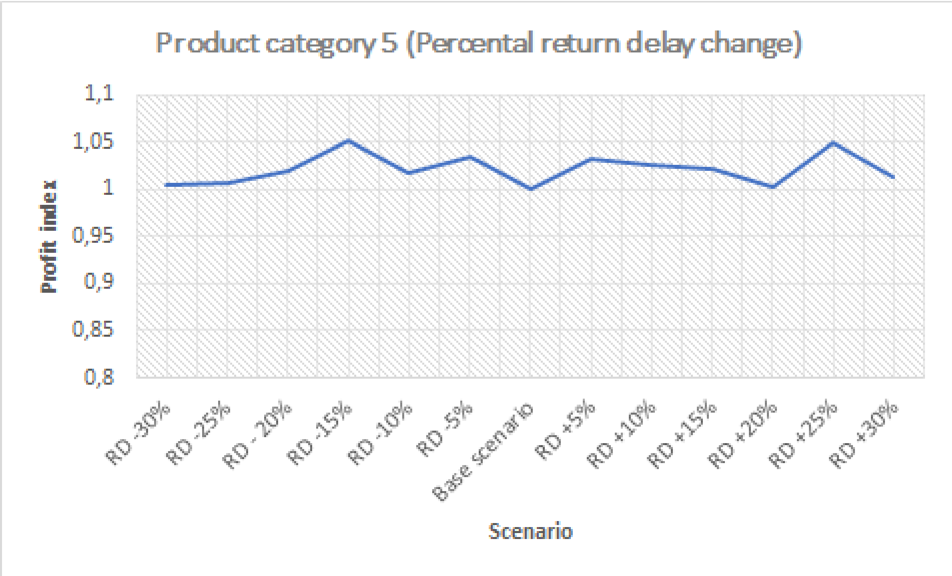

Figure B.59. Profit index change for product category 5.

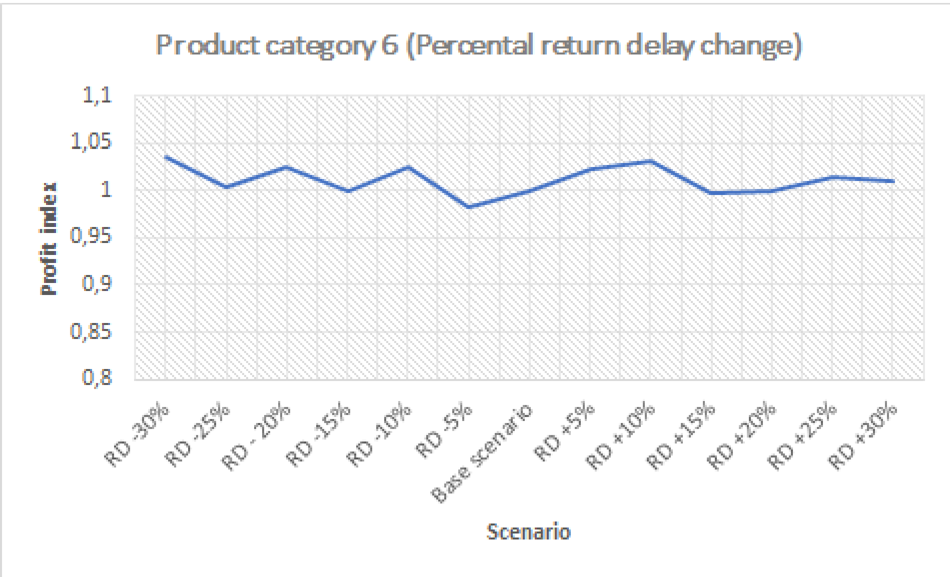

Figure B.60. Profit index change for product category 6.

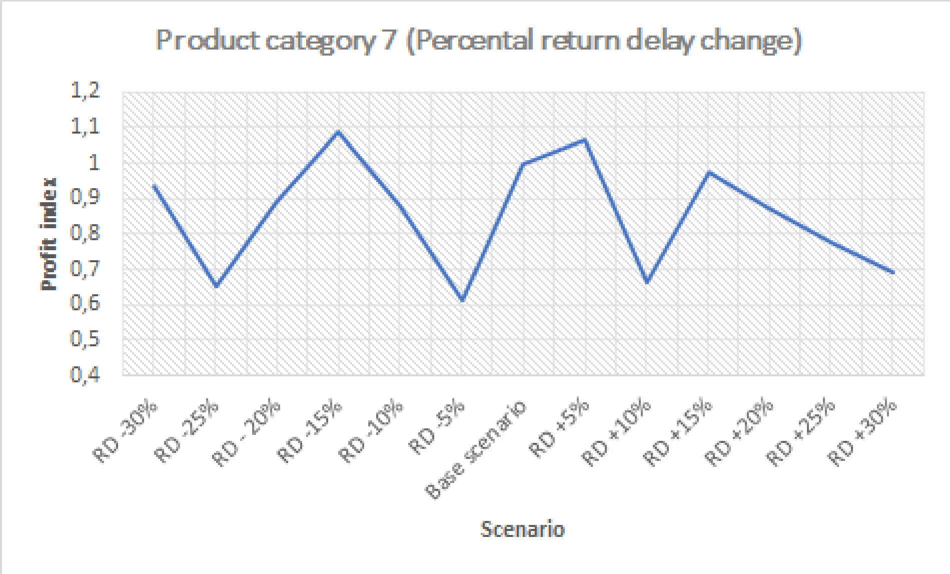

Figure B.61. Profit index change for product category 7.

