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THE IMPACT OF LEAD TIME ON CAPITAL EMPLOYED IN FINISHED GOOD INVENTORY, CASE: HILTI

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TIIVISTELMÄ

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Yrityksien käyttöpääomasta merkittävä osa on sidottuna materiaaleihin ja myytäviin tuotteisiin. Tehokas käyttöpääoman hallinta on merkittävä tekijä yrityksen kannattavuuden ja likviditeetin kannalta. Aiemmat tutkimukset osoittavat varastotasoon vaikuttavien tekijöiden kirjon olevan laaja sekä vaihtelevan liikeympäristöstä riippuen. Tiedetään, että toimitusajalla on vaikutus varastotasoon, mutta empiiristä tutkimusta ajan varsinaisesta määrällisestä influenssista ei aiemmin ole tehty.

Tämän pro gradun tarkoitus on tutkia varastoon sitoutuneen pääoman määrää ja tunnistaa ne tekijät, jotka vaikuttavat varastotasoon merkittävästi. Tutkimuksen pääpaino on löytää toimitusajan vaikutus, mutta teorian sekä tutkimuksen kulun myötä on selvää, että myös muita varastotasoon vaikuttavia tekijöitä on otettava huomioon. Tapaustutkimusta hyödyntäen, tutkimuksen tavoite on luoda ymmärrys toimitusajan vaikutuksesta varastotasoon, jotta tulevaisuudessa hankintapäätöksissä otettaisiin huomioon myös varastoon sitoutunut pääoma. Empiirisen tutkimuksen tuloksena voidaan todeta, että globaalit varastot ovat osa monimutkaista kokonaisuutta, joihin odotettavasti pääosin vaikuttaa kysynnän määrä. Todistettavasti myös toimitusajalla on merkittävä rooli, joka kvantitatiivisesti ja vaikuttavasti perustelemalla todistetaan tässä tutkimuksessa. Muita merkittäviä tekijöitä osoittautuvat olemaan kysynnän vaihtelu sekä vähimmäistilausmäärät. Tutkimuksen tulosta toimeksiantoyritys kykenee hyödyntämään suuntaa antavasti tulevaisuuden päätöksissään.

ABSTRACT

Author:	Julia Jokinen
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It is common, that a significant amount of organization's capital is tied into the inventories. Managing working capital is essential as it directly impacts the profitability and liquidity of the business. Existing literature has widely recognized the magnitude of factors impacting inventory levels in different business environments. It is known, that lead time is one of the influencing factors thus the impact in real-life context has rarely been empirically proven.

This case study aims at examining the level of capital invested in inventory and identifying the factors contributing to the level of inventory in a global business environment. Although the aspiration of the study has been to interpret explicitly the influence of lead time on inventory level, based on existing literature and earlier studies, it has been obvious that also other inventory drivers shall be investigated. The objective of the study has been to construct a comprehension of lead time's influence in order to generate knowhow which can be adopted in case organizations business operations. This empirical single case study conducted as a quantitative research, reveals that global inventories belong to a complex entity, driven by various factors, among which strongest the demand. However, the results prove, that lead time undoubtably is a driving factor for the level of inventory and presents a significant quantified proof to support that. Other factors proven to be significant drivers are demand volatility and minimum order quantity. The case organization may use the outcome of this case study as a guidance to support the managerial decision-making and to drive the future decisions into a direction which ties less working capital into company's inventory.

ACKNOWLEDGEMENTS

This master's thesis project has been so far the most instructive academical project in my learning path. Before I started, I was lacking the knowledge required to conduct statistical analysis. The project has required intensive learning, rehearsing and repetition in order to understand the fundamental methods and to be able to run and interpret the results. There have been many frustrating days which have turned out to a win-win, as I've learned incredibly lot, not only about statistics and analytics, but also cause and effect relations, and real-case decision-making. Surprising has been that inventory management, even though enormously discussed in existing publications, in reality is widely managed by humans and many decisions are taken disregarding the theoretical guidelines. More importantly, it has been proven again, that the support from colleagues is an irreplaceable asset, which can help to understand concepts and learn new perspectives, even if you knew nothing about them a while ago. In addition, the support from my supervising professor has been priceless and I am grateful for the advices and guidance I've received.

To conclude, I got two key learnings out of this thesis project. Firstly, learning path starts when you step into the unknown and get uncomfortable. Second, asking help, opinions, advices and experience is way of learning and understanding new concepts - thus people are generally enthusiastic to explain when you ask for an advice. With these words I want to encourage all students to choose the challenging path instead of the comfortable path – it's all worth it.

