MASTER

The influence of supply chain disruptions on pricing and inventory decisions

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The influence of supply chain disruptions on pricing and inventory decisions.

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Joris Corstens,
March, 2013
Abstract

Due to an increased focus on Just-in-Time principles supply chain disruptions have exhibited a devastating impact on the profits of global or locally operating companies. On the contrary, companies try to boost their profit by jointly or sequentially examining pricing and inventory decisions. In this thesis supply chain disruptions are incorporated in a pricing and inventory model. By using this model a combined inventory and pricing policy for mitigation of disruption risk is developed. This policy is characterized as follows: inventory management is done according to a base-stock policy. If net inventory is below or equal to a pricing reference inventory level the price is increased with a percentage. The effects of using this policy on a single retailer’s revenue, costs and profit for different scenarios are examined.
Management Summary

Recent incidents have exhibited a devastating impact on the profits and supply chains of global or locally operating companies. These incidents, so called supply chain disruptions, are characterized as random events that lead to a complete or partial stoppage of supply for a random amount of time (Snyder et al., 2010). Therefore, supply chain disruptions are described as the most severe form of supply chain uncertainty and characterized as low-likelihood high impact events (Oke and Gropalakrishan, 2009). Supply chain disruptions stem from several causes, the main causes are summarized in the bullets below (Chopra and Sodhi, 2004, p.54).

- Natural disaster
- Labor dispute
- Supplier bankruptcy
- War and terrorism
- Dependency on a single source of supply as well as the capacity responsiveness of the back up suppliers

In order to mitigate risks stemming from disruptions companies can use a variety of mitigation strategies. According to their nature these strategies are classified either as proactive or reactive. The former class deals with the mitigation of disruption risk ex ante, while the latter strategy deals with mitigation disruption risk ex post. On the contrary, companies try to boost their profits by using a variety of approaches for deciding on price and/or inventory. These approaches are generally discussed in the field of revenue management.

Although some attempts have been made in order to combine approaches from revenue management and knowledge on supply chain disruptions (see e.g. (Li and Zheng, 2006)), no comprehensive approach exist. Therefore, in this thesis a combined pricing and inventory policy is proposed. This combined policy is best characterized as a threshold like policy consisting of the following parts: an \((S,k)\) policy for inventory management while the price is determined according to an \((P,\delta)\) policy. Furthermore, pricing is done based on the current net inventory. The general outline of this combined inventory and pricing policy is that inventory is managed according to the traditional base-stock policy. Price is determined according to the following rule: when net inventory equals or is below the pricing reference level \((k)\) the initial offered price \((P)\) is increased with a percentage \((\delta)\). If net inventory is restored to a level above the pricing reference inventory level the price is restored to its initial value. The decisions of the retailer, based on net inventory, after incorporation of this policy are depicted in the following figure. In this figure it is assumed that lead time equals 0.
To measure the effects of disruptions on pricing and inventory decisions of a single retailer a price dependent demand function is used by incorporating customer reservation prices. Customer reservation prices are a customer’s individual valuation of a product against which a possible purchase is judged (Monroe, 1973). In this thesis it is assumed that customer reservation prices are lognormally distributed with an expected value equal to the initial price offered by the retailer. The variance of the customer reservation price is determined in such manner that the percentage of customers willing to buy the product is decreasing in price - i.e. approximate none of the customers are willing to pay a price 3 times the price initially offered by the retailer. Furthermore, it is assumed that customers behave non-strategically, which entails that their behavior do not change when there are changes in the retailer’s decision variables. Disruptions are generally characterized by a disruption profile (Snyder et al., 2010). For this thesis disruptions are represented with a two-state continuous time Markov chain, with an “up” state referring to the undisrupted state of the supplier and a “down” state indicating that the supplier is disrupted. In the “down” state the supplier is unable of delivering any orders. The disruption rate (\( \alpha \)) represents the rate of going from an “up” to a “down” state and the recovery rate (\( \beta \)) the rate of going in the reverse direction. The effects of disruptions on a single retailer’s revenue, costs and profit are examined in the following setting.

The main outline of the combined inventory and pricing policy is that due to an increase in price the demand rate decreases and as a result a decrease in revenue is observed. Another, and more important, effect of the decreased demand rate is the decrease in observed back orders, resulting in a dramatic decrease in costs. Therefore, the retailer’s profit is increased, especially for low base-stock levels, which stems from the fact that for high base-stock levels the retailer has ample inventory to sell even during disruptions. The main benefits of using the combined inventory and pricing policy is that base-stock levels can be decreased while profit is increased for frequent and infrequent disruptions with a low recovery rate.

The disruption profile consists of the disruption and recovery rate. From an extensive analysis it is observed that the recovery rate has a major influence on the combined inventory and pricing
policy and the traditional base-stock policy. Furthermore, it can be observed that for high recovery rates, using the combined inventory and pricing policy does not result in an increased profit for the retailer. A reason for this that it can be observed that for relatively short disruptions increasing the price will result in a decreased number of items sold and resulting in a decrease in revenue for which cannot be compensated by the abated costs.
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Chapter 1

Introduction

Recent history indicated that supply chain disruptions have a catastrophic effect on the performance of global or locally operating firms. Due to an increased use of Just-in-Time principles (JIT) combined with an increased focus on efficiencies companies are becoming increasingly vulnerable to supply chain disruptions (Snyder et al., 2010). Due to this increased vulnerability companies are risking long and short term negative financial operating performance in the form of decreased operating income, return on sales, and return on assets (Hendricks and Singhal, 2005). Therefore, current research is primarily focussed on the mitigation of risk stemming from supply chain disruptions.

On the contrary companies try to boost their profits and manage demand by using revenue management techniques to determine optimal price and corresponding ordering quantities (Chen and Simchi-Levi, 2010). Although some attempts have been made to merge supply chain disruption literature and revenue management (see e.g. Li and Zheng (2006)) no comprehensive approach exist. This thesis aims at developing and exploring the effects of a new mitigation strategy that incorporates supply chain disruptions into a pricing and inventory model. In this strategy inventory is managed according to an $(S,k)$ policy, in which $S$ represents the traditional base-stock policy and $k$ the pricing reference inventory level. Pricing is done according to an $(P,\delta)$ policy, in which $P$ represents the initial offered price and $\delta$ represents by which the price can be increased. Pricing is done according the following rule: if net inventory is equal or below the pricing reference inventory level ($k$) the initial offered price ($P$) is increased with a percentage ($\delta$). When net inventory is restored to a value above $k$ the price is changed to the initial value. Throughout this thesis to this combined inventory and pricing policy will be referred to as the proposed policy.

By changing the offered price it can be expected that demand is subjected to change. Therefore, a price dependent demand function is used by including a customer reservation price.

In Section 1.1 illustrative examples, in order to develop support for combining an inventory and pricing policy, are provided by indicating that prices are subject to change during disruptions. Furthermore, an example is provided in order to show the disastrous consequences of supply chain disruptions.

1.1 Illustrative examples

A lighting strike that caused a fire in a Philips plant in Albuquerque, New Mexico, forced Ericsson to exit the cell-phone market with an estimated loss in sales of 400 million dollar due to the unavailability of essential components. While Ericsson was forced to exit the cell-phone market, Nokia identified the problem quickly and reacted by switching orders to other manufacturing sides of the supplier. As a result Nokia became the number 1 cell-phone manufacturer in the world (Norrman and Jansson, 2004).

After the 1999 earthquake in Taiwan, factories of essential personal computer components were
severely damaged. Due to this damage supplies of motherboards, chip sets and other vital PC parts were disrupted (Burrows, 1999). Despite this major disruption of vital components Dell remained competitive, by using various demand management techniques. As a response to the earthquake Dell immediately deployed a low-cost-upgrade strategy in order to switch demand to computers with components from other suppliers. This dynamic pricing and promotion strategy enabled Dell to stay competitive during this disruption (Martha and Subbakrishna, 2002).

While Dell used demand management techniques in order to deal with disruptions some other examples of an increased price during a disruption can be found. Hurricane Katrina destroyed several drilling facilities in the Gulf region. In this region 7% of America’s oil consumption and 16% of its natural gas consumption production was forced to shutdown. In addition, after the hurricane 10% of America’s refining capacity was forced to shutdown. As a result of the expected shortage of gasoline, lines at gas stations were observed and an overnight increase in price per gallon of gasoline of over 50 dollar cent was observed (Mouawad and Romero, 2005).

1.2 Report structure

The remainder of this report is structured as follows. In Chapter 2 an overview of the current practice for mitigation of disruption risk and current models in revenue management are discussed. Chapter 3 discusses the methodology and provides the problem statement. The scope, conceptual model and mathematical model are presented in Chapter 4. For this model a base case scenario will be analyzed in Chapter 5. Based on this base case scenario several sensitivity analyses are conducted in Chapter 6. Chapter 7 concludes this thesis by stating its main conclusions, managerial implications, limitations, and directions for further research.
CHAPTER 2

Literature review

In this chapter the current practice in the research areas of revenue management and disruption modeling are discussed, in order to support the development of a new mitigation strategy in the form of a combined inventory and pricing policy. Although in both fields of research many modeling approaches exist, this chapter will only highlight some of the general approaches. For a comprehensive literature review on modeling approaches for mitigation of disruption risks we refer to Snyder et al. (2010). Modeling approaches that jointly examine pricing and inventory decisions are reviewed extensively in Chan et al. (2004), Chen and Simchi-Levi (2010), and Yano and Gilbert (2005).

2.1 Supply chain disruptions

From the examples in Section 1.1 it can be obtained that disruptions are best characterized as infrequent high impact events that negatively affect a firm’s operating income, return on sales, and return on assets (Hendricks and Singhal, 2005). In line with this observation Oke and Gropalakrishnam (2009) define disruptions as low-likelihood high impact events. Furthermore, disruptions are classified as the most extreme form of supply chain risks (Chopra and Sodhi, 2004). In order to develop a new policy and evaluate this policy disruptions are defined in a similar fashion as Snyder et al. (2010). In Snyder et al. (2010) disruptions are defined as random events that lead to a partial or complete stoppage of supply for a random amount of time. This stoppage of supply can stem from several causes. The main, and most general, causes are summarized in the bullets below (Chopra and Sodhi, 2004, p.54).

- Natural disaster
- Labor dispute
- Supplier bankruptcy
- War and terrorism
- Dependency on a single source of supply as well as the capacity responsiveness of the back up suppliers

Generally the characteristics of disruptions, the frequency of occurrence and duration, are captured in a disruption profile. This disruption profile states the probabilities for going from a disrupted to an undisrupted state and the other way around (Snyder et al., 2010).

2.1.1 Mitigation strategies

Disruptions are characterized by their high impact, in terms of financial losses or duration. Therefore, the majority of literature on disruptions is devoted to strategies for mitigation of disruption
risk. Mitigation strategies are concerned with minimizing losses when a disruption occurs. In literature several modeling approaches exist, each of these modeling approaches provide mitigation directions in a different manner. In order to develop broad understanding of the present mitigation strategies they are classified into two categories. The first category deals with modeling approaches that provide mitigation tactics for the disruption ex ante. While the second category deals with modeling approaches that deal with disruptions ex post. The former stream of literature embodies proactive strategies while the latter approaches are defined as reactive strategies.

**Proactive strategies**

Proactive strategies are characterized by their ex ante character, which entails that they provide mitigation directions before the actual occurrence of a disruption. Remark that a commonly used approach to deal with uncertainty in all forms - e.g. demand, lead time, etc. - is holding (extra) inventory. Therefore, a common approach to deal with disruptions is holding extra inventory. An excellent overview of inventory as mitigation strategy is provided by Atan and Snyder (2012). Although holding extra inventory is a proper mitigation strategy it is best usable in situations where disruptions are frequent and have a low impact profile, due to the costs associated with holding extra inventory for the mitigation of risks stemming from more infrequent severe disruptions. Therefore, for more severe and infrequent disruptions a sourcing mitigation policy is more preferable.

Sourcing mitigation is another well known proactive strategy that mitigates disruption risk by selecting different sources of supply. Sourcing mitigation has two different constituents: routine sourcing and contingent rerouting, which is a more reactive in nature. The former deals with dampening the effects of a disruption by selecting a mix of reliable and unreliable suppliers (Snyder et al., 2010). In many models for routine sourcing a newsvendor model, which takes into account supply uncertainty, is used for supplier selection (see e.g. Dada et al. (2007)). Contingent rerouting deals with the allocation of order quantities to different suppliers when one of the suppliers is disrupted. Although this strategy is characterized by dealing with a disruption ex post it is classified as proactive, because the selection of back-up suppliers happens upfront in the form business continuity plans (Kleindorfer and Saad, 2005).

A final proactive strategy is using contracts. Contracts can be used in order to create flexibility by adding incentives to a contract. These incentives are, for example, based on sharing information on disruptions between a supplier and retailer. The majority of approaches to add incentives to a contract are summarized in Snyder et al. (2010).

**Reactive strategies**

Reactive strategies provide mitigation directions after or during the occurrence of a disruption and are focussed on minimizing losses during or after a disruption. From Section 1.1 it is inferred that Dell used demand management in order to switch demand to other products by changing the price and using promotion tactics. While Dell managed demand via price there exist several other approaches to manage demand. Shao (2012) states three different additional approaches for demand management.

- Back order demand until supply has recovered
- Pay a penalty to customers of whom demand cannot be fulfilled
• Offer a menu of choices (leave, substitute, and buy a high or low value product)

By analyzing these strategies Shao (2012) indicates that back ordering demand is the worst strategy in an assemble-to-order multi-product system and offer a menu of choices outperforms the other strategies.

2.2 Revenue Management

In section 2.1.1 demand management is described as a reactive mitigation strategy. Although it can be used as a reactive mitigation strategy, the majority of research on demand management is conducted within the field of revenue management. In this thesis revenue management will be defined as the field of research devoted to increase profit by deciding on prices and/or inventory. More explicitly revenue management is defined as: “the art of maximizing profit generated from a limited capacity of a product (resource) over a finite horizon by selling each product to the right customer at the right time for the right price” (Pak and Piersma, 2002, p.1).

Although it seems that pricing and revenue management are similar, there exist a difference between the two concepts. In literature pricing is concerned with the price conditional on a sale, while revenue management takes into account that a sale does not always have to occur (Lazear, 1986). Therefore, in this thesis pricing is used to define the actual determination of the offered price by the retailer. Furthermore, based on the three types of decisions within revenue management, pricing can be considered as a part of revenue management. All the decisions within revenue management are summarized in the following bullets (Talluri and van Ryzin, 2004).

- **Structural decisions**: strategic decisions on which tactics should be used
- **Quantity decisions**: acceptance or rejection of an order or allocation of capacity
- **Price decisions**: deal with decisions how to set price

Within these three fields of decision making there exist a variety of modeling approaches, the focus of this thesis, however, is to develop a policy that jointly examines inventory and pricing decisions when supplies are possibly disrupted. Therefore, modeling approaches on pricing and inventory decisions will be discussed in the subsequent sections.

2.2.1 Demand modeling

In order to understand the differences in results for approaches that jointly examine pricing and inventory decisions some clarification on demand modeling is requisite. In revenue management there exist several approaches to model demand as a price dependent function. General approaches for modeling price dependent demand are either considering deterministic demand or stochastic demand (Yano and Gilbert, 2005). When stochastic demand is considered there exist multiple approaches to take demand uncertainty into account. The two commonly used approaches for taking demand uncertainty into account are to include additive or multiplicative demand uncertainty (Yano and Gilbert, 2005). For the former case demand is modeled by a sum of a price dependent deterministic demand function and a price independent random noise term. The latter case consists of the product of a price dependent demand function and a price independent random noise term.
Another common approach to model customer demand is by using a reservation price or a so-called reference price. A customer reservation price is best described as a customer individual valuation against which a purchase is judged (Monroe, 1973). By using a reservation price distribution a researchers assumes the following simple decision rule for each customer: “...if his reservation price (or valuation) equals or exceeds the offered price the customer purchases the product” (Talluri and van Ryzin, 2004, p.303).