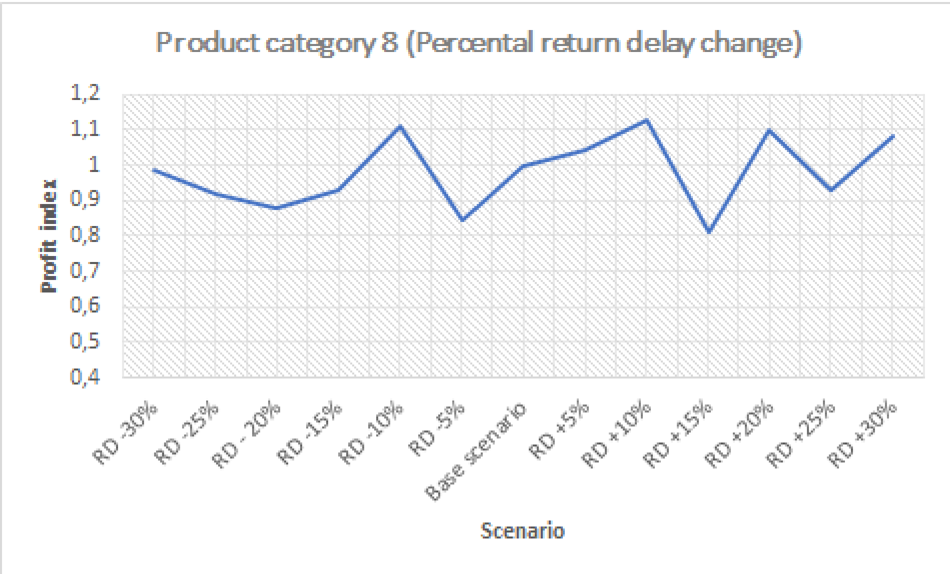

Figure B.62. Profit index change for product category 8.

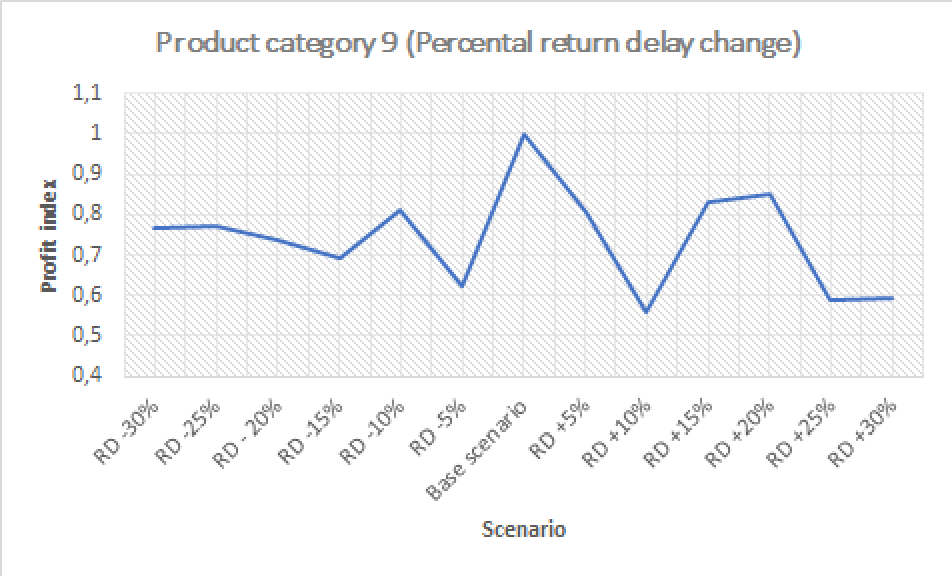

Figure B.63. Profit index change for product category 9.

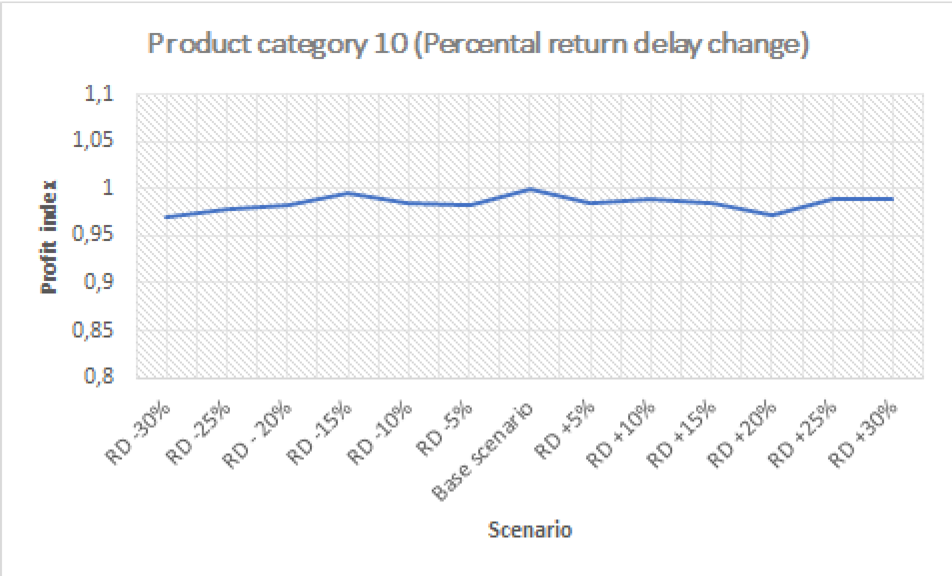

Figure B.64. Profit index change for product category 10.