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LIST OF ABBREVIATIONS

ANOVA	Analysis of variance
CHF	Swiss francs
CV	Control variable
DP	Decoupling point
DOH	Days on hand
EOQ	Economic order quantity
ICLa	Inventory Coverage Level a
KPI	Key performance indicator
MOQ	Minimum order quantity
MOH	Months on hand
MoV	Moderating variable
MRO	Maintenance repair and operating
MRP	Material requirements planning
OOS	Out-of-stock
PFC	Product Family C
PFN	Product Family N
PSM	Purchasing and supply management
ROP	Re-order point
SCM	Supply chain management
USA	United States of America
WC	Working capital
WIP	Work-in-process

LIST OF EQUATIONS

APPENDICES

1 INTRODUCTION

Globalization and increasing competition have driven organizations to construct global supply chains. Consequently, the emerging complexity has resulted in higher vulnerability of supply chain functions and increased the need for advanced operations management (Yang et al. 2005). Therefore, purchasing and supply management (PSM) has reached an increasingly essential share of corporate strategy. Many organizations have implemented initiatives to increase revenue, reduce costs and improve overall efficiency. Especially PSM aims at effectively optimizing costs in the supply chain. (Ellram et al. 2002.)

Inventory management is an essential function of supply chain management. In fact, in most of the organizations, inventory is one of the major investments which, when properly managed, improves business flexibility, financial wealth and consequently customer satisfaction (Bonney 1994). Inventory is by default directly related to financial performance of an organization, as it significantly contributes to working capital (Yang et al. 2005). This paper examines the capital invested into inventory and explores the significance of lead time as a driving factor of inventory level. Since it is obvious and evident that the main reason to hold inventory is for the existing demand, it is necessary to consider also other inventory drivers, not only lead time. In order to argue the mentioned aim, the research examines how major the impact of lead time on inventory levels is and what other factors have a significant influence. This research aims at justifying these aims with an empirical case study approach investigating qualitative data from the case company. In order to reach these arguments, the inventory functionality of the case company will be examined. Inventory behavior of different product families in different regions will be investigated.

This study is completed as a case study at Hilti Group, which is well-known as a product and service provider for the construction industry. The case organization operates globally, has several manufacturing locations and hundreds of suppliers. Today, cost is the main driver for make-or-buy decisions as well as for supplier selection. Thus, only purchase price and transportation costs are mainly considered. In this industry, demand is seasonal and volatile which consequently results in difficulties in accurate demand forecasting. In a global organization as such, the inventory management is affected by various parameters and

inventories are managed locally. In the case organization's supply operations, lead times are expected to possess a significant influence on inventory levels, but there is a lack of evidence which would proof that the influence in reality is critical. The interest of the case organization is to comprehend the influence of lead time, in order to consider it in future decision-making. Unless lead time is proven to have a notable influence, the purchase price may remain as the main decision factor for supply decisions.

A global manufacturing industry provides an appealing context to examine the role of lead time because the supply chain is complex, industry is hectic, lead times vary from a few days to several weeks, and gigantic capital is invested in inventories in various warehouses around the world. Companies are increasingly setting effort to reduce lead times, while still uncertain of the positive impacts shorter lead times would have on reducing excess inventory and the cost of stockouts (Fisher & Raman 1996). The desired outcome of this case study declares the inventory behavior, reveals the parameters driving inventory levels and creates evidence to state the role of lead time as an influencing parameter. For the case company this study provides detailed insights on their inventory behavior and a declaration of the capital tied up to inventory. Furthermore, a conceptual model has been developed in order to transfer the learnings of lead time impact into a practical and ready to use tool to help decision-making. The simple thus informative model allows a supply manager to comprehend the impact of taken lead time decision on inventory among the selected product family and other crucial inventory drivers.

Many authors have argued lead time being an influential factor, however practical business case proof have not been provided. This paper will provide practitioners and researchers a throughout business case investigation of the role of lead time on inventory and furthermore, the relationship of lead time between other elements closely related to inventory levels. The paper explicitly focuses on one business case only, studying the causation of lead time on finished goods inventories. For literature, this study provides a reality-based business study, not only determining the impact of lead time on inventory, but also providing a valuable insight into real business case inventory levels in a global supply chain environment. The result will be reflected to the existing proof of inventory drivers.

1.1 Purpose and aim of the research

Kothari (2009) has described research as a systematic and scientific examination of relevant information on specific phenomenon. In the existing literature, inventory management is a widely discussed and investigated field of business operations. Existing literature proves inventory being driven by various factors, such as customer demand, lead time, lot sizes and many other factors. Lead time has been extensively studied, especially in production environment and lean activities. Nonetheless, less studies focus on the impact of transportation lead time on inventory level. To the knowledge of the author, no study with empirical prove on the causal effect of supply chain transportation lead time on the level of inventory has been published. This research aims at filling this gap, by finding causal relationships between supply chain lead time and inventory level by examining a case study.