2.2.2 Pricing and inventory decisions

In line with Elmaghraby and Keskinocak (2003) literature on pricing and inventory decisions is divided in two classes based on the existence of a replenishment option. In modeling approaches which do not consider a replenishment option, price is characterized as clearance sale price - i.e. the price used to obtain an inventory level at the end of planning horizon. When there exists a replenishment option several approaches are present in literature. Research considering a replenishment option can be divided into single-period and multi-period models. Both modeling approaches are concerned with jointly or sequentially examining inventory and pricing decisions. However, in single and multi-period models differences exist in the conditions under which solutions are optimal (Chen and Simchi-Levi, 2010). First of all this difference stems from the fact that demand is modeled either stochastic or deterministic (see Section 2.2.1). Due to this variety in price dependent demand modeling approaches differences in the variances and coefficients of variation for the considered demand modeling approach are obtained. As a result of these differences the conditions for optimality differ (Yano and Gilbert, 2005). Furthermore, modeling approaches differ in how to incorporate costs especially with regard to fixed and proportional costs. In models in which a combined fixed (setup) and proportional cost structure is considered, the cost function tends to be concave due to economies of scale or for example incremental discounts provided by the supplier. While, solely considering proportional ordering costs, the cost function tends to be convex - e.g. the marginal cost of purchasing increases when the company orders more (Chen and Simchi-Levi, 2010). In modeling approaches with convex cost functions research is focused on finding conditions under which a base-stock list price policy is optimal. The base-stock list price policy manages inventory via a normal base-stock policy. Pricing is done according to the following rules: when inventory is above the base-stock level a discount is given, if inventory is below or equal to the base-stock level the list price is charged (see e.g. Federgruen and Heching (1999)). When the cost function is concave literature is focused on finding conditions under which an \((s, S, p)\) policy is optimal in case of additive demand and an \((s, S, a, p)\) policy is optimal for other forms of stochastic demand. In these policies an \((s, S)\) policy is used in order to manage inventory. In addition, for non-additive demand cases the set \(a\) consists of inventory levels for which an order may or may not be placed and the offered price is dependent on the current level of inventory (Chen and Simchi-Levi, 2004).

Besides to the policies mentioned in the previous part there exists a study that examines pricing decisions by using pricing reference inventory levels. Feng and Chen (2003) examine policies of the following type \((s, S, d, D)\). In this policy inventory is managed according to an \((s, S)\) policy. Furthermore, \(d\) and \(D\) represent pricing reference inventory levels. These levels indicate that the price is equal to either the price level \(P_1\) or \(P_2\) when inventory equals, exceeds, or is between these levels.
2.2.3 Supply uncertainty and pricing

To our knowledge there exists no research that incorporates supply chain disruptions and pricing decisions into a single model. However, there are models known that incorporate another exhibition of supply chain uncertainty by considering yield uncertainty - i.e. the delivered quantity differs from the ordered quantity. Furthermore, all of these models are responsive of nature which entails that a pricing decision is made after all forms of uncertainty are observed.

The first model that incorporates yield uncertainty is developed by Li and Zheng (2006). In their model Li and Zheng (2006) indicate that pricing takes place after all forms of uncertainty are observed and is therefore characterized as a responsive pricing model. By using this approach Li and Zheng (2006) indicate that production is triggered by a threshold value, which is independent of the yield variability. Furthermore, the authors indicate that a system with yield uncertainty will always charge higher prices compared to a system with certain yield. This model is further extended by Kazaz (2008) in three directions; (1) by using a two period model in which supply variability and demand are observed consecutively; (2) the model is extended for the back orders and lost sales case; (3) a yield dependent price for the back-up supplier is used. By making these adjustments Kazaz (2008) indicates that just setting the price based on the sum of ordering and production costs is not sufficient. The last modeling approach is developed by Qi (2010) who indicates that a threshold value exists; when inventory reaches this threshold value a new order is placed and the optimal price and order quantity are chosen in order to achieve a constant target safety stock.

This thesis will contribute to the above mentioned literature in several ways. First of all this thesis is among the first approaches to incorporate a pricing reference inventory level to manage demand when a disruption occurs. A second contribution is made by being the first pricing approach, in contrary to the approaches discusses above, which is proactive in nature - i.e. the pricing reference inventory level and price increase are determined ex ante. The final contribution to existing literature of this thesis is that it incorporates customer reservation prices into a traditional base-stock model for inventory management.

2.3 Summary

From the reviewed literature in this chapter it can be inferred that there exist many approaches to mitigate disruption risk. Furthermore, there are many approaches known in which companies try to boost profit by managing demand or by jointly examining pricing and inventory decisions. However, until now no attempt has been made to incorporate supply chain disruptions into a pricing and inventory model. The only form of supply uncertainty that has been taken into account is yield uncertainty.
CHAPTER 3
Methodology

By combining the reviewed literature in Chapter 2 with the examples presented in Section 1.1, this chapter provides the problem definition for this thesis. The structure of this thesis will be discussed by using the research design of Mitroff et al. (1974) cited by Betrand and Fransoo (2002). This chapter will be concluded by discussing the main goals and contributions of this thesis and the research questions derived from them.

3.1 Problem definition

Currently companies are focused on decreasing costs by using JIT principles. Due to this change in focus companies are becoming increasingly vulnerable to supply chain disruptions in their day to day operations (Snyder et al., 2010). Hendricks and Singhal (2005) indicate that in addition to short term losses, disruptions negatively affect a company’s long term operating income, return on sales and return on assets. Therefore, due to the (financial) damage caused by a disruption and the increased focus on JIT principles a proper mitigation strategy is becoming a competitive advantage as indicated in the Ericsson example (Norman and Jansson, 2004) in Section 1.1.

In order to prevent itself against all sorts of supply chain risks and disruptions in particular, a retailer may use a variety of disruption mitigation strategies (see Section 2.1.1 for an overview). Although, these different strategies do decrease risk, there exists no general approach to manage the risk stemming from disruptions. Furthermore, based on the discussed literature no general approach exists in order to examine pricing decisions when supplies are uncertain. The current and most common approach to model supply uncertainty combined with pricing is by incorporating yield uncertainty. However, all of these approaches use a responsive pricing model in which the price is determined after all forms of uncertainty are observed (see e.g. Li and Zheng (2006)).

It can be argued that due to a shortage of products, caused by disruptions, the offered price is subjected to change. The Dell example in Section 1.1 provides support for the argument that demand management is a useful tool in mitigation of risks when a disruption occurs. Based on these observations the following problem statement is defined.

Companies face supply chain disruptions in their day to day operations. Several mitigation strategies for minimizing the risk stemming from these disruptions exist. Although several approaches are known to manage demand via price it is never examined if these approaches are useful for mitigating disruption risk.

3.2 Research design

For this thesis the research model developed by Mitroff et al. (1974) and cited by Betrand and Fransoo (2002) is used as backbone. This model is depicted in Figure 3.1.
In the previous section the problem statement is provided. Based on this problem statement a conceptual and scientific model will be developed throughout Chapter 4. In order to examine the behavior of this model a base case scenario is developed in Chapter 5 and a sensitivity analysis for all the relevant parameters is conducted in Chapter 6. In the concluding chapter of this thesis the implications for managers are stated and the main conclusions are outlined.

This thesis is characterized by its exploratory nature. Within this thesis the influence of several parameters on a newly developed combined inventory and pricing policy are examined and the influence of this policy on a single retailer’s revenue, costs, and profit is examined. Therefore, no optimization is carried out.

3.3 Objective

Based on the problem definition, the aim of this thesis is to develop a new mitigation strategy that incorporates knowledge from literature on revenue management and on mitigation strategies.

From Section 2.2.3 it can be inferred that the majority of the models which incorporate supply chain uncertainty use a threshold like policy to set price or to trigger production. Therefore, this thesis will develop a policy along similar lines as Feng and Chen (2003) in which multiple threshold values are used in order to select a high or low pricing level. In this thesis, however, only a single threshold value is used. The general logic behind this new mitigation strategy, in the form of a combined inventory and pricing policy, is that in order to minimize costs, price is increased to minimize the number of back orders. Therefore, the following pricing policy is proposed: the price of the product is increased, with a percentage $\delta$, when net inventory is below or equal to the pricing reference inventory level $k$. When net inventory is restored to a level above this threshold the price is restored to the initial value. Based on this outline the proposed policy is characterized as follows: inventory is managed according to an $(S, k)$ policy and pricing is done according to an $(P, \delta)$ policy. In Figure 3.2 an overview of the decisions based on the net inventory (orange line) for a case in which zero lead time is assumed is depicted.
By means of a numerical analysis the influence of several parameters in the model will be examined in order to develop some managerial insights for cases in which a retailer’s supplies are uncertain due to disruptions.

3.4 Contribution and relevance

To our knowledge current research is either focused on revenue management or mitigation of disruption risks by changing the price or by taking either proactive or reactive measures in order to minimize the risks stemming from disruptions. However, in line with the literature review from Chapter 2 it can be inferred that there exists no mitigation strategy that uses a price changing policy when net inventory is lower than or equal to a threshold value. Therefore, this thesis will contribute to existing literature by being among the first approaches that uses a pricing reference inventory level - i.e threshold value - in order to manage demand when a disruption occurs.

Some of the examples in Section 1.1 provide an excellent overview of currently used demand management techniques by companies. However, all of these strategies are characterized by their reactive nature - e.g. all decisions are made at the time of disruption and no pre-determined plan is set up for the case when a disruption occurs. This policy however, determines the price increase and the threshold value ex ante. Therefore, this policy is more proactive in nature.

Another contribution of this thesis is that it considers a price dependent demand function by incorporation of a customer reservation price into a traditional base-stock model. While a traditional approach to incorporate demand uncertainty in inventory models is to consider a known demand distribution independent of the offered price.

It must be noted that this project is conducted internally at the Eindhoven University of Technology and is therefore not tested with real world data and makes reasonable assumptions on customer behavior, inventory management, lead time, and the supplier disruption profile. However, this thesis provides usable insights for managers in order to minimize losses caused by supply chain disruptions by changing the price after net inventory is equal to or below a certain threshold inventory level.
3.5 Research questions

The main points of interests for the effects of the proposed policy are presented in 6 research questions below. These questions are used in order to evaluate the proposed policy and provide directions for the remaining parts of this thesis.

In the literature there exist many mitigation strategies (see Chapter 2). Furthermore, different strategies are suitable for different characteristics of the disruptions. First of all, Atan and Snyder (2012) state that an useful mitigation strategy is depending on the disruption characteristics and as a result inventory is a good mitigation strategy for frequent low impact disruptions. Furthermore, responsive pricing is argued to be a valuable tool when supply uncertainty is high (Tang and Yin, 2007). As a final addition, from the hurricane Katrina example in Section 1.1 it can be inferred that during infrequent high-impact disruptions prices will increase dramatically. Therefore, the first research question is the following:

1. What is the influence of disruptions on pricing decisions of a single retailer?

In this thesis a new mitigation strategy is developed. However, in order to examine the influence of this new policy the effects of disruptions on the new policy need to be examined. The first element of the new policy that will be influenced by disruptions is the pricing inventory reference level ($k$). It can be argued that when disruptions are infrequent and have a low impact prices do not have to be changed frequently, which results in a low value for $k$. However, when disruptions have a high impact and a similar rate of occurrence it can be argued that $k$ is higher compared to the low impact case in order to prevent the retailer for excessive back orders and the associated costs. Therefore the following research questions is denoted.

2. What is the influence of disruptions on the pricing reference inventory level?

In extension to research question 2 it can be obtained that $k$ and the base-stock level ($S$) are also influenced by each other. When $S$ is low it can be argued that $k$ is low as well, otherwise the retailer will charge the high price for a large amount of time and will eventually sell less. In order to examine the behavior of the base-stock level and pricing reference inventory level the following research question is denoted.

3. How is the pricing reference inventory level affected by the base-stock level?

Another extension for research question 2 is to examine the influence of disruptions on the price increase $\delta$. It can be argued that for different disruption and recovery rates, the price increase is affected.

4. What is the influence of disruptions on the price increase?

By using the second research question the effect of the base-stock level on $k$ is examined. However, it can be argued that due to an increase in price the retailer will sell less items and in return needs a lower base-stock level in order to prevent stock-outs. In order to examine this reasoning the following research question is denoted.
5. What is the effect of the pricing reference inventory level and price increase on the base-stock level?

By using research questions 1 through 5 the behavior of the policy is examined. However, none of these research questions examine if the obtained values for the policy parameters will be optimal or near-optimal. Hereof, research question 6 is denoted in order to examine if there exist optimal or near-optimal values for the policy parameters of the proposed policy.

6. Do there exist any conditions under which the policy parameters are optimal?
4 Chapter 4

Model

In this chapter the basic setting for examining the influence of supply chain disruptions on a single retailer’s pricing and inventory decisions is discussed. In order to limit the model behavior in Section 4.1 the scope is defined and an elaboration on the basic assumptions is provided. In Section 4.2 these assumptions are translated to each of the corresponding constituents of the model, by describing the conceptual model. An overview of all assumptions is provided in Appendix B.

4.1 Scope

In order to examine the behavior of the system and to analyze the effects of implementing the proposed policy the scope for this thesis is narrowed to a single location - e.g. a retailer - single supplier, single product setting. The use of a single supplier setting results in a dependent relationship for the retailer and supplier. Due to this dependency an opportunity to examine the influence of disruptions on a single retailer’s pricing and inventory decisions is provided. However, it is assumed that the retailer does not have any information on the current state of the supplier and can solely obtain this information by means of the supply process - i.e. when orders are not delivered on time. Furthermore, it is generally assumed that orders already shipped by the supplier are not affected by disruptions. Further elaboration on this assumption is provided in Section 4.2.3.

From academic literature on revenue management it can be inferred that the majority of researchers use a setting in which the retailer under consideration operates in an environment that is characterized by imperfect competition - i.e. the retailer acts as a price setter or, to a further extent, the retailer is a monopolist (Chan et al., 2004; Chen and Simchi-Levi, 2010). Based on this observation in revenue management literature the scope of this thesis will be narrowed to a retailer with the ability to set prices. This setting provides the possibility to examine the influence of disruptions on actual pricing decision(s), due to the fact that demand is directly influenced by changes in the offered price, by using a price dependent demand function.

In order to examine the influence of customer behavior - e.g. whether or not the customer buys the product - a business-to-customer (B2C) setting is selected. By assuming that the retailer acts as a price setter further entails that customer’s buying decisions are affected by the retailer’s pricing decisions.

The retailer charges a price based on the current on-hand inventory. By comparing this offered price to his reservation price each customer decides whether or not to buy the product. Therefore, the retailer uses a posted price strategy and does not try to discover the customer reservation prices via, for example, an auction. In several pricing research papers assumptions are made on customer behavior - e.g. the customer acts as strategic buyer and the arrival rate of the customer. In this thesis it is assumed that customers will arrive according to a Poisson process, which is discussed in more detail in Section 4.2.2. In extension to the customer arrival process, each customer will act as a non-strategic buyer, which entails that each customer will not adapt his behavior - e.g. arrival rate and reservation price - owing to pricing and inventory decisions made by the retailer.
Furthermore, similar to the retailer it is assumed that customers do not have any information on the current state of the supplier. This is in line with the non-strategic behavior assumption and will help to prevent customer panic buying (Shou et al., 2011) or the Reverse Bullwhip Effect (RWBE) which states that customer anticipate differently to changes in price than expected (Rong et al., 2009)

It is possible to roughly divide products into two distinct classes: perishable and durable products. The main difference between these product classes is the fact that perishable products have a time dimension. This dimension entails that a product must be sold before a specified time horizon and is considered as scrap afterwards. By focusing on pricing and inventory decisions, product perishability is left out of scope. By considering durable goods it is assumed that products can be held on stock for an infinite duration of time. Furthermore, in order to limit the possible solution space it is assumed that the product is heterogenous and no substitute for the product exists.