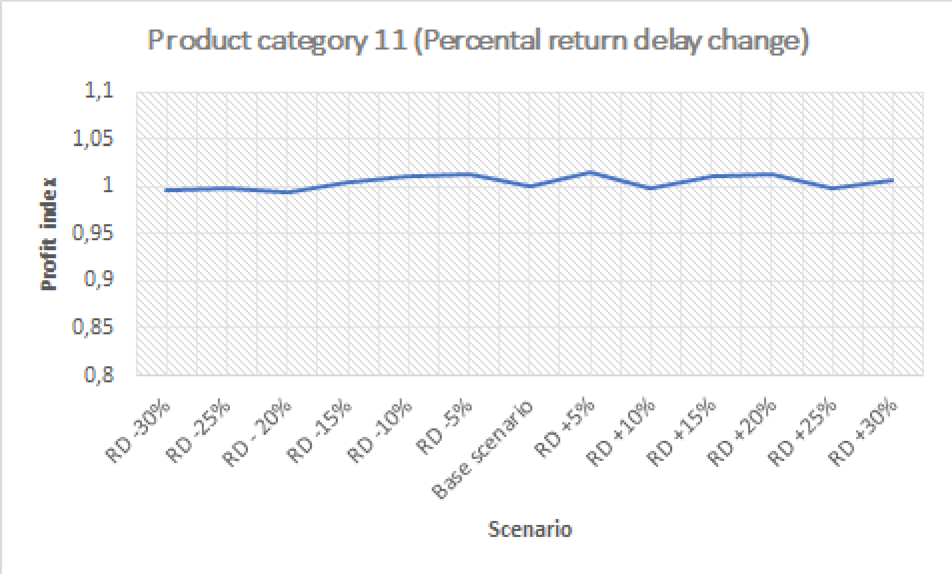

Figure B.65. Profit index change for product category 11.

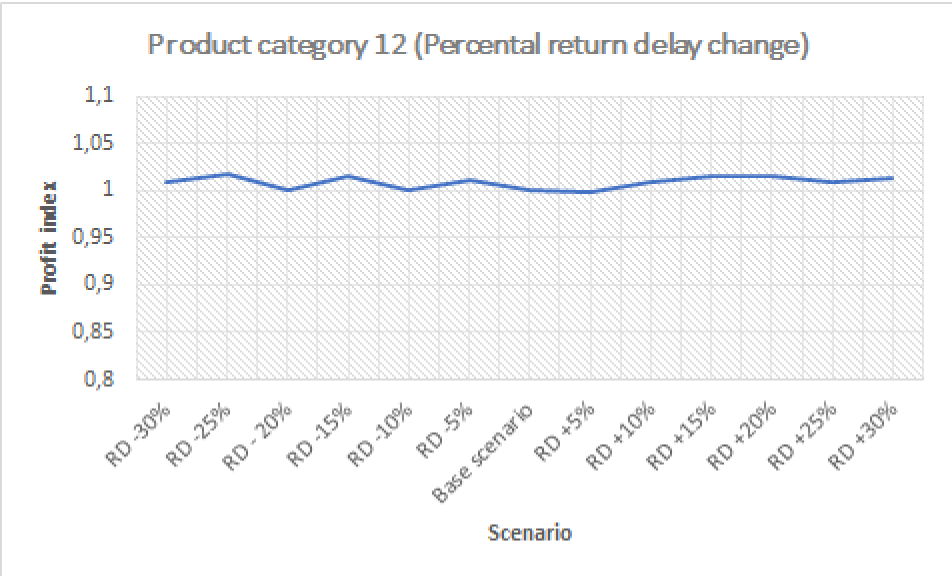

Figure B.66. Profit index change for product category 12.

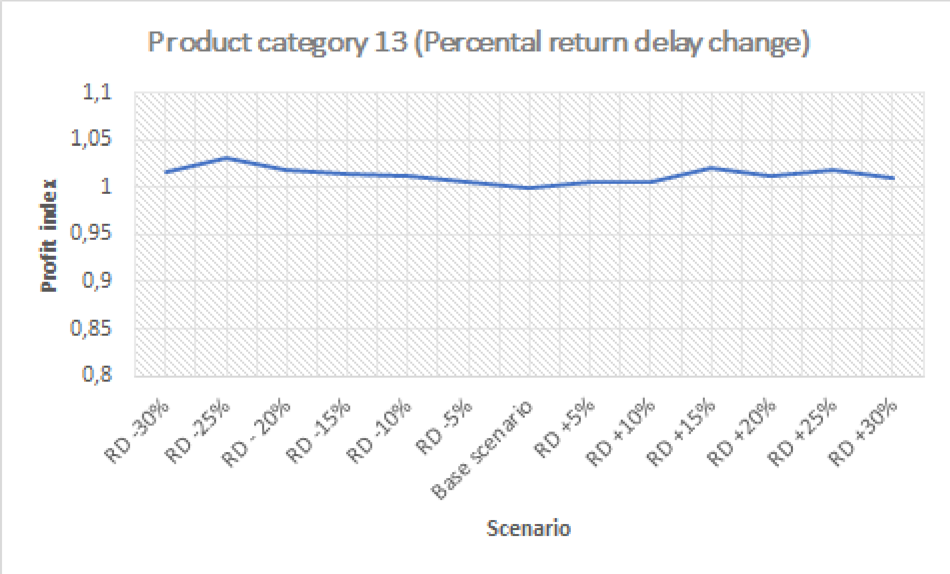

Figure B.67. Profit index change for product category 13.

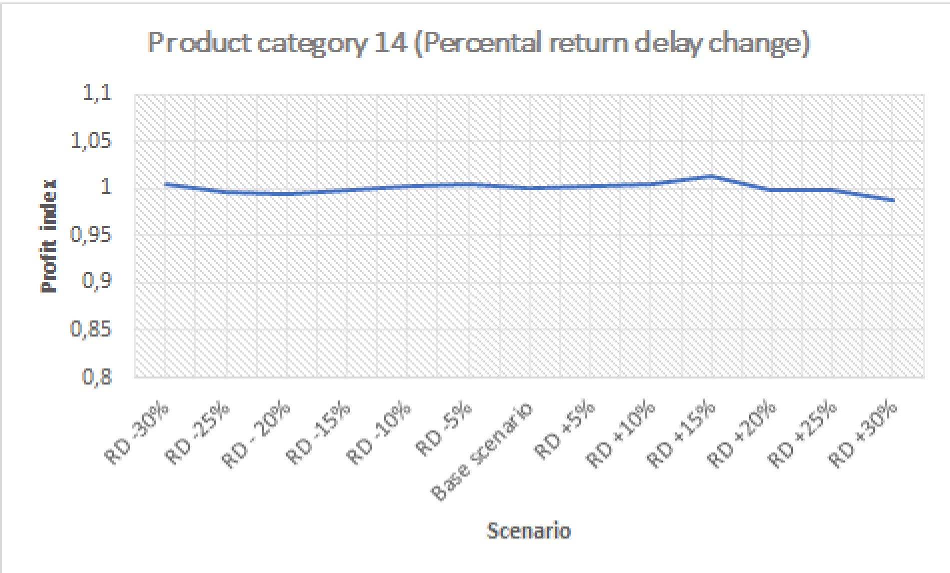

Figure B.68. Profit index change for product category 14.

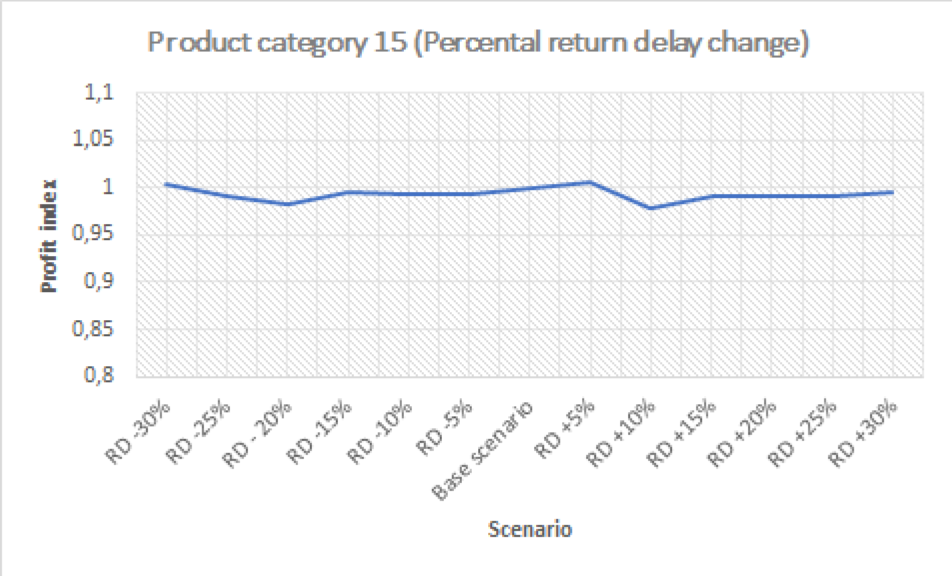

Figure B.69. Profit index change for product category 15.