This thesis aim is to increase a single retailer’s profit, when supplies are considered to be uncertain, by using a combined inventory and pricing policy. A number of possible parameterizations of this combined policy will be evaluated based on their long run expected profit. The objective function for this thesis is provided in Section 4.3.

![Diagram](image)

**Fig. 4.1: Scope**

### 4.2 Conceptual model

The previous section defined the scope and narrowed it to a single retailer, single supplier single product setting. In line with this scope this section elaborates on the individual assumptions made for each part of the system depicted in Figure 4.1. Throughout this section and the remainder of this thesis the subscript \(i\) represents the arrival of the \(i^{th}\) customer. The total number of customers is represented by \(N\).

The remainder of this section starts by discussing the relevant assumptions with regard to the retailer. In Section 4.2.2 the demand process characteristics will be discussed, followed by a section on the characteristics of the supplier and a section on the supply process.

#### 4.2.1 Retailer

The retailer faces demand via the demand process - arrow 1 in Figure 4.1 - and orders are received via the supply process - arrow 2 in Figure 4.1. When demand cannot be fulfilled directly from stock it will be back ordered. In addition, it is assumed that in case the retailer has stock customer orders are delivered immediately - i.e. the customer lead time equals 0.

In this section the retailer’s decision variables are discussed. The retailer can influence its profit by changing the following variables; the base-stock level \((S)\), the pricing reference inventory level \((k)\), and the price increase \((\delta)\).
Base-stock level

For inventory management a continuous-review base-stock policy is selected. A continuous-review policy is selected for the fact that inventory is reviewed after each customer arrival. Furthermore, by using a continuous review policy the retailer can obtain information on the state of the supplier within less amount of time compared to a periodic review policy, especially when no lead time is assumed.

By using a continuous review inventory model it is implied that every time when inventory hits a level below the base-stock level $S$ an order is placed to restore inventory back to $S$. Furthermore, this entails that the inventory position ($IP_i$) - i.e. the net on-hand inventory ($Y_i$) plus the total outstanding orders ($O_i$) minus the total outstanding back orders ($B_i$) will always be equal to $S$ after each customer arrival.

$$IP_i = S \quad (4.1)$$

By incorporating the statements for the inventory position into condition 4.1 this results in.

$$IP_i = Y_i + O_i - B_i \quad (4.2)$$

Pricing reference inventory level

Recall from Section 4.1 that the goal of this thesis is to develop a combined inventory and pricing policy in order to maximize a single retailer’s profit under uncertain supplies. In this policy $k$ entails the pricing reference inventory level which is used in order to prevent the retailer for major stock outs and associated back order costs. When on-hand inventory, at time of a customer arrival, is below this level the price will be increased with a percentage $\delta$. To prevent that the retailer will solely charge the increased price $k$ is limited to be between 0 and $S - 1$. Therefore, the following statement for the pricing reference inventory level is obtained.

$$k \in (0,..,S - 1) \quad (4.3)$$

Although it is assumed that unmet demand is back ordered the values for $k$ are restricted to solely positive integers in order to limit the possible solution space.

Price

The offered price by the retailer at the time of a customer arrival is represented by $P_i$. This value is either $P$ - i.e. the price initial offered by the retailer - or $(1 + \delta)P$ - i.e. increased posted price when net inventory is equal or below $k$. Based on the previous it holds that $P < (1 + \delta)P$. In order to limit the possible solution space it is assumed that the price can be doubled at maximum - i.e. the highest value for $\delta$ equals 100%.

$$\delta \in (10\%,...,100\%) \quad (4.4)$$

Furthermore, due to the exploratory design of this thesis incremental steps of 10% are used when exploring the long run expected profit maximizing setting for the proposed policy.
4.2.2 Demand process

Demand is characterized by the arrival process of customers and their reservation prices. Furthermore, it is assumed that the customer order quantity is unaffected by the retailer’s decision on price. The buying quantity for each customer is assumed to be equal to 1 unit.

Arrival process

In line with the general assumption in inventory management literature it is assumed that customers arrive with an exponentially distributed inter arrival time ($IAT$). This entails that the customers arrive according a Poisson process with an average number of customers arriving per day ($\lambda_c$). Recall from the scope of this thesis that the customer acts as a non-strategic buyer. Therefore, $\lambda_c$ is not subjected to change over time and is unaffected by the retailer’s pricing and inventory decisions.

\[ Arrivals \sim \text{Poisson} (\lambda_c) \]  \hspace{1cm} (4.5)

And subsequently.

\[ IAT \sim \text{Exponential} \left( \frac{1}{\lambda_c} \right) \]  \hspace{1cm} (4.6)

Reservation price

In Section 2.2.1 several approaches to model demand are discussed. For this thesis a customer reservation price approach is selected, because this approach makes it possible to determine individual product valuations for each arriving customer. Individual customer reservation prices are represented by $P_r$. In order to determine the reservation price of an individual customer there exist two major approaches. The first approach is a memory based approach and the second approach uses a cumulative distribution function.

The first approach to model the customer reservation price is a memory based approach. In this approach a weighted average or exponential smoothing of historical prices is used in order to determine the current reference price (Greenleaf, 1995). By using these estimation methods an underlying demand curve is developed. However, the use of this approach can lead to a more volatile demand curve due to customer anticipation on changes in price (Rong et al., 2009). Recall from the scope of this thesis that customer behavior is assumed to be non-strategic, therefore, customers will not adapt their reservation price according to changes in price made by the retailer. Furthermore, there is no previous pricing data available. Therefore, a cumulative distribution function is selected in order to generate customer reservation prices. In this thesis it is assumed that customer reservation prices are lognormally distributed. The lognormal distribution is selected due to the fact that this distribution has normality in it and does not allow for negative values - i.e. customer valuations cannot be negative. In order to model the customer reservation prices by means of a lognormal distribution the mean ($\mu_r$) and variance ($V_r$) need to be specified. The expected reservation price is similar to the initial offered price by the retailer $P$. It seems reasonable to assume that on average customers arriving at the retailer have an expected reservation price equal to the initial offered price. For selecting the variance it must be remarked that when the variance is increased the percentage of customers willing to pay a higher price is increasing as well. Therefore, the variance is selected in a manner such that for low prices, approximately all the
customers are willing to buy the product. Furthermore, the variance is selected in a way that for a price 3 times $P$ approximate no customers are willing to buy the product. If the mean and variance are selected the lognormal distribution could be parameterized by using the following statements.

$$m = \log \left( \frac{\mu_r}{\sqrt{\mu_r^2 + V_r}} \right)$$  \hspace{1cm} (4.7)  

$$v = \sqrt{\log \left( \frac{V_r}{\mu_r^2} + 1 \right)}$$  \hspace{1cm} (4.8)  

By using these parameters reservation prices have the following distribution.

$$P_r \sim \text{Lognormal} (m, v)$$  \hspace{1cm} (4.9)  

### 4.2.3 Supplier

As described in Section 4.1 the research setting is limited to a single retailer, single product, and a single supplier. In which the supplier faces random distributed disruptions characterized by the disruption profile. Snyder et al. (2010) indicate that a common approach to model disruptions is to represent the disruption profile with a two state Markov chain, with an “up” and a “down” state. In line with this observation a two state continuous time Markov chain ($CTMC$) is used in order to represent the supplier’s disruption profile (see Figure 4.2). In the “up” state the supplier is able of delivering all the orders on time. In addition, to examine the influence of the disruption profile on inventory and pricing decisions, it is assumed that during an “up” state the supplier has infinite capacity. This assumption further entails that orders placed before disruptions are unaffected by the suppliers disruption, due to the immediate shipment of orders. On the contrary in a “down” state the supplier still has infinity capacity but is unable to deliver any order. For both states it is assumed that the supplier is for an exponential distributed amount of time. The rate of going from a “up” state to a “down” state is represented by $\alpha$ - i.e. the disruption rate. The rate for the reverse direction is given by $\beta$ - i.e. the recovery rate. In addition, the expected average time spent in each of the states is given by $\frac{1}{\alpha}$ for the “up” state and $\frac{1}{\beta}$ for the “down” state.

![Fig. 4.2: Supplier Markov chain](image)

From a modeling perspective it is assumed that at time 0 the supplier is in an “up” state.

### 4.2.4 Supply process

The supply process consists of the orders placed by the retailer and the shipped orders.
Ordering

By assuming a continuous-review base-stock policy the retailer will immediately place an order at the supplier when demand occurs. If the supplier is in an “up” state orders will be shipped directly with lead time $L$. Therefore, a flow of individual orders is created between supplier and retailer. When the supplier’s state changes from a “down” state to the “up” state it is assumed that all orders placed during the disruption are combined and shipped with lead time $L$.

Lead time

For the base case model and the majority of the sensitivity analysis it is assumed that lead time equals 0. This assumption provides a way to analyze the influence of the disruption profile and other relevant parameters on the pricing and inventory decisions of the retailer. However, using zero lead time results in a constant net inventory equal to the base-stock level $S$ whenever the supplier is undisrupted. Therefore, assuming zero lead time will probably allow the retailer to maintain a lower base-stock level compared to cases in which lead time is a fixed integer greater than 0. Furthermore, when orders placed during a disruption are delivered immediately after the supplier becomes available again the possibility arises that, from a retailer’s perspective, supply disruptions are favored in order to minimize holding costs. Therefore, in extension to the zero lead time assumption in the sensitivity analysis the influence of lead time is examined. This lead time is fixed in order to minimize the number of stochastic variables and for the ease of analysis.

4.3 Objective function

The objective is to evaluate different settings - i.e. different values for $S$, $k$, and $\delta$ - of the proposed policy based on its corresponding long run expected profit. In order to determine the objective function the cost parameters and associated costs functions have to be identified and the resulting profit function needs to be determined.

4.3.1 Costs

By assuming a base-stock policy, it is implicitly assumed that fixed ordering or setup costs are negligible. Furthermore, due to the use of this policy no proportional ordering costs are considered. Therefore, solely back ordering ($b$) and holding ($h$) costs will be included in the model. Back ordering costs represent the cost paid for the loss of customer goodwill when the customer has to wait until the product is delivered by the supplier. Holding costs represent the costs paid by the retailer for carrying one unit of inventory for a specified unit of time. Furthermore, it is assumed that back ordering and holding costs are proportional to the number of outstanding back orders and on-hand inventory respectively. In the scope of this thesis it is stated that the performance of each of the model parameterizations will be evaluated according to the corresponding long run expected profit. Therefore, the following expression states the total expected costs resulting from the selected $S$, $k$, and $\delta$ values.

$$C (S, k, \delta) = hE[I (S, k, \delta)] + bE[B (S, k, \delta)] \quad (4.10)$$
4.3.2 Profit

In order to evaluate the effects of the selected $S$, $k$, and $\delta$ values the long run expected profit of each combination is used. Therefore, the expected revenue corresponding to the selected values needs to be determined. In Section 4.2.1 the offered price at the retailer at time of customer arrival, which is indicated by the subscript $i$, is represented by $P_i$. Therefore, total revenue, for each parametrization of the combined policy, is defined by.

$$\pi (S, k, \delta) = \sum_{i=1}^{N} P_i D(P_i)$$

(4.11)

In equation 4.11 $D(P_i)$ refers to the demand corresponding to the offered price during the time of a customer arrival. In Section 4.2.2 the buying quantity of an individual customer was assumed to be equal to 1. Furthermore, recall from Section 4.2.2 that the customer decides to buy the product based on the price charged at the time of his arrival ($P_i$) and his own reservation price ($P_r$). This results in the following expression for the buying decision for each customer.

$$D(P_i) = \begin{cases} 1 & \text{if } P_r \geq P_i \\ 0 & \text{if } P_r < P_i \end{cases}$$

(4.12)

Equation 4.11 provides the total revenue over the simulation time. In order to determine the expected revenue, the total revenue for a single simulation run is divided by the total simulation time elapsed. Therefore, the expected revenue is given by equation 4.13.

$$E[\pi (S, k, \delta)] = \frac{\pi (S, k, \delta)}{T}$$

(4.13)

In this statement $T$ represents the time of the last customer arrival ($N$) and is similar to the total simulation time elapsed. Using this statement the total expected long run profit can be obtained, by including the cost expression from the previous section.

$$E[\tau (S, k, \delta)] = E[\pi (S, k, \delta)] - C(S, k, \delta)$$

(4.14)

By incorporating the cost statement the following objective function is obtained.

$$E[\tau (S, k, \delta)] = E[\pi (S, k, \delta)] - hE[I(S, k, \delta)] - B E[B(S, k, \delta)]$$

(4.15)

4.4 Simulation model

From Section 4.2 it can be obtained that there exist a large number of stochastic variables in the considered problem. Due to these stochastic variables it is hard to obtain analytical results for the model in Section 4.4.1. Therefore, a simulation model will be used in order to obtain the answers to the research questions of Section 3.5 and provide a numerically analysis of the model. For analysis a Visual Basics for applications (VBA) code for Excel is written which repeats the sequence depicted in Figure C.1 in Appendix C. Furthermore, in order to generate input of the input models the random generating function of MATLAB for the lognormal and exponential distribution are used.
4.4.1 Mathematical relations

Based on the assumptions made in Section 4.1 through Section 4.2 the following mathematical model is constructed. In Appendix A an overview of all relevant variables is provided in Table A.1 through Table A.5.

Model

Recall from Section 4.1 that the goal of this thesis is to determine the profit maximization parameterizations of a combined inventory and pricing policy with decision variables $S$, $k$, and $\delta$. This results in the goal function to maximize equation 4.15.

$$\max_{\tau(S, k, \delta)} \mathbb{E} \left[ \tau(S, k, \delta) \right] = \mathbb{E} [\pi(S, k, \delta)] - h \mathbb{E} [I(S, k, \delta)] - B \mathbb{E} [B(S, k, \delta)]$$

Subjected to.

- $Y_i + O_i - B_i = S$
- $k \in (0, ..., S - 1)$
- $\delta \in (10\%, ..., 100\%)$
- $P_i \in (P, (1 + \delta)P)$
- $D_i = D(P_i)$
- $i \in (1, ..., N)$
- $S, h, b \geq 0$

All these conditions are derived from Section 4.2.

4.4.2 Validation

In order to examine if the model holds plausible results a validation step is carried out. There exist several methods to validate a simulation model (Sargent, 2007). This model is validated by using an extreme condition test. In an extreme condition test it is checked if the model holds plausible results for cases of extreme values of certain parameters (Sargent, 2007). This method is used by having extreme values for; disruption and recovery rate, customer reservation price, price, and for some cases lead time. For all of these conditions it can be obtained that the model holds plausible results. For example, when the expected customer reservation price was higher than the offered price it holds that the retailer had to hold extra stock in order to prevent for back orders and the associated costs.
4.5 Evaluation criteria

In order to use the results from the model some evaluation criteria have to be determined. A traditional approach in inventory management literature is to check for the cost minimizing value of the base stock level. However, in this thesis price is subjected to change and it is expected that by charging a higher price the demand rate is changed. Due to this changing price and demand, policies will be evaluated based on their long run expected profit. In order to compare some parameter settings and to evaluate if the proposed policy is an improvement compared to a base-stock policy the expected costs and revenue will be incorporated in the analysis as well. All the evaluation criteria are summarized in the bullets below.

- Expected revenue
- Expected costs
- Expected long run profit
- Expected inventory
- Expected back orders
- Average price paid

4.6 Heuristic

To determine near-optimal values for \( S, k, \) and \( \delta \) a heuristic is developed. The heuristic consists of two subsequent steps. An initial step to determine the values of \( S, k, \) and \( \delta \) in a simulation run and an iterative step in which it is checked if the selection of some of the variables is affected by the selection of the other variables. When the decision variables are not changed in the iteration step the profit maximizing setting is selected.

1. Initial step
   (a) Determine the profit maximizing base-stock level, when disruptions are taken into account by using simulation
   (b) Use the obtained base-stock level to determine the initial values for \( k \) and \( \delta \)

2. Iterative steps
   (a) Determine if the base-stock level changes by the incorporation of \( k \) and \( \delta \)
   (b) If \( S \) changed use this new base-stock level to obtain values for \( k \) and \( \delta \)

This two step heuristic is depicted in Figure 4.3.
Fig. 4.3: Heuristic for determining the profit maximizing values of $S$, $k$ and $\delta$

In Chapter 5 this heuristic will be used in order to determine near-optimal values for the base case scenario developed throughout that chapter. In the sensitivity analysis of Chapter 6 solely the initial step of this heuristic is used in order to determine the effects of several parameters on the combined pricing and inventory policy, in addition it is examined if using the proposed policy results in different base-stock levels - i.e. the first step within the iteration.
CHAPTER 5

Base case scenario

In order to determine if the policy proposed in Chapter 3 can be used as a mitigation strategy, a base case scenario is developed. This chapter starts with determining the initial values of parameters discussed in Chapter 4. Afterwards, the base case scenario is analyzed for the traditional base-stock policy and the proposed policy. In the concluding section the heuristic from Section 4.6 is used in order to determine near-optimal values of $S$, $k$, and $\delta$ for the developed scenario.

5.1 Parameters

This section presents an overview of the initial values for all relevant parameters for the model in Chapter 4. An overview of the initial values of the relevant parameters is presented in Table 5.1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.5</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.5</td>
</tr>
<tr>
<td>$\lambda_c$</td>
<td>4</td>
</tr>
<tr>
<td>$P$</td>
<td>5</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>5</td>
</tr>
<tr>
<td>$V_r$</td>
<td>20</td>
</tr>
<tr>
<td>$h$</td>
<td>0.125</td>
</tr>
<tr>
<td>$b$</td>
<td>3</td>
</tr>
<tr>
<td>$N$</td>
<td>5,000</td>
</tr>
<tr>
<td>$L$</td>
<td>0</td>
</tr>
</tbody>
</table>

5.1.1 Disruption and recovery rate

The initial values for the disruption and recovery rate are selected to be 0.5. This stems from the fact that these rates reflect either no short or long disruptions and have no frequent or infrequent rate of occurrence. By using an initial simulation run for the setting presented in Table 5.1 it can be inferred that not all customers are affected by disruptions. Furthermore, comparing the results of a non-disrupted case with the results obtained in the simulation it is indicated that costs for the disruption case are higher. Therefore, it can be concluded that the selected disruption and recovery rate negatively affects the retailer’s costs and consequently its profit.
5.1.2 Customer arrivals

For the base case scenario an average number of 4 arriving customers per day is selected with a total number of customers arriving of 5,000. By using these numbers and the previous examined effects of the disruption and recovery rate on the retailer’s costs and profit it is concluded that by using these parameter settings a possibility to examine the influence of disruptions on the retailer’s pricing and inventory decisions is provided.

5.1.3 Reservation price

In the conceptual model it is assumed that the expected value of the customer reservation price distribution is equal to the price initially offered by the retailer. As a result the expected value of the customer reservation price distribution equals 5. Furthermore, the conceptual model provided conditions for the selection of variance of customer reservation price. Recall that the variance will be selected in such a manner that the total percentage of arriving customers that is willing to buy the product is decreasing in price, and for low prices it holds that the percentage of customers that is willing to buy the product is almost equal to 100%. Furthermore, the percentage of customers that is willing to pay a price 3 times the initial offered price is approximate none. Therefore, based on Figure 5.1 the variance of the customer reservation price is selected to be equal to 20.

By assuming an expected value of 5 and a variance of 20 for the customer reservation price distribution results in an initial demand rate of: \( \lambda_c \Pr (P_r \geq P_i) = 4 \times 0.351 = 1.40 \) units a day. Recall that in the proposed policy prices are subjected to change - i.e. increased when net inventory is below or equal to \( k \). As a result the demand rate decreases because \( \Pr (P_r \geq P_i) \) is decreasing in price (see Figure 5.1).
5.1.4 Cost parameters

Holding costs are selected to be 2.5% of the initially offered price. This percentage approximates the long run average interest percentage in the Netherlands until 2012\textsuperscript{1}. Although, the selected holding costs are low compared to the back ordering costs, this setting provided the possibility to examine the effect of disruptions. It must, however, be noted that using low holding costs will result in increased base-stock levels.

By assuming that back ordering costs are 60% of the initially offered price, a large proportion of the costs are related to back orders. Therefore, the majority of the costs consists of back ordering costs and as a result base-stock levels will be high especially due to the low holding costs. However, these high back ordering costs do not affect the examination of the influence of disruptions on pricing and inventory decisions.

5.2 Analysis

In this section the results and analysis of the base case scenario are presented. This section starts by examining the convexity of the cost function in the base-stock level. By using this convexity it is examined if using the proposed policy has any effect, positive or negative, on the retailer’s revenue, cost, and profit compared to the traditional base-stock policy.

As a final analysis the heuristic from Section 4.6 is used in order to determine the near-optimal base-stock level, pricing reference inventory level and price increase by using the settings from the base case scenario (see Table 5.1).

5.2.1 Cost function analysis

A cost function analysis is conducted in order to examine if the cost function is convex in the base-stock level. By assuring the convexity of the cost function in the base-stock level it can be obtained that a minimum exists. The examination of convexity of the cost function is done by means of graphical analysis. This is selected because no mathematical expression could be derived for the cost function due to the number of stochastic variables in the problem. The graphical analysis is conducted for several holding and back ordering costs.

Holding costs

In order to analyze if the cost function is convex in the base-stock level for several holding costs these are varied as shown in Table 5.2. Note that in Table 5.2 the holding costs are represented as a percentage of the price initially offered by the retailer.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
\textbf{h} & 2.5\% & 5\% & 10\% & 20\% & 40\% \\
\hline
\end{tabular}
\caption{Different holding costs}
\end{table}

\textsuperscript{1}http://www.tradingeconomics.com/netherlands/interest-rate
Combing the percentages from Table 5.2 and the expected inventory and back orders from Table D.1 in Appendix D results in the graph of Figure 5.2. In this analysis all other variables are kept similar to the values in Table 5.1.

From Figure 5.2 it can be observed that by increasing the holding costs the optimal base stock level shifts to 1 for \( h = 40\% \) from 8 for \( h = 2.5\% \). Furthermore, by dramatically increasing the holding costs - e.g. up to 40\% - it is observed that the cost function is almost linear. This behavior stems from the fact that there exists an interplay between the back ordering and holding costs. When holding costs are high the retailer wants to reduce the inventory in order to increase profit. On the contrary the retailer is protected by using high base-stock levels for excessive back orders. As a result of increased base-stock levels holding costs are increased and back ordering costs become negligible. Therefore, a linear pattern is emerging in Figure 5.2. Based on this analysis it can be observed that the cost function is convex in the base-stock level for different holding costs values.

**Back ordering costs**

In the previous section the convexity of the cost function in the base-stock level for different holding costs was examined. A similar analysis will be conducted in order to study if the cost function is also convex in the base-stock level for different back ordering costs. The different back ordering costs are presented in Table 5.3.

<table>
<thead>
<tr>
<th>( b )</th>
<th>20%</th>
<th>40%</th>
<th>60%</th>
<th>80%</th>
<th>100%</th>
</tr>
</thead>
</table>

By using the cost parameters combined with the data from Table D.1 in Appendix D the following cost graphs are obtained. In this analysis all other parameters are equal to the values in Table 5.1.
From Figure 5.3 it can be obtained that by increasing the back ordering costs the value for the base-stock level is increasing as well. This behavior is opposite to the resulting behavior of varying the holding costs, note that the base-stock level is decreasing in holding costs. By increasing the base-stock level it can be inferred that the number of back orders is minimized and therefore the associated back orders costs will be decreased. Furthermore, the “savings” from having less back orders will outweigh the increased holding costs as a result of holding extra inventory. Similar to the holding costs analysis it can be obtained from Figure 5.3 that for high base-stock levels costs are almost linear, due to an increased protection against back orders by holding ample inventory.

From this graphical analysis it can be concluded that the cost function is convex, in the base-stock level, with regard to the back ordering costs.

Conclusions

Based on the analysis of the holding and the back ordering costs it can be concluded that by means of a graphical analysis the cost function is convex in the base-stock level. By observing that the cost function is convex in the base-stock level it can further be assumed that the profit function is concave and therefore it is possible to select profit maximizing base-stock levels.

5.2.2 Analysis of base case scenario

In the previous section the convexity of the cost function in the base-stock level was observed. In this section this convexity will be used in order to determine if disruptions have any effect on the base-stock level and if using the combined inventory and pricing policy withholds any effects on the retailer’s revenue, costs, and profit compared to the traditional base-stock policy. An initial analysis is conducted in order to examine if disruptions have any effect on the traditional base-stock policy. Subsequently, the effects of the proposed policy on revenue, costs, profit, and base-stock levels of the retailer are examined.

From Figure 5.4 it can be observed that disruptions have an effect on the selection of the base-stock level. For the base case scenario a base-stock level of 8 is selected in order to maximize profit. This
in contrast to the situation in which no disruptions are considered for which a base-stock level of 1 is selected in order to maximize profit. Thereof, by considering disruptions the base-stock level is increased by 7 units. Furthermore, the profit is 18.45% higher for the case when no disruptions are considered.

![Fig. 5.4: Profit and costs for the base case scenario by using a base-stock policy](image)

In subsequent analysis the base-stock level will be fixed to 8 in order to determine the values of $k$ and $\delta$. Recall from Section 4.2.1 that $\delta$ is selected from the set (10%, ..., 100%) with increments of 10%. Furthermore, the pricing reference inventory level is selected from the set (0, ..., $S - 1$) this results in a variation of $k$ between 0 and 7. In Figures 5.5 and 5.6 profit and cost functions for some combinations of $k$ and $\delta$ are presented. In these figures a selection of the profit and costs functions for $k$ and $\delta$ combinations is presented. The pattern that emerges is, however, similar among all combinations.

![Fig. 5.5: Profit for combinations of $k$ and $\delta$ when $S = 8](image)  
![Fig. 5.6: Costs for combinations of $k$ and $\delta$ when $S = 8](image)

Figure 5.5 provides an overview of the profit function for several $k$ and $\delta$ combinations when $S$ is fixed to 8. From this figure it can be observed that the maximal profit is obtained for $\delta = 90\%$ and $k = 0$. Another interesting observation is made by comparing the cost functions of Figure 5.6 with the profit functions depicted in Figure 5.5. From this comparison it can be concluded that the profit maximizing $k$ in Figure 5.5 does not correspond to the cost minimizing $k$ in Figure 5.6.
- i.e. the costs corresponding to $\delta = 90\%$ are minimized for $k = 4$ while profit is maximized for $k = 0$. This observation is caused by the change in demand rate. In the undisrupted situation the demand rate is 1.40 units a day, however due to disruptions price can be increased by 90% resulting in a demand rate of 0.44 units a day. As a result of this changing demand rate inventory is increasing in $k$ and $\delta$, simultaneously less back orders are observed (see Figure D.3 in Appendix D). Furthermore, due to the decreased demand rate, for all combinations of $k$ and $\delta$ the revenue is decreasing (see Figure D.1 in Appendix D). Albeit this decrease in revenue, from Figure 5.5 it can be inferred that profit is increasing, due to the diminution of costs.

From Figure 5.5 it can further be observed that profit decreases dramatically for high levels of $k$. Due to the increased pricing reference inventory level price is changed earlier compared to low pricing reference inventory levels. As a result the time of having a low demand rate is increased. Therefore, the number of items sold is decreasing and the retailer’s holding costs will increase. In addition, this behavior can be observed for high values of $\delta$ which correspond to a more severe decrease in demand rate. Therefore, the decrease in costs cannot compensate for the decrease in revenue and subsequently the profit is lower for high $k$ and $\delta$ values.

If the cost functions in Figure 5.6 are examined more closely it can be observed that the cost function is relatively insensitive to $k$. The cost functions of Figure 5.6 are determined by varying $k$ and $\delta$ and having a base-stock level constant at 8 units. This base-stock level is obtained by using the normal demand rate of 1.40 units a day. Due to price increase the demand rate is decreased and back orders are minimized due to the selected $k$ and $\delta$ values. However, due to the fact that for the normal demand rate the back orders are already minimized by using a base-stock level of 8 only a small decrease in back orders is observed and consequently a small increase in inventory is observed. Therefore, the cost function is almost constant in $k$ for fixed base-stock levels.

From Figure 5.5 the profit maximizing pricing reference inventory level and price increase are obtained; $k = 0$ and $\delta = 90\%$. After selecting a price increase of 90% the demand rate is reduced with 68% - i.e from 1.40 units a day to 0.44 units a day. By fixing these parameters their influence on the base-stock level is examined. This results in the revenue, cost and profit functions presented in Figures 5.7, 5.8, and 5.9. The difference (grey line) between these graphs is given in percentage of difference between the traditional base-stock policy (orange line) - i.e. only using a base-stock policy- and the proposed policy (yellow line) - i.e. a pricing reference level $k$ and price increase $\delta$ are used.

From Figure 5.7 it can be observed that revenue for low base-stock levels is lower for the proposed
policy compared to using the normal base-stock policy. This difference stems from the change in demand rate resulting from the increased price. However, due to this change in demand rate the number of back orders is reduced and the associated costs are decreased dramatically (see Figure 5.8). By this dramatic change in costs, the profit is higher for low base-stock levels for the proposed policy (see Figure 5.9). However, when base-stock levels are increased the difference in profit between both policies is reduced to 0%. The main logic behind this observation is that for high base-stock levels, the retailer has ample inventory to deliver to the customer even during disruptions. Therefore, prices do not have to be changed frequently which results in a similar demand rate for both policies. However, when net-inventory is below 0 prices are changed when using the combined inventory and pricing policy which results in a changed demand rate. Therefore, revenue and subsequently profit is lower for high base-stock levels when the proposed policy is used. Furthermore, although back ordering costs are decreased this decrease cannot compensate for the increased holding costs.

Another important observation from Figure 5.7 through Figure 5.9 is that as an effect of the changed demand rate the base-stock level could be reduced to 6 when implementing the combined inventory and pricing policy. Contrary to an expected decrease in profit, profit is increased with 1.79% compared to the profit of solely using a base-stock policy.

5.2.3 Heuristic results

In order to determine near-optimal values for the decisions variables in the proposed policy the heuristic form Section 4.6 is used. In the previous section the initial step and the first step of the iteration step indicated that by implementing the proposed policy the base-stock level could be reduced to 6. In this section the iteration steps are repeated until none of the observed values for $S$, $k$ and $\delta$ change and the profit maximizing setting is selected. In Table 5.4 the results of using the heuristic are presented.

<table>
<thead>
<tr>
<th>Step</th>
<th>Initial</th>
<th>Iteration 1</th>
<th>Iteration 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S$</td>
<td>8</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>$k$</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0%</td>
<td>90%</td>
<td>90%</td>
</tr>
<tr>
<td>Costs</td>
<td>1.21</td>
<td>0.78</td>
<td>0.77</td>
</tr>
<tr>
<td>Profit</td>
<td>5.92</td>
<td>6.03</td>
<td>6.04</td>
</tr>
</tbody>
</table>

From Table 5.4 it can be concluded that after 2 iteration steps parameters of the values of $S$, $k$ and $\delta$ in the proposed policy do not change anymore. Recall from the heuristic in Figure 4.3 that when there are no changes observed in $S$, $k$ and $\delta$ the profit maximizing setting is selected. Therefore, for the base case scenario after using the heuristic it is obtained that $S = 6$, $k = 1$ and $\delta = 90\%$ in order to maximize profit.
5.3 Conclusion: base case scenario

In this chapter a base case scenario is developed and analyzed. By means of a graphical analysis the convexity of the cost function in the base-stock level was examined. By using the convexity of the cost function it was concluded that the base case scenario resulted in higher base-stock levels compared to a situation with no disruptions. Further analysis pointed out that the combined inventory and pricing policy resulted in a higher profit and lower base-stock levels are obtained.