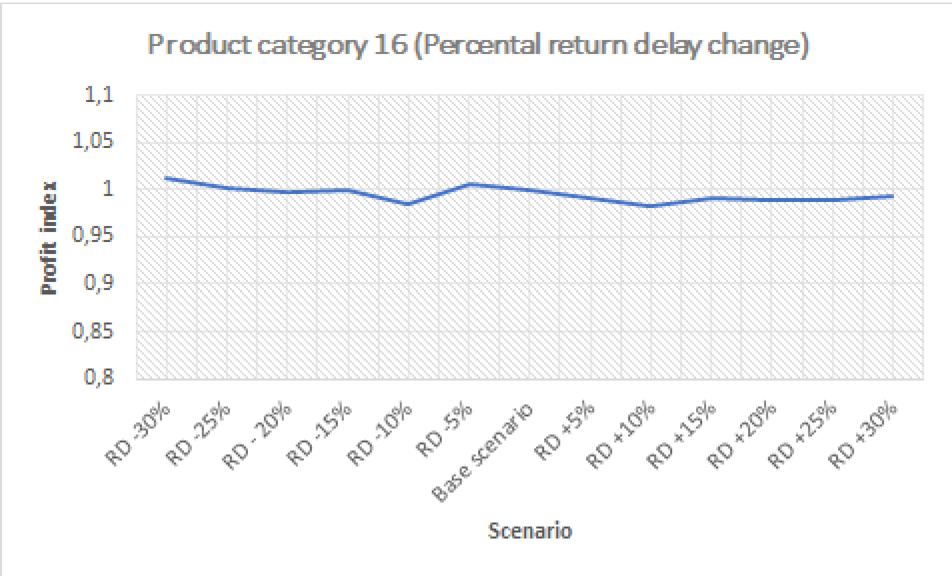

Figure B.70. Profit index change for product category 16.

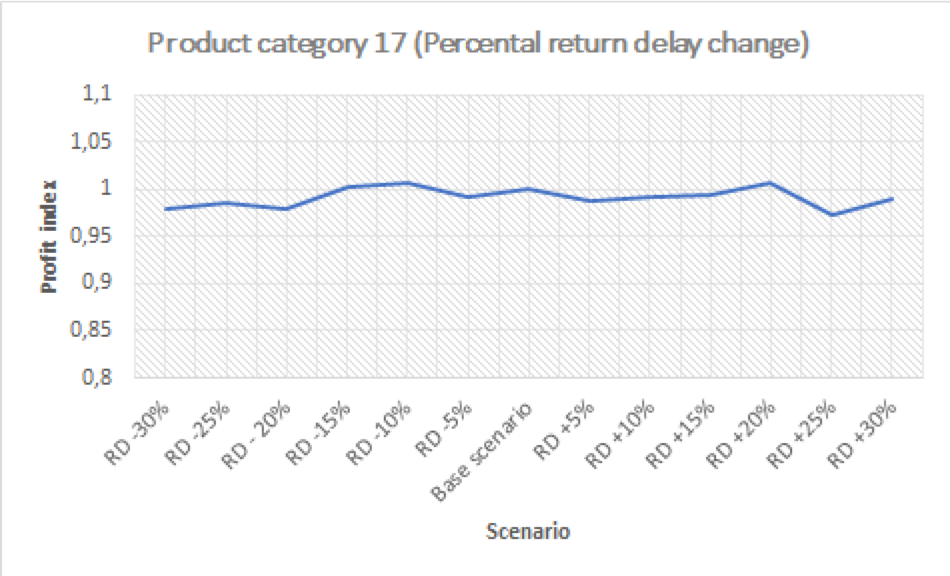

Figure B.71. Profit index change for product category 17.

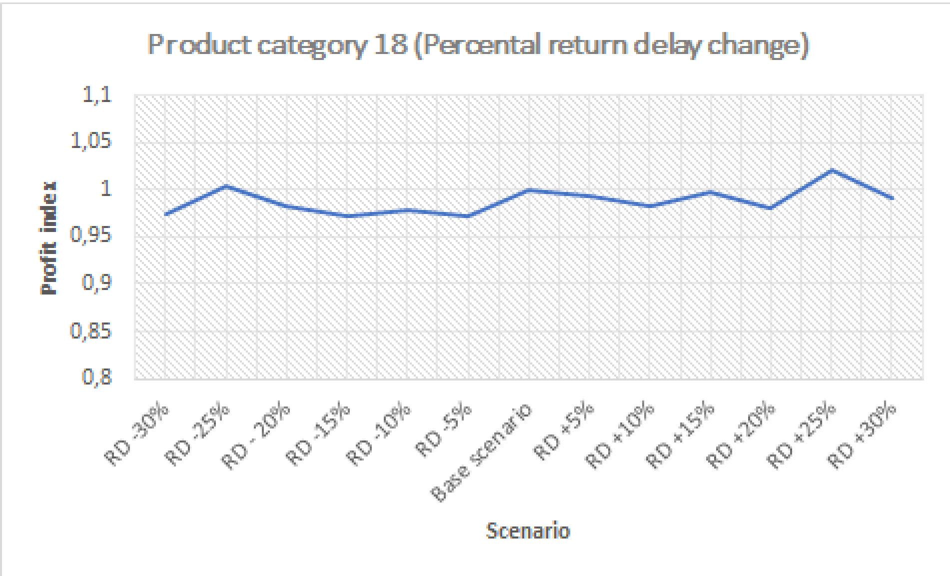

Figure B.72. Profit index change for product category 18.