Using the heuristic to determine the near-optimal values for $S$, $k$, and $\delta$ resulted in the following values: $S = 6$, $k = 0$, and $\delta = 90\%$ with a corresponding profit of 6.03 which is an increase of 2.99% compared to using the traditional base-stock policy.
CHAPTER 6

Sensitivity analysis

In this chapter a sensitivity analysis is conducted with regard to the disruption profile consisting of the disruption rate ($\alpha$) and recovery rate ($\beta$), lead time, and demand process. Throughout this chapter a general assumption of zero lead time is made, with exception for the sensitivity analysis on lead time in Section 6.4. Furthermore, the analyses in this chapter are conducted in ceteris paribus settings which entails that, except the parameter considered, all parameters are equal to the values presented in Table 5.1.

The sensitivity analysis with regard to different parameters is conducted similar to the base case scenario analysis in Chapter 5. However, the aim of this chapter is not to find near-optimal values for the different settings of the parameters considered, but to indicate the directions and influences of the parameters discussed. As a result only the initial step and the first step of the iteration of the heuristic developed in Section 4.6 will be used. In addition, recall that this thesis focusses on the effects of disruptions on a single retailer’s inventory and pricing decisions. Therefore, in this chapter the sensitivity of the model to the disruption profile is more extensively analyzed compared to the sensitivity analysis with regard to lead time and the demand process.

For examining the influence of several parameters this chapter aims at providing answers to the following questions.

- What is the impact of each parameter on the base-stock level?
- What is the effect of each parameter on the retailer’s profit?
- What is the benefit, if any, using the combined inventory and pricing policy?
- What is the influence of the considered parameter on the combined inventory and pricing policy?

Throughout this chapter simulation is used in order to obtain results for examining the influence of several parameters. Due to the number of stochastic variables in the considered problem some of the results are somewhat dispersed. However, the results provide good indications of the underlying relationships between the examined variables and a single retailer’s pricing and inventory decisions.

6.1 Disruption rate

In Section 4.2.3 the supplier’s disruption profile was discussed. This section examines the influence of the disruption rate ($\alpha$) with regard to inventory and pricing decisions of a single retailer. For this analysis the disruption rate is changed according to Table 6.1.
Table 6.1: Disruption rates for sensitivity analysis

<table>
<thead>
<tr>
<th>$\alpha$</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
</thead>
</table>

6.1.1 Results

The first analysis aims to examine if the base-stock level ($S$) is influenced by the disruption rate. In Figure 6.1 base-stock levels corresponding to different disruption rates are depicted. For obtaining this figure solely a base-stock policy is used.

Fig. 6.1: Base-stock levels for disruption rates using a base-stock policy

From Figure 6.1 a clear pattern emerges. For disruptions with a low frequency - e.g. $\alpha = 0.1$ - base-stock levels are lower compared to frequent disruptions - e.g. $\alpha = 1$. In order to examine if profit and costs are affected by the disruption rate, graphs for different base-stock levels and the corresponding profit and costs functions are depicted in Figure 6.2 and 6.3. In similar fashion to Figure 6.1 for obtaining the subsequent figures solely a base-stock policy is used.

Fig. 6.2: Costs for different disruption rates

Fig. 6.3: Profit for different disruption rates

From Figure 6.3 the influence of the disruption rate on profit for different base-stock levels is
obtained. It can be observed that in Figure 6.3 the profit is lower for frequent disruptions compared to infrequent disruptions. For infrequent disruptions - i.e. $\alpha = 0.1$ - the observed profit is 4.93% higher compared to frequent disruptions - i.e. $\alpha = 1$. By Figures 6.2 and 6.3 the observed effect of the disruption rate on base-stock levels of Figure 6.1 is confirmed. Furthermore, by increasing base-stock levels profit for different disruption rates tend to converge. This convergent behavior stems from the fact that for high base-stock levels the retailer has ample inventory to mitigate disruptions risk and the associated costs largely consist of holding costs.

In order to develop understanding of the influence of the disruption rate on the pricing reference inventory level ($k$) and the price increase ($\delta$), frequent disruptions are compared to infrequent disruptions. Therefore, $\alpha = 0.8$ is selected to represent frequent disruptions and $\alpha = 0.2$ is selected for the representation of infrequent disruptions, recall that for this analysis it is assumed that the recovery rate equals 0.5. In Figures 6.4 and 6.5 for different combinations of $k$ and $\delta$ profit is depicted with base-stock levels fixed to 6 for $\alpha = 0.2$ and 8 for $\alpha = 0.8$.

![Fig. 6.4: Profit for combinations of $k$ and $\delta$ when $\alpha = 0.2$ and $S = 6$](image1)

![Fig. 6.5: Profit for combinations of $k$ and $\delta$ when $\alpha = 0.8$ and $S = 8$](image2)

From Figures 6.4 and 6.5 it can be observed that profits are decreasing for increasing values of $k$. Furthermore, it can be obtained that for both disruption rates profit is maximized when $k$ is low and $\delta$ is high. As a result for $\alpha = 0.2$ profit is maximized for $k = 0$ and $\delta = 100\%$ and for $\alpha = 0.8$ profit is maximized by using the following combination: $k = 1$ and $\delta = 80\%$. Furthermore, similar effects of $k$ and $\delta$ on revenue and costs as for the base case scenario are obtained for both considered disruption rates (see Section E.1 in Appendix E).

From Section 5.2.2 it can be obtained that by incorporating the proposed policy base-stock levels can be decreased compared to the traditional base-stock policy. Therefore, it is expected that a similar observation can be made when incorporating $k$ and $\delta$ for both disruption rates. In Figures 6.6 and 6.7 the orange line depicts the traditional base-stock policy and the yellow line represents the proposed policy. Note that due to the assumptions on $k$ the profit for $S = 1$ for $\alpha = 0.8$ is not depicted.
From Figures 6.6 and 6.7, in line with the expectations from the base-case scenario, it can be obtained that for low base-stock levels profit is increased and for high base-stock levels profit is decreased when using the proposed policy compared to the traditional base-stock policy. Another observation is that for both cases the base-stock level can be decreased by using the proposed policy. For $\alpha = 0.2$ the profit can be increased with 2.86% and the base-stock level can be reduced to 5. For $\alpha = 0.8$ the profit can be increased with 1.89% while the base-stock level could be decreased to 7.

An overview of revenue, costs, and profit for different disruption rates by using the base-stock policy and the proposed policy is presented in Appendix E Section E.2.

### 6.1.2 Conclusion

The disruption rate affects the profit of the retailer for the traditional base-stock policy and the proposed policy in the following manner: for an increased disruption rate the profit will be lower (see Appendix E Section E.2). From the figures in Section E.2 in Appendix E, in line with the analyzed disruption rates in the previous section, it can be concluded that by incorporating the combined inventory and pricing policy profits can be increased for low base-stock levels. Although revenue is decreased when using the proposed policy, changing the price results in lower demand rates and as a result less back orders are observed. As a result of the decreased back orders, total costs decline. This major decline in costs results in increased profit. An extra observation from Appendix E is that by increasing the disruption rate differences in profit between the normal base-stock policy and the proposed policy increase. This indicates that using the proposed policy is a useful mitigation strategy for frequent and infrequent disruptions.

From Section 6.1.1 it can be inferred that base-stock levels can be reduced when implementing the proposed policy for $\alpha = 0.2$ and $\alpha = 0.8$. In order to examine if implementing the proposed policy results in lower base-stock levels for all disruption rates considered, a similar analysis for these rates is conducted. Furthermore, it is examined if the determination of the pricing reference inventory level is influenced by the disruption rate. In Figure 6.8 the different base-stock levels and $k$ levels for different disruption rates, for using the proposed policy, are presented.
From Figure 6.8 it is observed that for an increased disruption rate base-stock levels, when using the proposed policy, are demonstrating a similar pattern to the pattern observed in Figure 6.1 when solely a base-stock policy is used. Note that the pattern in Figure 6.8 is not smooth due to the number of stochastic variables in the simulation. By comparing Figure 6.1 and Figure 6.8 it can be inferred that using the proposed policy base-stock levels could be reduced except for the most frequent disruptions - i.e. $\alpha = 1$. Furthermore, from the figures in Appendix E Section E.2 it can be observed that for all considered disruption rates profit increases when the combined inventory and pricing policy is implemented.

On the contrary to the base-stock level, values for $k$ remain almost constant at 0 for different disruption rates, due to the number of stochastic variables in the simulation study a peak is observed for $\alpha = 0.8$. This indicates that $k$ is affected more by the demand rate, which in return is determined by $\delta$ and $k$, instead of the disruption rate. However, the difference between the base-stock level and $k$ is increasing in the disruption rate, which results in extra inventory held by the retailer in order to be protected against frequent disruptions. Although it was expected that, due to this extra inventory, for an increased difference between the base-stock level and $k$ the average price paid would decrease the opposite was observed (see Figure 6.9). For an increased difference between the base-stock level and $k$ the average price increases, which stems from the fact that due to an increased frequency of disruptions prices change more often - i.e. net inventory is equal or below $k$ more times. Note that this direct translation of more frequent disruptions to an increased number of price changes can be made due to the fact that the recovery rate is similar across all cases.
Based on Figure 6.9, it is concluded that an increased disruption rate increases the average price paid. From this it is expected that due to the increase in disruption rate, $\delta$ will be increasing as well. Therefore, the profit maximizing $\delta$ values for the disruption rates are presented in Figure 6.10.

From Figure 6.10 it is observed that the expected behavior for $\delta$ does not hold and no real effect of the disruption rate on $\delta$ can be observed. A reason for this behavior can be found in the assumption on reservation prices. Based on the reservation price the customer decides to buy the product or not. Recall that the demand rate is provided by $\lambda_c \Pr (P_r \geq P_i)$ and that due to the price increase the probability of customers willing to pay the increased price is decreasing, resulting in a decrease in the number of items sold. In order to maximize profit, a trade-off between offered price and pricing reference inventory level has to be obtained. Therefore, the maximal price increase of 100% is not always selected for different disruption rates.

### 6.2 Recovery rate

The previous section examined the influence of the disruption rate on the traditional base-stock policy and the proposed policy. In this section the influence of the recovery rate ($\beta$) is examined. In order to represent long and short disruptions the recovery rate is varied from 0.1 - i.e. a low
recovery rate to represent long disruptions - to 1.0 - i.e. a high recovery rate for short disruptions - see Table 6.2.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
</thead>
</table>

### 6.2.1 Results

In order to examine the effects of the recovery rate similar steps as in the analysis of effects for the disruption rate are carried out in this section. Note that in Figure 6.11 and the remainder of this section the results for $\beta = 0.1$ are left out, because, this value leads to more extreme results. By excluding $\beta = 0.1$ useful observations can be still made. The first analysis conducted is to determine if the recovery rate affects the selection of the base-stock level when using the traditional base-stock policy. In Figure 6.11 the profit maximizing base-stock levels are presented.

![Fig. 6.11: Base-stock levels for recovery rates when using a base-stock policy](image)

From Figure 6.11 it can be observed that for low recovery rates high base-stock levels are needed for the retailer in order to maximize its profit. Furthermore, a clear relationship between the recovery rate and base-stock level can be observed in Figure 6.11: the base-stock level is decreasing in the recovery rate. Similar to the disruption rate it can be observed that, due to the selected holding and back ordering costs, a minimum base-stock level of 4 is observed.

From the increased base-stock levels in Figure 6.11 it is expected that costs and profit are dramatically affected by the recovery rate as well. Note that in these figures for $\beta \geq 0.4$ only the profit functions until $S = 15$ are depicted. This is done because the maximal (or minimum, in case of the cost function) is already obtained.
From Figure 6.12 and 6.13 it can be inferred that for long disruptions - i.e. a low recovery rate - the profit is lower than for short disruptions - i.e. a high recovery rate. Furthermore, the pattern observed in Figure 6.11 is confirmed.

With the previous figures the effect of the recovery rate on profit and costs, when using the traditional base-stock policy, are examined. In order to examine if the recovery rate has any effect on the proposed policy first of all $k$ and $\delta$ need to be determined. In order to compare the effects of different recovery rates on the proposed policy it is selected to represent long disruptions - i.e. $\beta = 0.2$ - and short disruptions - i.e. $\beta = 0.8$. The corresponding initial base-stock levels for these rates are 24 for $\beta = 0.2$ and 5 for $\beta = 0.8$.

From Figures 6.14 and 6.15 it can be concluded that for more severe disruptions profit is lower regardless of the price increase used. Furthermore, it can be observed that for $\beta = 0.2$ the profit is maximal for the following combination of the pricing reference inventory level and price increase: $k = 5$ and $\delta = 80\%$. For $\beta = 0.8$ the profit is maximized for the following combination: $k = 0$ and $\delta = 70\%$. For an overview of the associated revenue and costs functions see Appendix F Section 39.
F.1. By comparing the difference in obtained $k$ levels a direction for the influence of the recovery rate is observed. From this observation it is derived that $k$ is decreasing in the recovery rate.

In order to examine if base-stock levels can be reduced by using the obtained $k$ and $\delta$ values for both the recovery rate cases the following figures are constructed.

**Fig. 6.16:** Profit for $\beta = 0.2$ using base-stock policy and $k = 5$ and $\delta = 80\%$

**Fig. 6.17:** Profit for $\beta = 0.8$ using base-stock policy and $k = 0$ and $\delta = 70\%$

The first observation from Figure 6.16 is that for $S \leq 5$ no profit line is depicted, due to the fact that $k = 5$. Recall from Section 4.2.1 that the pricing reference inventory level is selected from the following set $(0, ..., S - 1)$. Since $k = 5$ the base-stock level has to be at least 6. In line with the observed results for the disruption rate, incorporation of the proposed policy resulted in a decrease of the base-stock level of 8 units and a profit increase of 19.24% for $\beta = 0.2$. For $\beta = 0.8$ the base-stock level is not changed and due to implementing the policy the profit is decreased. These differences stem from the fact that when net inventory is below or equal to $k = 0$ price is increased. Although by changing the price the number of back orders is decreased, the decreased costs cannot compensate for the abated revenue. This results in a lower profit observed for every base-stock level when $\beta \geq 0.6$.

An overview of the effects of different recovery rates on revenue, costs and profit when using the traditional base-stock policy and the proposed policy is presented in Appendix F

### 6.2.2 Conclusion

In order to examine the influence of the recovery rate on the proposed policy, the obtained new base-stock levels and the profit maximizing pricing reference inventory level ($k$) after implementing the proposed policy are presented in Figure 6.18 for different recovery rates. In this figure a clear pattern is emerging. Note that the pattern of $k$ values in Figure 6.18 is similar to the pattern in Figure 6.11 for base-stock levels when using the traditional base-stock policy. Therefore, it is stated that $k$ is decreasing in the recovery rate.
Another observation from Figure 6.18 is made when base-stock levels, obtained when using the proposed policy, are compared with the base-stock levels from Figure 6.11. It can be observed that for $\beta \leq 0.7$ lower base-stock levels can be obtained by using the proposed policy. For example, for $\beta = 0.2$ the base-stock level could be reduced with 8 units when using the proposed policy. However, when the recovery rate is high the policy does not result in lower base-stock levels compared to the traditional base-stock policy (see Appendix F). In addition, it must be noted that for $\beta \geq 0.6$ profit is decreased when using the proposed policy, due to a decreased demand rate. This stems from the fact that for relatively short disruptions the retailer can be protected against back orders by holding extra inventory for the time of the disruptions (see Figures F.9 and F.10 in Appendix F). Therefore, contrary to results of the disruption rate, it can be concluded that the reverse pattern -i.e. the differences between the traditional policy and the proposed policy is decreasing in the recovery rate - is emerging.