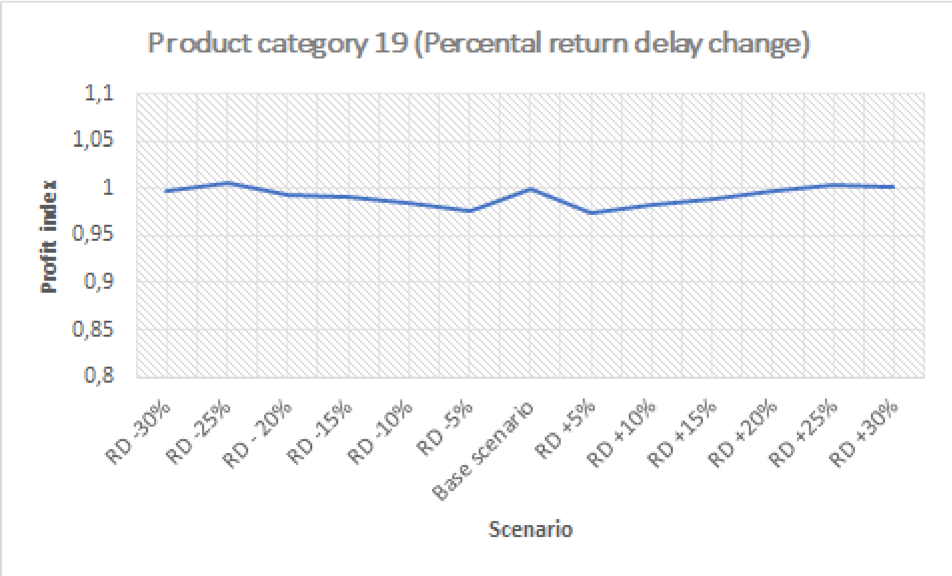

Figure B.73. Profit index change for product category 19.

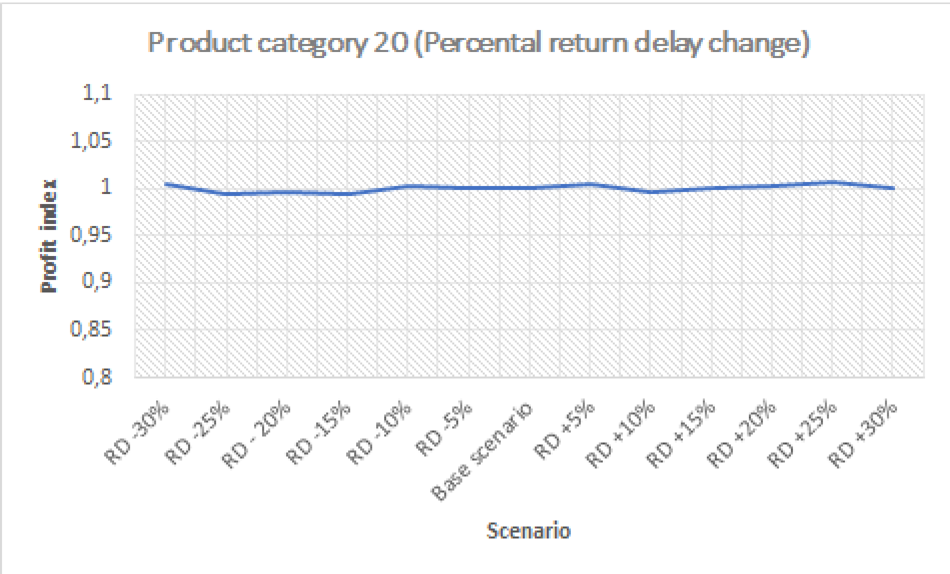

Figure B.74. Profit index change for product category 20.

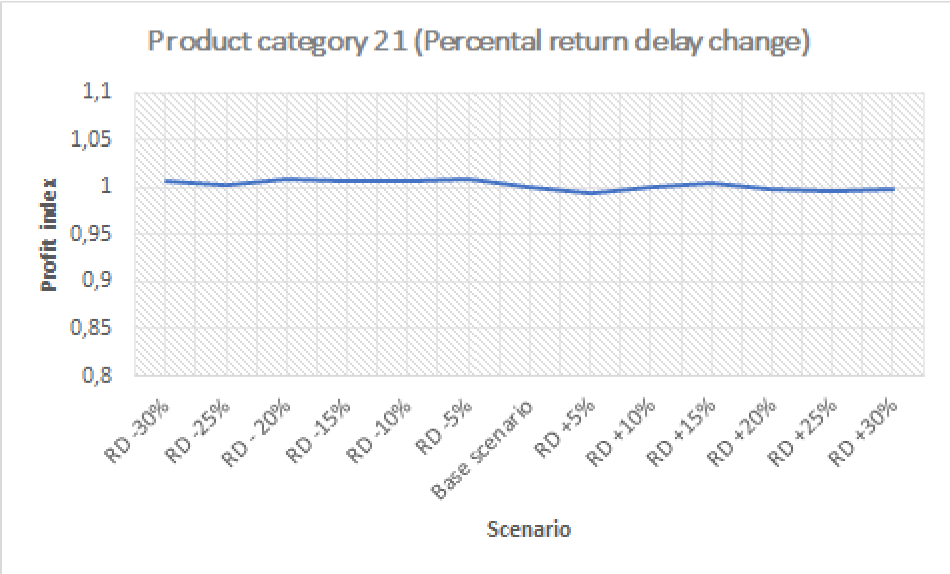

Figure B.75. Profit index change for product category 21.