The effect of the recovery rate on the base-stock level and ($k$) is examined in the previous part of this section. In order to examine the influence of the recovery rate on $\delta$, the profit maximizing $\delta$ values for different recovery rates are depicted in Figure 6.19. In Figure 6.20 the average price paid for the different recovery rates is depicted.

From Figure 6.19 it can be observed that for an increasing recovery rate, $\delta$ is decreasing. Although
no clear pattern is emerging it can be obtained that $\delta$ is influenced by the recovery rate - i.e. $\delta$ decreases in the recovery rate. This stems from the fact that for short disruptions a major increase in price will affect the demand rate negatively. As a result revenue is decreased dramatically and profit is not increased, due to the fact that the abated costs cannot compensate for the decrease in revenue. With regard to the average price paid it can be concluded that the average price paid for low recovery rates is higher compared to high recovery rates (see figure 6.20). This stems from the fact that in case of long disruptions the number of back orders has to be minimized more dramatically compared to short disruptions due to the fact that a major cost component is back ordering costs. The number of back orders is determined by the demand rate, recall that for high $\delta$ values the demand rate is decreased dramatically. Therefore, for situations with a low recovery rate price is increased more dramatically compared to situations in which a high recovery rate is considered.

### 6.3 Disruption and recovery rate comparison

In the analysis of Section 6.1 and 6.2 different effects of the disruption rate and recovery rate are discussed. In this section a comparison between the effects of both rates is made in order to determine which of the rates has a major influence on pricing and inventory decisions of a retailer.

In Figure 6.21 base-stock levels for using the base-stock policy and proposed policy for different disruption and recovery rates are presented. In Figure 6.22 the profits, when using the base-stock policy and the proposed policy, for the analyzed disruption and recovery rates are compared and presented.

![Fig. 6.21: Base-stock levels for different disruption and recovery rates](image)

![Fig. 6.22: Profit for different disruption and recovery rates](image)

From Figure 6.21 it can be obtained that for low recovery rates base-stock levels are significantly higher for both the base-stock policy and the proposed policy compared to obtained levels for the disruption rate. Furthermore, it is obtained that using the proposed policy results in a lower profit increase for different disruption rates compared to gains in profit for the recovery rates. Furthermore, for high recovery rates - e.g. $\beta \geq 0.6$ - using the proposed policy does not result in an increased profit and base-stock levels are not increased - e.g. for $\beta \geq 0.7$. Based on this
comparison and the analysis in Sections 6.1 and 6.2 it can be concluded that the recovery rate has a major influence on the base-stock policy and the proposed policy.

6.4 Lead time

In the analysis of the base case scenario and the previous analysis it is assumed that lead time equals 0. Although this assumption allows for a good examination on the influence of the disruption profile on inventory and pricing decisions it also provides somewhat idealized results. Therefore, in this section the influence of lead time will be examined by using the lead times presented in Table 6.3.

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<tbody>
<tr>
<td>1</td>
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<tr>
<td>2</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>8</td>
</tr>
<tr>
<td>10</td>
</tr>
</tbody>
</table>

The lead times from Table 6.3 will be incorporated in the base case scenario from Chapter 5.

6.4.1 Results

The results for lead time are examined in similar manner to the results of the disruption and recovery rate. Therefore, it is examined if the base case scenario disruption profile combined with lead time will affect the selection of base-stock levels. For an overview of different base-stock levels for the lead time from Table 6.3 see Figure G.1 in Appendix G. The general outline for these cases is that base-stock levels are increased when lead time is increased. Furthermore, it can be stated that lead time has a negative effect on the retailer’s profit especially for low base-stock levels. Both observations stem from the fact that lead time affects all the orders in the supply process, resulting in increased base-stock levels for the different lead times considered. Furthermore, due to lead time the number of back orders is increased. As a result profit is decreased more dramatically for cases in which a long lead time is considered.

In order to examine the effect of lead time on proposed policy a case with short lead time (2 days) and long lead time (10 days) are compared to the results of the base-case scenario from Section 5.2.2. The determination of $k$ and $\delta$ is done in similar fashion as in the previous sections. See Appendix G from which it is inferred that $k = 1$ and $\delta = 100\%$ when lead time equals 2. In addition, $k = 0$ and $\delta = 80\%$ for the case in which lead time equals 10.
When Figure 6.24 is compared to Figure 6.23 it can be inferred that using the proposed policy results in lower base-stock levels. Furthermore, incorporating the proposed policy results in higher profits. Furthermore, no effects of lead time are observed when implementing the proposed policy. This entails that using the proposed policy will increase profit and decrease base-stock levels regardless of lead time. This observation is further supported by the figures for revenue, costs, and profit in Appendix G.1. For which no discrepancy can be found with the results for the disruption and recovery rate.

In comparison to the base case scenario in which a profit increase of 1.79% by incorporation of the combined inventory and pricing policy. For the lead time case it was observed that profit was increased with 4.42% when lead time equals 2 days and with 2.90% for lead time equals 10 days when using the proposed policy. These results support that the incorporation of the proposed policy results in increased profits. Furthermore, the base-stock levels were reduced to 10 and 22 respectively.

6.5 Demand process

In the previous sections of this chapter the analyses conducted, were focussed on the supply side of the problem. In this section the focus is on the demand process. In Section 6.5.1 the customer arrival rate characteristics will be changed. In Section 6.5.2 the sensitivity of the model for different reservation price distributions is examined. For this section the gamma distribution is selected because distribution does not allow for negative values. The uniform distribution is used due to the fact that boundaries for the reservation price can be adjusted which results in the selection of solely non-negative values.

6.5.1 Customer arrival rate

In this section the influence of the customer arrival process on the proposed policy will be examined. As a result of a different arrival rate the demand rate is subject to change as well. In Table 6.4 different values for $\lambda_c$ are depicted.
Table 6.4: Customer arrival rates for sensitivity analysis

<table>
<thead>
<tr>
<th>$\lambda_c$</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>16</th>
</tr>
</thead>
</table>

Results

Due to the change in demand rate the selection of base-stock levels is changed. For an increased $\lambda_c$ it can be obtained that the base-stock levels are increasing compared to the base case scenario. This stems from the fact that the demand rate is given by $\lambda_c \Pr (P_r \geq P_i)$. Because the reservation price distribution is not changed, increasing $\lambda_c$ results in a higher demand rate and subsequently in higher base-stock levels. Another effect of the increased arrival rate is the increase in revenue and subsequently an increase profit. This stems from the fact that the time to achieve 5,000 arriving customers is decreasing when $\lambda_c$ increases. Because $\alpha = 0.5$ and $\beta = 0.5$ are not changed the number of customers affected by disruptions increases, which translates into the increased number of back orders for the normal base-stock policy (see Figure H.1 in Appendix H). Another effect of the increasing arrival rate is the fact that expected values are increased, due to fact that the expected values used in the simulation study are divided by the total time elapses. Because $N$ is fixed to 5,000 and $\lambda_c$ increases the total time elapsed decreases and as a result expected values increase. Therefore, the results of this analysis need to interpreted with relative care.

The results of using the different arrival rates when incorporating the proposed policy are depicted in Table 6.5.

Table 6.5: Results for arrival rates by using the proposed policy

<table>
<thead>
<tr>
<th>$\lambda_c$</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>30%</td>
<td>90%</td>
<td>70%</td>
<td>20%</td>
</tr>
</tbody>
</table>

From Table 6.5 the logic that for an increased demand rate the base-stock level has to be increased is observed. Furthermore, these results indicate that for an increased number of customers that is affected by disruptions $k$ is increased. From Table 6.5 no clear pattern or relationship between the customer arrival rate and the price increase is obtained.

6.5.2 Different demand distribution

In the previous section it is assumed that customer reservation prices are represented by a lognormal distribution. However, in the literature a variety of other distributions is used in order to model customer reservation prices (Talluri and van Ryzin, 2004). In order to study the effect of the selected reservation price, the reservation price distribution is changed to a gamma distribution or an uniform distribution with the expected value equal to the price initially offered price by the retailer.
Gamma distribution

From the introduction to this section it can be obtained that the expected value of the gamma distribution equals 5. Furthermore, in order to have comparable results the variance will be set equal to the variance of the lognormal distributed reservation prices used throughout this thesis. When using the gamma distributed reservation prices no differences, compared to the base case scenario, is obtained in the initial simulation run. Therefore, a base-stock level of 8 is used for determining $k$ and $\delta$. When $k$ and $\delta$ are determined it can be observed that using gamma distributed reservation prices results in a higher profit for all combinations of $k$ and $\delta$, see Figures 6.25 and 6.26. From these figures it is obtained that using gamma distributed reservation prices profit is maximized for $k = 2$ and $\delta = 70\%$ which differs from the lognormally distributed reservation prices for which $k = 0$ and $\delta = 90\%$ result in a maximal profit when the base-stock level is fixed to 8.

Fig. 6.25: Gamma distributions profit for combinations of $k$ and $\delta$ when $S = 8$

Fig. 6.26: Lognormal distribution profit for combinations of $k$ and $\delta$ when $S = 8$

The higher profits in case of the gamma distributed reservation is caused by the different Probability Density Functions (PDF) of the gamma and the lognormal distribution which are depicted in Figure 6.27.

Fig. 6.27: PDF for gamma and lognormal distributions

By comparing the probability density functions of Figure 6.27 it can be obtained that the probability for a customer having a reservation price between 5 and 10 is higher when gamma distributed
reservation prices are considered, this is translated into an increased demand rate when using the gamma distribution when price equals 5 (demand rate is 1.68 when $\lambda_c = 4$). Therefore, higher profits are obtained when using gamma distributed reservation prices. Furthermore, the profit decreases less steep in $k$ for multiple $\delta$ values when using gamma distributed reservation prices. Which is another effect of the shape of the probability graph of the gamma distribution compared to the lognormal distribution.

Although there exists a difference in profit for the two considered reservation price distributions there exists no difference in the obtained effect for the proposed policy when using gamma distributed instead of lognormally distributed reservation prices. In Appendix H the effects of the policy are depicted for the revenue, costs and profit. Furthermore, a profit increase of 3.42% is obtained and the base-stock level is reduced to 7.

**Uniform distribution**

In the introduction of this section it is stated that for both distributions it was assumed that the expectation is equal to the initial offered price. Furthermore, for the gamma distribution the variance was assumed to be equal to the variance considered for the lognormally distributed reservation prices. For the uniform distribution, however, when using an expected value of 5 results in a different variance (8.33), due to the fact the boundaries for this distribution have to be set to 0 and 10. A direct result of using the uniform distribution is an increased number of items sold compared to the base-case scenario. It can be expected that 50% of the customers is willing to pay the initial offered price and therefore the demand rate changes to 2, due to the fact that $\lambda_c = 4$. This change in demand rate stems from the PDF differences between the lognormal distribution and the uniform distribution for which every customer valuation is between 0 and 10 is equally likely to occur (see Figure 6.28).

![Fig. 6.28: PDF for uniform and lognormal distribution](image)

Due to the change in demand rate as a result of uniform distributed reservation prices mentioned above, the base-stock level is increased to 11. In order to determine $k$ and $\delta$ and compare these values to the results of the lognormally distributed reservation prices from Figure 6.26 the following figure is depicted.
When comparing Figure 6.29 with Figure 6.26 it is obtained that, due to different demand rates, profits are higher when using uniform distributed reservation prices. Furthermore, it can be obtained that profit is maximized for $k = 4$ and $\delta = 30\%$. Incorporating these results leads to a base-stock level of 9 and a profit increase of 2.05\%. From Appendix H it can further be obtained that for revenue, costs and profit no differences in the overall effects of the proposed policy are obtained when using uniform distributed reservation prices.

### 6.5.3 Conclusion

In this section the influence of the customer arrival rate and the selected reservation price distribution was examined. It can be concluded that for all of these parameters the demand rate changes. This change in demand rate is translated into the different base-stock levels before and after the incorporation of the proposed policy. However, when comparing the results for the different arrival rates and demand distributions with the results from the previous sensitivity analysis no real differences are obtained with regard to the general outline of the policy.
In this chapter answers to the research questions from Section 3.5 combined with the main observations and conclusions from Chapter 6 are presented. Furthermore, managerial implications are discussed in order to provide guidance in using the combined inventory and pricing policy. Due to assumptions and the setting considered in this thesis some limitations arises, which will be discussed in Section 7.3. This chapter is concluded with a discussion on directions for further research.

7.1 Conclusions

In this thesis the influence of supply chain disruptions on a single retailer’s pricing and inventory decisions was examined. By implementing a combined inventory and pricing policy a retailer has the possibility to be better protected against the (financial) losses stemming from disruptions. In the following sections conclusions with regard to the supplier’s disruption profile, the proposed policy itself, and optimality conditions are discussed. The answers to the research questions in Section 3.5 form the basis for the conclusions provided in the subsequent sections.

7.1.1 Disruption profile

In this section the main observations and conclusions with regard to the disruption profile are discussed. From the analyses in Chapter 6 it can be inferred that the base-stock level is affected by both constituents of the disruption profile. With regard to the disruption rate it can be concluded that base-stock levels are increasing in the disruption rate until a maximum value, due to the selected holding and back ordering costs, is obtained. The recovery rate has an opposite influence on base-stock levels - i.e. base-stock levels are decreasing in the recovery rate. The range of base-stock levels, when the disruption rate is fixed to 0.5, for different recovery rates is between 4 (for $\beta = 1$) and 24 (for $\beta = 0.2$) while the range of base-stock levels, when the recovery rate is fixed to 0.5, for different disruption rates is between 4 (for $\alpha = 0.1$) and 8 (for $\alpha = 1$). Therefore, it can be concluded that the recovery rate has a significantly higher impact on the selection of the base-stock levels when using the traditional base-stock policy.

When implementing the proposed policy similar effects for the disruption and recovery rate on base-stock levels are observed. However, it must be noted that by using the proposed policy base-stock levels could be lowered for cases with a low recovery rate ($\beta \leq 0.7$) compared to using a traditional base-stock policy. When the recovery rate is high - i.e. $\beta = 0.6$ - using the proposed policy has a negative effect on the retailer’s profit. This decrease in profit is caused by a decreased demand rate, which will be discussed in more detail in Section 7.1.2.
In similar fashion it was examined if the disruption profile has any effects on the pricing reference inventory level \( (k) \) and the price increase \( (\delta) \). For this analysis opposite results with regard to the disruption and recovery rate were obtained. The disruption rate does not withhold any significant influence on the determination of \( k \) and \( \delta \). For approximate every disruption rate considered in this thesis \( k \) remained constant at 0. Furthermore, for \( \delta \) no clear pattern was emerging for the different disruption rates considered. This stems from the fact that due to disruptions back orders are observed. The resulting number of observed back orders is determined by the pricing reference inventory level, price increase, and the duration of the disruption. Stated differently, due to \( k \) and \( \delta \) the demand rate is changed and the period for this different demand rate is determined by the recovery rate. The frequency - i.e. disruption rate - only determines the occurrence of the disruption and the number of demand rate changes. This further explains the effect of the recovery rate on \( k \) and \( \delta \). With regard to \( k \) it can be concluded that it is decreasing in the recovery rate. Furthermore, with regard to \( \delta \) it is observed that it is as well decreasing in the recovery rate, although the pattern is less clear to observe than for \( k \). As a result it can be concluded, in line with previous statements, that the recovery rate has a major influence on the determination of the base-stock level, pricing reference inventory level, and the price increase.

7.1.2 Combined inventory and pricing policy

In the previous section is was concluded that the disruption profile and in particular the recovery rate affects the decision variables. It can be concluded that implementing the proposed policy will result in an increased profit and a lower base-stock level for frequent and infrequent disruptions with a high impact - e.g. low recovery rates - compared to holding extra inventory, in the form of increased base-stock levels.

The main logic behind the increased profit is the following: as a consequence of changing the price the demand rate is changed, due to the use of customer reservation prices. The demand rate is given by \( \lambda_c \Pr (P_r \geq P_i) \) and due to an increase in price \( \Pr (P_r \geq P_i) \) is decreasing when net inventory is equal to or below \( k \). As a result of the decreased demand rate the number of back orders is decreasing as well. Throughout this thesis it was assumed that back ordering costs represent 60% of the initial offered price and holding costs were 2.5% of the initial offered price. Due to disruptions the number of back orders increases which results in an increase in the associated back ordering costs. Therefore, the effect of disruptions is translated into the back ordering costs of the retailer. Combining this observation and the decreased demand rate as a result of implementing the proposed policy results in dramatically decreased costs observed for all cases in the sensitivity analysis of Chapter 6. However, another effect of the decreased demand rate is a decrease in revenue. This decrease in revenue is, however, compensated by the abated costs resulting in an increase in profit. Note that this logic only holds for low base-stock levels. If the retailer has a high base-stock level there is ample inventory to sell to the customer even during disruptions. Furthermore, for high recovery rates having ample inventory proved to be a useful mitigation strategy - i.e. for \( \beta \geq 0.6 \) - no profit increase was obtained by using the proposed policy. Which stems from the fact that having back orders for a short period of time - e.g. during the disruption - can still increase the profit of the retailer, due to the fact that the retailer still makes a margin on a back order.

In the previous part the effect of implementing the proposed policy on revenue, costs, and profit was discussed with regard to the effect of a changing price on the demand rate. Another conclusion of this thesis states that the base-stock level and \( k \) are defined independent of each other and are individually determined by the disruption profile, and the recovery rate in particular. Furthermore,
no pattern emerges for an increase or decrease of the difference between \( k \) and the base-stock level with a relationship to the retailer’s profit.

A final examination of the interplay between the pricing reference inventory level and the price increase is carried out. A general pattern that is emerging among all analyzed cases is that \( k \) is decreasing in \( \delta \), due to the fact that the demand rate is decreased. The magnitude of this decrease is determined by \( \delta \). The duration of the low demand rate period is partially determined by the recovery rate and partially by the pricing reference inventory level. In order to maximize profit a trade-off between \( k \) and \( \delta \) is obtained in order to minimize back orders. Therefore, not for all cases considered the maximal price increase of 100% was selected.

7.1.3 Optimality conditions

Throughout this thesis no conditions for selecting optimal values of \( S \), \( k \), and \( \delta \) are determined. This can be explained by using figure 7.1 in which net inventory development is depicted for the case in which lead time equals 0 and the retailer faces disruptions in its supply chain.

![Fig. 7.1: Net inventory changes when implementing the proposed policy](image)

From figure 7.1 it can be obtained that during the period that the supplier is undisrupted net inventory remains equal to the base-stock level (\( S \)), due to the zero lead time assumption. When the supplier is disrupted net inventory is decreasing with a demand rate depending on the initial offered price. When net inventory is below or equal to \( k \) the price is increased with \( \delta \). Due to this price increase the demand rate is decreased, recall that the demand rate is given by \( \lambda_c \Pr (P > P_i) \). As an effect of the decreased demand rate net inventory is decreasing more gradually until the supplier is available again and net inventory is restored to a value above \( k \) which results in a price decrease to the initial offered price. No optimality conditions could be derived from this process, because it is not possible to determine if net inventory is below or equal to \( k \) and thus the timing of the price increase resulting in a change in demand rate cannot be determined. This demand rate is necessary to determine expectations for inventory level and back orders. Furthermore, due to the fact that the supplier’s disruption profile is represented with a two state continuous time Markov chain, it is not possible to determine the durations of multiple disrupted and undisrupted periods. Therefore, no conditions similar to for example the newsvendor model could be derived.
Although no optimality conditions could be determined a heuristic is developed to determine near-optimal solutions for the decisions variables. By using this heuristic the near-optimal strategy for the base case scenario is to have a base-stock level of 6, a pricing reference inventory level of 0, and a price increase of 90%. This resulted in a profit increase of 2.99% compared to using solely the traditional base-stock policy.

7.2 Managerial implications

This chapter started by stating the main conclusions of this thesis and indicated that implementing the proposed policy has a positive effect on the retailer’s profit, especially when base-stock levels are low and disruptions have a high impact. Although the main determinants and behavior of this policy are discussed, throughout this thesis no real guidelines for managers are provided. This section discusses some scenarios in order to determine for which disruption profile the policy is most relevant. Furthermore, some guidelines for implementing this policy are discussed.

7.2.1 Different scenarios

In order to provide information for which disruption profile the proposed policy is most usable, four different scenarios are developed. For these scenarios the disruption profile is characterized in the following manner.

1. Infrequent low impact
2. Frequent low impact
3. Infrequent high impact
4. Frequent high impact

The rates for these different scenarios are depicted in Table 7.1. In order to analyze these different scenarios the other variables are kept similar to the base case scenario in Table 5.1. In this analysis only the effect of implementing the proposed policy is measured and no optimization is carried out.

<table>
<thead>
<tr>
<th>Table 7.1: Different scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario</td>
</tr>
<tr>
<td>α</td>
</tr>
<tr>
<td>β</td>
</tr>
</tbody>
</table>

In this section only the main conclusions for these different scenarios will be stated. For a brief discussion on the results see Appendix I. In Table 7.2 the differences in base-stock levels, costs, and profits when using the proposed policy compared to the traditional base-stock policy are depicted.
From Table 7.2 it can be concluded that using the proposed policy is most profitable when disruptions are frequent and have high impact. For the infrequent high impact case the second best results of using the proposed policy are observed. The observation that the policy is most suitable for infrequent and frequent high impact disruptions is in line with the conclusions of this thesis. Furthermore, from figures in Appendix I and the results in Table 7.2 support for the conclusion that the recovery rate has a major influence on the proposed policy is obtained.

In Table 7.2 negative results for scenario 2 are obtained. These results can be explained by the results from the sensitivity analysis of the recovery rate which states that when the recovery rate is greater than 0.6 implementing the policy has a negative effect on the profit. Although the same recovery rate is used in scenario 1 and 2; scenario 1 has some positive results. This indicates that some small changes in profit could be observed when the disruption rate is decreased.

### 7.2.2 Disruption rate or recovery rate investment

For managers it is of particular interest which of the parameters in the disruptions profile one should invest in order to minimize the financial losses caused by disruptions. From the sensitivity analysis, conclusions, and the previous analyzed scenarios it can be inferred that the recovery rate has a major influence on the retailer’s profit compared to the disruption rate. Therefore, a manager should invest in increasing the recovery rate.

### 7.2.3 Implementation

This thesis proposed and analyzed a policy that changes price when net inventory is below a pricing reference inventory level when supplies are disrupted. Thereof, a continuous monitoring of a retailer’s net inventory is required. Due to the use of computer systems inventory management can easily be done with a continuous review model. Another pre-requisite for implementing this policy is that prices can be changed easily. By using these two conditions this policy could be easily implemented in an online retail environment.

This policy could be less applicable for supermarkets in which prices cannot be changed easily and people have a better understanding of the price, product and many substitutes exist. However, some adjustments to the model and more research on substitution of goods or perishability could make this policy applicable for supermarkets.

### P2 service level

In traditional inventory management literature the $P_2$ service level is defined as the fraction of demand that is directly delivered from stock and is also known as the fill rate. The fill rate is given
by:

\[ P_2 = 1 - \frac{\mathbb{E}(B)}{\mathbb{E}(D)} \]

In which \( \mathbb{E}(B) \) represents the expected back orders and \( \mathbb{E}(D) \) represents the expected demand in a simulation run. By implementing the proposed policy it can be obtained that the demand rate is decreasing and as a result the expected back orders are decreasing, due to this decreasing behavior the \( P_2 \) service level for implementing the proposed policy is increasing. For example, the service level for the base case scenario is increased from 90.17\% to 94.74\%.

### 7.3 Limitations

This thesis is conducted internally at the Eindhoven University of Technology and therefore several assumptions on customer behavior, inventory management, and the supply process are made. Based on the sensitivity analysis in Chapter 6 the limitations of this study are discussed. In Section 7.4 some possibilities to omit these limitations are discussed.

#### 7.3.1 Customer behavior

A first limitation of this thesis stems from the assumptions on customer behavior. In Section 4.1 it was assumed that customers act non-strategically. The main limitation from this assumption stems from the fact that in real life customers are more aware of prices. Therefore, it seems more natural to assume that customer behavior is affected by the changes in price made by the retailer. Another implication of the non-strategic assumption is the fact that customers are not aware of the disruptions. Although this assumption is valid for short and frequent disruptions - e.g. a truck delay - the opposite is true for infrequent and long disruptions - e.g. a hurricane that destroys important parts of the supply chain. Due to these differences in disruptions it could be argued that when customers are aware of disruptions as a consequence ordering quantities are changed for example customer panic buying (Shou et al., 2011). This points out another important limitation of this thesis, namely that customer orders are limited to 1. This assumption limits the study because the quantity ordered by the customer can change when the offered price is increased. Changing the above mentioned assumptions will result in more realistic customer behavior patterns.

#### 7.3.2 Price and costs

In the conceptual model in Section 4.2 the price increase was limited to be doubled at maximum. However, it could be argued that due to a severe disruption the retailer wants to increase the price with more than 100\%.

Another important assumption on price stems from the assumption that customers act non-strategically. As a result the retailer can increase and decrease the price against no costs. However, it is more reasonable to assume that the retailer has to pay some costs due to the loss of goodwill or brand equity when price is increased.
7.3.3 Optimality

From Section 7.1 it can be inferred that there exist no optimality conditions for the problem analyzed in this thesis. Therefore, some of the solutions found for the analyzed settings in this thesis cannot be translated into general guidelines for managers, or conditions for a supply chain design. However, this thesis provides insight in the behavior of a retailer that has uncertain supplies and manages demand via price.

7.3.4 Assumptions validity

The assumptions in this thesis are used in many of the studies on supply chain disruptions and revenue management. Although these assumptions are based on literature in order to increase the validity of the results the assumptions could be checked with an external party.

7.3.5 Sensitivity analysis

Although the main conclusion obtained from the analysis in Section 6.1 through 6.3 is that the recovery rate does the retailer more harm a general remark must be made. It has to be stated that both rates are analyzed in isolation. Therefore, the results represent only the effect of that rate. However, based on the results for different scenarios in Section 7.2.1 it can be obtained that a sensitivity analysis which incorporates more scenarios results in broader examination of the effects of the disruption profile than the sensitivity analysis conducted in this thesis.

In the conceptual model it was stated that assuming a zero lead time in the sensitivity analysis could make disruptions preferable for the retailer in order to minimize holding costs. From Section 7.1.2 and the sensitivity analysis in Chapter 6 it is inferred that for high recovery rates using the proposed policy does not improve the retailer’s profit. Furthermore, in Chapter 6 lead time was examined to have a negative influence on the retailer’s profit. Therefore, it is stated that for a broader examination of the effects of the recovery rate lead time should be included in the sensitivity analysis.

7.4 Directions for further research

In the previous section the main limitations of this thesis were discussed. In this section directions for further research and possibilities to omit the previous discussed limitations are provided. The new directions are discussed for customer behavior, retailer, product, supplier, and system considered. However, it must be noted that many of the directions mentioned in this section will increase the complexity of the problem.

7.4.1 Customer behavior

The first limitation discussed was concerned with the assumptions on customer behavior. Further research should examine what the influences is of using individual customer reservation price distributions. In this thesis a general customer reservation price distribution with parameters equal for all customers was assumed. However, when using customer individual parameterized reservation
price distributions diversified reservation prices are obtained and subsequently, results more in line with reality are obtained. In addition, to this model extension in combination with reservation price distribution, a decreasing price dependent customer order quantity distribution can be used. This omits the assumption of a customer ordering quantity of 1 and provides more realistic results - i.e. customers are willing to pay a higher price but are buying less. Another important implicit assumption made in this thesis is that the retailer can increase or decrease price against no costs, because the customer acts as a non-strategic buyer. However, it is more reasonable to assume that customers are aware of the prices and the retailer has to pay some costs for increasing the price for the loss of customer goodwill or brand equity.

Section 6.5.1 examined the influence of an increased or decreased customer arrival rate. Recall from Section 6.5.1 that the results needed to be interpreted with care. This stems from the fact that an increased arrival rate results in an increased number of customers affected by a disruption. Furthermore, an increased arrival rate reduces the time elapsed until a number of 5,000 customers is observed. Consequently the expected values increase. Therefore, in order to obtain more reliable results on the effects of the customer arrival rate the total number of arriving customers has to be increased simultaneously. In that case results for different arrival rates become more reliable. Therefore, a combination between total customers and the arrival rate has to be found.

7.4.2 Product

For this thesis it was assumed that customers do not have an outside option or a substitute for the product. In the Dell example of Section 1.1 a strategy to switch demand to undisrupted components was used. In order to analyze the benefits of using the proposed policy a substitutive product could be considered. When a substitute is considered one must make reasonable assumptions on the price of the substitute and the availability of the substitute. The model presented in this thesis can be further extended by including reservation price distributions for both products, on the contrary it seems natural to assume a similar reservation price distribution for both products because they are substitutes. Furthermore, switching costs - i.e. what are the costs of one customer switching to the other product - could be included in the model.

Another possible extension of the model is to incorporate product perishability. Incorporating product perishability leads to different use of the policy. Instead of using a price increase price could be decreased in order to sell the products before it is considered scrap. Decreasing the price with a percentage leads, according to the observed logic in this thesis, to an increased demand rate. Due to this increased demand rate the number of items sold will increase and the retailer will be out of stock quicker, which will in turn results in a larger amount of the retailer’s inventory that does not have to be scrapped.

7.4.3 Retailer

Making the assumption that the retailer is unaware of the supplier’s disruption is valid. However, in literature arguments are provided for sharing information on disruptions in order minimize the risks stemming from them. From Snyder et al. (2010) it could be inferred that using contracts to share information on disruptions could have valuable results for both the retailer and supplier. Similarly it can be argued that by a collaboration between the supplier and retailer the proposed
policy leads to different results, because, if the retailer is aware of the suppliers recovery rate the retailer can adjust the pricing reference inventory level and price increase.

Feng and Chen (2003) consider a retailer with multiple pricing reference inventory levels. In this thesis a single pricing reference inventory level was used. For future research multiple levels could be included. For example, for multiple levels the price increase is between 0% and 50% for \( k_1 \) and between 50% and 100% for \( k_2 \), note that \( S > k_1 > k_2 \). Hereof, the demand rate is changed multiple times. In extension multiple levels could be used to either indicate a price increase or decrease. In Federgruen and Heching (1999) it is obtained that when inventory exceeds the base-stock level the price is decreased. However, it must be noted that using multiple pricing inventory reference levels and different pricing tactics will increase the possible solution space of the problem and therefore it’s complexity. In the previous section the extension of the model for product perishability is discussed, using multiple pricing reference inventory levels could be of value for cases in which perishable products are considered. Another application of time dependent pricing reference inventory levels is to use these levels as a guidance for product introduction and price becomes an indicator for the product maturity.

Another direction for further research on the pricing reference inventory level is to allow \( k \) to be negative as well. In Section 4.2.1 it was assumed that \( k \) was not allowed to have negative values. However, due to the assumption that all demand, not directly delivered from stock, is back ordered it can be argued that the retailer allows for some partition of the demand to be back ordered and price is increased dramatically if this level is reached.

This thesis assumed relatively high back ordering costs compared to the holding costs. This resulted in a major component of the costs consisting of back ordering costs. Therefore, by changing the demand rate a major decrease in costs was observed due to the fact that back orders are decreased dramatically. However, different results could be obtained when the ratio of back ordering and holding costs differs from the one considered in this thesis due to the effect of the selected costs on the selection of base-stock levels. However, more research is needed in order to determine the influence of costs on the proposed policy.