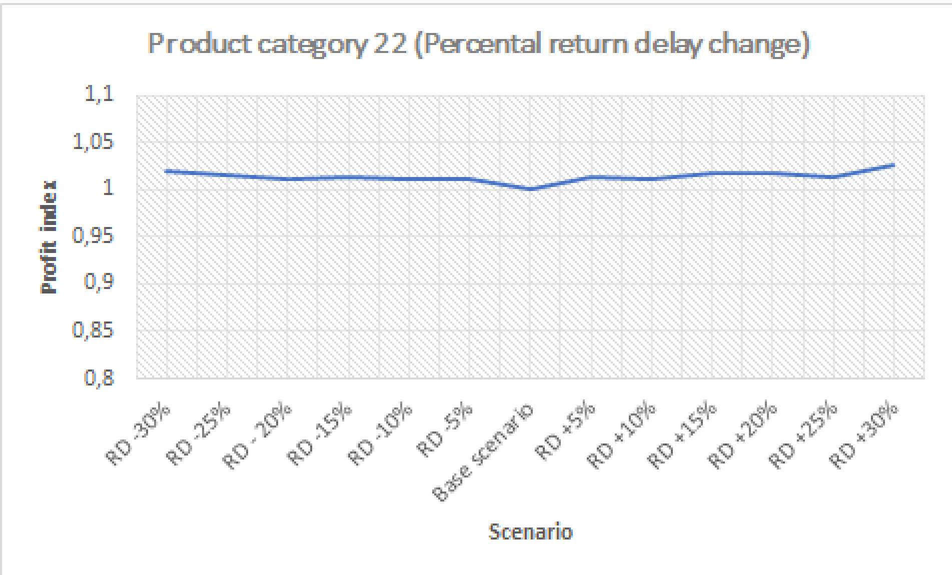

Figure B.76. Profit index change for product category 22.

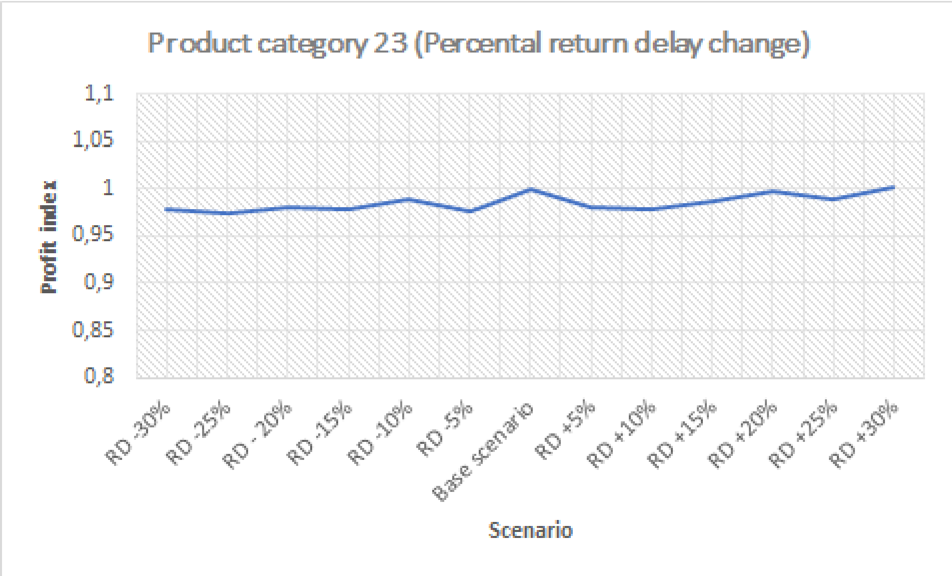

Figure B.77. Profit index change for product category 23.

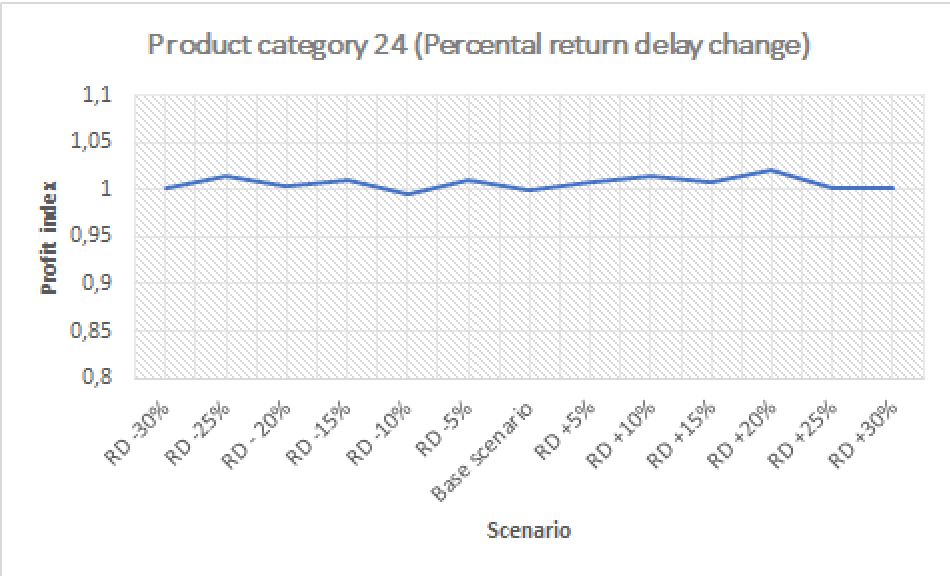

Figure B.78. Profit index change for product category 24.

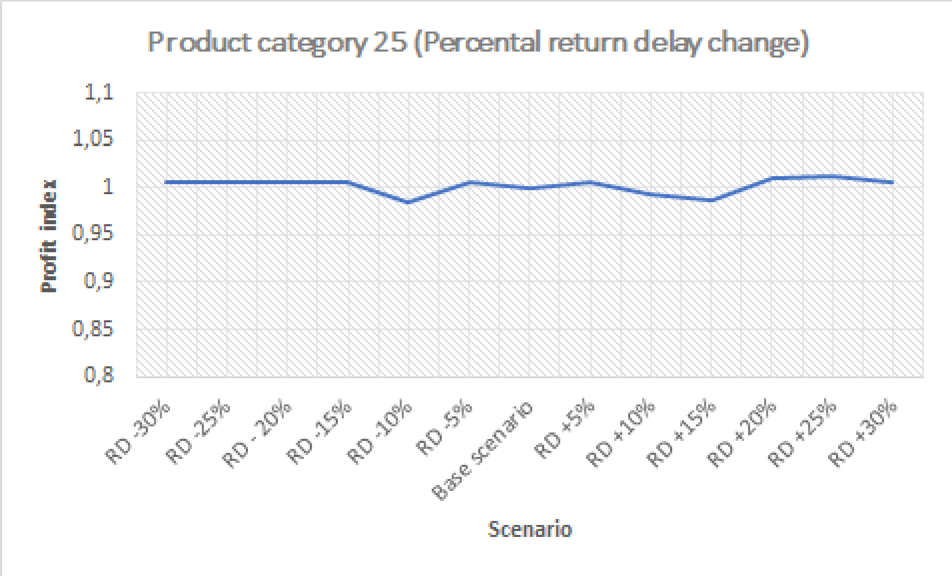

Figure B.79. Profit index change for product category 25.

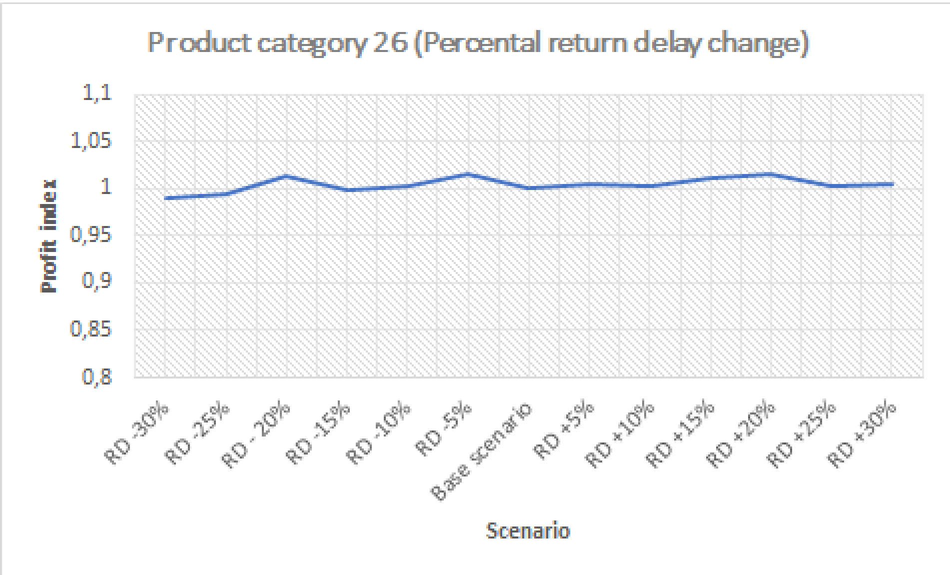

Figure B.80. Profit index change for product category 26.

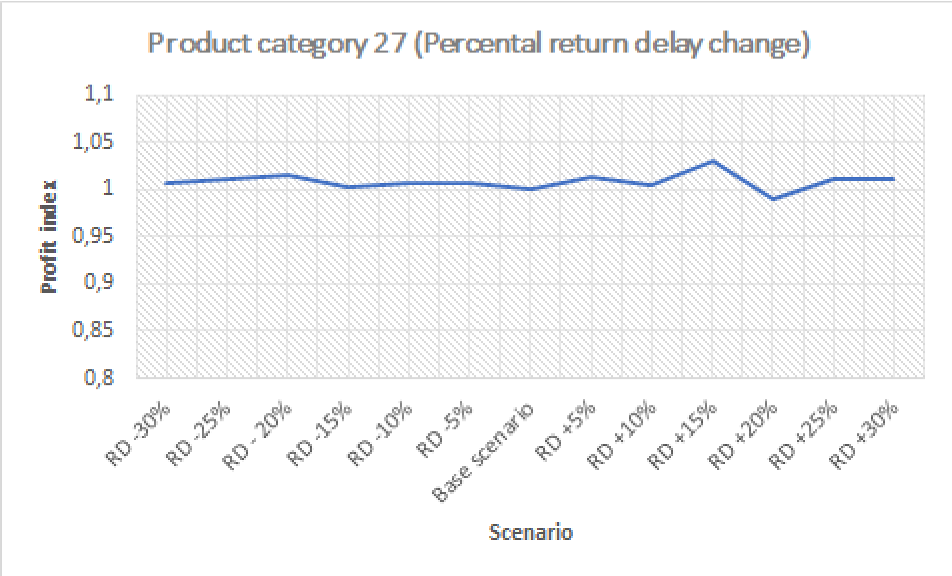

Figure B.81. Profit index change for product category 27.