7.4.4 Supplier

In this thesis the sensitivity of the policy with regard to the disruption and recovery rate was examined. In Section 7.2.1 four different scenarios were discussed and it was concluded that the policy is most effective when disruptions are frequent and have a high impact. In order to develop more understanding of the effects of the policy on retailer’s revenue, costs, and profit more scenarios should be considered in future research. This could be extended with the incorporation of lead time in order to determine in which situations the policy has the best results.

From the sensitivity analysis in Chapter 6 it can be inferred that the main influence of disruptions on the proposed policy is the recovery rate. Furthermore, it can be stated that in a situation in which no disruptions are present lead time affects the base-stock level in the following manner; the base-stock level increases in lead time. However, the effects of lead time are less dramatic compared to the influence of the recovery rate on base-stock levels. Therefore, it could be stated that for cases in which lead time is short and the recovery rate is low, lead time does not have an effect on the retailer’s profit anymore. On the contrary, lead time could influence the effects of the proposed policy in cases where the recovery rate is high. In Section 6.4.1 it was observed that implementing the proposed policy in the base case scenario extended with lead time will result
in lower base-stock levels and increased profits. Therefore, it is argued that implementing the proposed policy results in decreased base-stock levels and increased profits for cases in which lead time used in combination with high recovery rates.

7.4.5 System

In this thesis a two-echelon system - i.e. a retailer and supplier - was considered. However, supply chains nowadays consist of multiple echelons or different systems - e.g. assembly or distribution. Thereof, the effects of using a proposed policy should be examined in a multi-echelon system in which several of all constituents could be disrupted. In Atan and Snyder (2012) approaches for different multi-echelon systems with disruptions are discussed. However, in these systems a known demand rate is used, while in this thesis a price dependent demand function was incorporated. When this demand function is incorporated in a multi-echelon system it provides the opportunity to extend for example the model of Shang and Song (2003) in which policies in an undisrupted serial system for optimal base-stock levels are developed. In line with the extension to a multi-echelon system research could be focussed on settings in which multiple suppliers are present. For example, the model for supplier selection of Dada et al. (2007) could be extended by incorporation of pricing decisions and a price dependent demand function.

7.4.6 Applications

Final directions for further research arise when possible applications for the developed proposed policy are examined. It could be argued that due to its nature of the proposed policy it is valuable in the airline industry in which an increasing scarcity of the resource can lead to price increase. In this thesis scarcity can be found during disruptions - i.e. shortage of supplies. Note that this research could be combined with using multiple levels for the pricing reference inventory level.
Bibliography


APPENDIX A

list of variables

In this appendix an overview of all the variables used in the model is presented.

A.1 List of variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>i</td>
<td>Counter</td>
<td>Customer arrival</td>
</tr>
</tbody>
</table>

A.2 Decision variables

In Table A.2 an overview of the decision variables in the model is provided.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>S</td>
<td>Units</td>
<td>Base-stock level</td>
</tr>
<tr>
<td>k</td>
<td>Units</td>
<td>Pricing reference inventory level</td>
</tr>
<tr>
<td>δ</td>
<td>Percentage</td>
<td>Price increase</td>
</tr>
</tbody>
</table>

A.3 Input parameters

In Table A.3 an overview of all the input parameters is provided.
Table A.3: Input parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$h$</td>
<td>€/unit/day</td>
<td>Holding costs</td>
</tr>
<tr>
<td>$b$</td>
<td>€/unit/day</td>
<td>Back ordering costs</td>
</tr>
<tr>
<td>$P$</td>
<td>€/unit</td>
<td>Initial price charged</td>
</tr>
<tr>
<td>$P_i$</td>
<td>€/unit</td>
<td>Price charged a time of $i^{th}$ customer arriving</td>
</tr>
<tr>
<td>$L$</td>
<td>Days</td>
<td>Lead time</td>
</tr>
<tr>
<td>$D_i$</td>
<td>Units</td>
<td>Demand based on the offered price($P_i$)</td>
</tr>
<tr>
<td>$N$</td>
<td>Customers</td>
<td>Total number of customers arriving</td>
</tr>
</tbody>
</table>

A.4 Input model parameters

Table A.4 provides an overview of the input parameters used for the stochastic models.

Table A.4: Input model parameters

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_c$</td>
<td>Customers</td>
<td>Average number of arriving customers</td>
</tr>
<tr>
<td>$\mu_r$</td>
<td>€/unit</td>
<td>Average reservation price of customers</td>
</tr>
<tr>
<td>$V_r$</td>
<td></td>
<td>Variance of the reservation price</td>
</tr>
<tr>
<td>$\alpha$</td>
<td></td>
<td>Disruption rate</td>
</tr>
<tr>
<td>$\beta$</td>
<td></td>
<td>Recovery rate</td>
</tr>
</tbody>
</table>

A.5 Other variables

In Table A.5 an overview of the other important variables in the model is provided.

Table A.5: Other variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Q_i$</td>
<td>Units</td>
<td>Number of units ordered by the retailer</td>
</tr>
<tr>
<td>$O_i$</td>
<td>Units</td>
<td>Total outstanding orders</td>
</tr>
<tr>
<td>$I_i$</td>
<td>Units</td>
<td>Inventory</td>
</tr>
<tr>
<td>$Y_i$</td>
<td>Units</td>
<td>Net inventory $max(0, I_i)$</td>
</tr>
<tr>
<td>$B_i$</td>
<td>Units</td>
<td>Total number of back orders $max(0, -I_i)$</td>
</tr>
<tr>
<td>$T$</td>
<td>Time</td>
<td>Time of the $N^{th}$ arriving customer</td>
</tr>
</tbody>
</table>
APPENDIX B

Overview of assumptions

In Figure B.1 an overview of all the assumptions made in Chapter 4 is presented.

<table>
<thead>
<tr>
<th>General assumptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single supplier single location (retailer)</td>
</tr>
<tr>
<td>Durable goods</td>
</tr>
<tr>
<td>Imperfect competition the retailer under consideration is a monopoly i.e. price setter</td>
</tr>
<tr>
<td>During a disruption the supplier is not able to deliver any goods, and the retailer obtains information of the supplier’s state via the supply process</td>
</tr>
<tr>
<td>Business-to-customer</td>
</tr>
<tr>
<td>Customer is not aware of disruptions and the company influences customer behavior via price</td>
</tr>
</tbody>
</table>

**Fig. B.1: Overview assumptions**
Appendix C

Simulation model

In Figure C.1 the steps taken by the simulation model are presented.

Fig. C.1: Simulation model
Appendix D

Base case scenario

In Chapter 5 a base case scenario was presented. In this appendix the results for this scenario not presented in Chapter 5 are presented.

D.1 Results

Note that in Table D.1 the $E(Costs)$ and $E(Profit)$ are determined by using the variables in Table 5.1

<table>
<thead>
<tr>
<th>$S$</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E(Costs)$</td>
<td>2.98</td>
<td>2.32</td>
<td>1.87</td>
<td>1.57</td>
<td>1.39</td>
<td>1.29</td>
<td>1.21</td>
<td>1.23</td>
<td>1.28</td>
<td>1.34</td>
<td>1.41</td>
<td>1.49</td>
<td>1.58</td>
<td>1.68</td>
<td></td>
</tr>
<tr>
<td>$E(Profit)$</td>
<td>4.16</td>
<td>4.82</td>
<td>5.27</td>
<td>5.56</td>
<td>5.74</td>
<td>5.85</td>
<td>5.90</td>
<td>5.92</td>
<td>5.90</td>
<td>5.80</td>
<td>5.73</td>
<td>5.65</td>
<td>5.55</td>
<td>5.46</td>
<td></td>
</tr>
<tr>
<td>$E[I]$</td>
<td>0.59</td>
<td>1.28</td>
<td>2.04</td>
<td>2.85</td>
<td>3.70</td>
<td>4.57</td>
<td>5.46</td>
<td>6.35</td>
<td>7.26</td>
<td>8.18</td>
<td>9.10</td>
<td>10.03</td>
<td>10.96</td>
<td>11.89</td>
<td>12.83</td>
</tr>
<tr>
<td>$E[B]$</td>
<td>0.97</td>
<td>0.72</td>
<td>0.54</td>
<td>0.41</td>
<td>0.31</td>
<td>0.24</td>
<td>0.18</td>
<td>0.14</td>
<td>0.11</td>
<td>0.08</td>
<td>0.07</td>
<td>0.05</td>
<td>0.04</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

In Section 5.2.2 the profit and costs functions for several combinations of $k$ and $\delta$ are discussed. In the following graph the effect on revenue is presented.

![Fig. D.1: Revenue for different $k$ and $\delta$ combinations, $S = 8$](image)

When the price is increased, the demand rate changes. This change in demand rate is reflected in a change in inventory and back orders. For different $\delta$ values inventory and back orders are presented for a varying $k$ levels.
Fig. D.2: Inventory for different $k$ and $\delta$ combinations when $S = 8$

Fig. D.3: Back orders for different $k$ and $\delta$ combinations when $S = 8$
Appendix E

Disruption rate

E.1 Revenue and costs for $\alpha = 0.2$ and $\alpha = 0.8$

In Section 6.1.1 the results of $k$ and $\delta$ on profit functions for disruption rates of 0.2 and 0.8 are depicted. In this section of the appendix the results for combinations of $k$ and $\delta$ on revenue and costs are presented. First of all an overview of $\alpha = 0.2$ is presented followed by the results for $\alpha = 0.8$.

![Fig. E.1: Revenue for $\alpha = 0.2$ different combinations of $k$ and $\delta$](image1)

![Fig. E.2: Costs for $\alpha = 0.2$ different combinations of $k$ and $\delta$](image2)

![Fig. E.3: Revenue for $\alpha = 0.8$ different combinations of $k$ and $\delta$](image3)

![Fig. E.4: Costs for $\alpha = 0.8$ different combinations of $k$ and $\delta$](image4)
E.2 Results different disruption rate

For these figures, $k$ and $\delta$ are obtained after discovering the base-stock level for the traditional base-stock policy, which is depicted as the orange line in figures below. When $k$ and $\delta$ are determined a new analysis was run in order to obtain the yellow lines, which depict revenue, costs, and profits for implementing the combined inventory and pricing policy. The difference (%) in these graphs (grey lines) are determined by comparing the revenue, costs and profit of the base-stock policy with the proposed policy.

Fig. E.5: Revenue, costs, and profit for $\alpha = 0.2$ when using the base-stock policy or the proposed policy

Fig. E.6: Revenue, costs, and profit for $\alpha = 0.3$ when using the base-stock policy or the proposed policy

Fig. E.7: Revenue, costs, and profit for $\alpha = 0.8$ when using the base-stock policy or the proposed policy
Fig. E.8: Revenue, costs, and profit for $\alpha = 1.0$ when using the base-stock policy or the proposed policy
Appendix F
Recovery rate

F.1 Revenue and costs for $\beta = 0.2$ and $\beta = 0.8$

In Section 6.2 the profit for different $k$ and $\delta$ combinations for $\beta = 0.2$ and $\beta = 0.8$ are presented. In this section the revenue and costs graphs for similar combinations of $k$ and $\delta$ are presented.

Fig. F.1: Revenue for $\beta = 0.2$ for combinations of $k$ and $\delta$

Fig. F.2: Costs for $\beta = 0.2$ for combinations of $k$ and $\delta$

Fig. F.3: Revenue for $\beta = 0.8$ for combinations of $k$ and $\delta$

Fig. F.4: Costs for $\beta = 0.8$ for combinations of $k$ and $\delta$
F.2 Results for different recovery rates

In this section the results for the traditional base-stock policy (orange line) and the combined inventory and pricing policy (yellow line) and the difference (%) between the two (grey line) for revenue, costs, and profit are presented in the graphs below.

Fig. F.5: Revenue, costs, and profit for $\beta = 0.2$ when using the base-stock policy or the proposed policy

Fig. F.6: Revenue, costs, and profit for $\beta = 0.3$ when using the base-stock policy or the proposed policy

Fig. F.7: Revenue, costs, and profit for $\beta = 0.8$ when using the base-stock policy or the proposed policy
Fig. F.8: Revenue, costs, and profit for $\beta = 1.0$ when using the base-stock policy or the proposed policy

F.3 Back orders

In order to examine the differences between high $\beta$ and low $\beta$ values the number of expected back orders are compared for $\beta = 0.2$ and $\beta = 0.8$ for the traditional base-stock policy and the combined inventory and pricing policy.

Fig. F.9: Back orders for $\beta = 0.2$ for using base-stock and proposed policy

Fig. F.10: Back orders for $\beta = 0.8$ for using base-stock and proposed policy
Appendix G

Lead time sensitivity

In Figure G.1 the base-stock levels for different lead times are presented. Note that in Figure G.1 the triangles represented the corresponding $S$ values for the lead times from Table 6.3.

![Fig. G.1: Base-stock levels for different lead times using a base-stock policy](image)

In Figure G.2 the profit for varying lead times and base-stock levels are presented when the retailer uses solely a base-stock policy.

![Fig. G.2: Profit for different lead times for using the base-stock policy](image)

In order to determine the $k$ and $\delta$ values for the cases when lead time equals 2 and 10 it is checked which combinations of $k$ and $\delta$ maximize the retailer’s profit. In Figure G.4 not for all $k$ values the profit is presented for different $\delta$ values due to the fact that for increasing $\delta$ values $k$ is decreasing.
G.1 Results for the proposed policy

In this section the results for incorporation of $k$ and $\delta$ for lead time of 2 days and 10 days.

Fig. G.5: Revenue, costs, and profit for $L = 2$ when using a base-stock or proposed policy

Fig. G.6: Revenue, costs, and profit for $L = 10$ when using a base-stock or proposed policy
APPENDIX H

Results sensitivity demand process

H.1 Arrival rate

Fig. H.1: Back orders for different arrival rates

H.2 Gamma distribution

In these figures the traditional base-stock policy (orange line) is compared to the combined inventory and pricing policy (yellow line). The differences between the base-stock policy and the combined inventory and pricing policy are presented with the grey line.

Fig. H.2: Revenue, costs, and profit for gamma distributed reservation prices when using a base-stock or proposed policy

H.3 Uniform distribution

In these figures the traditional base-stock policy (orange line) is compared to the combined inventory and pricing policy (yellow line). The differences between the base-stock policy and the combined inventory and pricing policy are presented with the grey line.

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Fig. H.3: Revenue, costs, and profit for uniform distributed reservation prices when using a base-stock or proposed policy
APPENDIX I

Scenario results

In this appendix the results for the different scenarios are presented. The results of the traditional base-stock policy are presented with the orange line. The yellow line represents the use of the combined inventory and pricing policy. The difference (%) between both policies is presented by the grey line.

Scenario 1

Fig. I.1: Revenue, costs, and profit for scenario 1 when using a base-stock or proposed policy

Scenario 2

Fig. I.2: Revenue, costs, and profit for scenario 2 when using a base-stock or proposed policy
Scenario 3

![Graphs showing revenue, costs, and profit for scenario 3 when using a base-stock or proposed policy.]

**Fig. I.3:** Revenue, costs, and profit for scenario 3 when using a base-stock or proposed policy

Scenario 4

![Graphs showing revenue, costs, and profit for scenario 4 when using a base-stock or proposed policy.]

**Fig. I.4:** Revenue, costs, and profit for scenario 4 when using a base-stock or proposed policy

I.1 Conclusion

In this appendix the results for the four different scenarios from Section 7.2.1 are presented. It can be observed that for a situation in which disruptions are frequent and have a high impact - i.e scenario 4 - the policy has the best overall effects. This observation is inline with the overall conclusion of this thesis that the proposed policy is best suitable for situations in which disruptions have a low recovery rate. Another important observation from this appendix is that for the case in which disruptions are short and frequent the policy does not result in increased profits. This stems from the fact that for short disruptions inventory proved to be a valuable mitigation strategy. Furthermore, due to an increased price the demand rate is decreased. However, when disruptions are short having back orders still results in an increased profit compared to no back orders at all.