The purpose of this thesis is fourfold as shown in figure 1. First, existing literature on inventory management will be examined as well as the financial role of inventory in organizations. The aim is to comprehend the theoretical base of inventory functions and to examine the factors influencing inventory behavior. Secondly, relevant data from the case organization is collected with the aim to comprehend the current inventory volumes and to agree, disagree, and argue the theoretical inventory drivers. The volumes of inventory, as well as inventory distribution along the global supply chain will be examined.

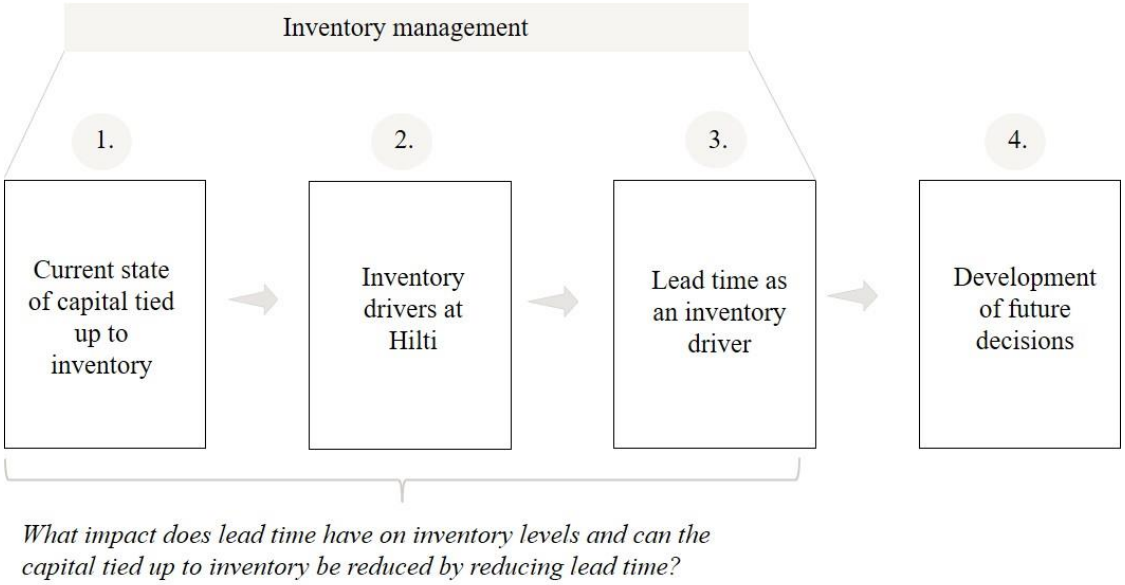

Figure 1. Purpose and objectives of the case study

Later, more in detail, the research focuses exclusively on defining the significance of lead time as an inventory driver and considering it from financial point of view, as a contributor to working capital. Finally, this study aims to prove that capital invested to inventory should be taken into consideration in supply chain decisions which consider or plan an adjustment of transportation lead time.

The outcome of the study will include a quantitative assessment of the inventory data analysis but as well, will provide a conceptual model which can be utilized in the future decision-making of supply managers. The aim is to provide an outcome which allows the case organization to consider decisions from inventory point of view and consequently to reduce the amount of unnecessary capital invested into inventory. Suitable decisions to consider lead time as influencing factor would be for example a hypothetical situation of two otherwise equivalent suppliers with different lead times. Additionally, when more profitable decisions can be taken in the upstream level (suppliers), the decisions and cost efficiency in downstream (warehousing) level can consequently be improved. This research project aims to contribute to the improvement of the overall capital efficiency of the supply chain by investigating the behavior of inventory and the relationship of lead time and inventory level.

The purpose of the case study reflects to the vision of the case company. Hilti Group (2020) aims to be an innovative global leader in the construction business. Therefore, the supply chain must be highly optimized in order to comprehend and manage the business better and more cost effectively. Cost effective supply chain management, including inventory management, will leave and release more capital to research and development activities which are necessary to succeed in the general aim of the corporation.

1.2 Research structure

This research is divided into four sections, as shown in in figure 3. The four blocks include introduction, theoretical base, empirical study and, result and conclusion. Each section includes several sub sections.

The first section describes the purpose and content of the study, including objectives, research method, research questions and hypothesis, as well as the theoretical framework and key words. The purpose of the second section is to examine the existing literature.

Theoretical review examines three literature concepts including mainly inventory management, but also supply chain complexity from inventory point of view, as well as financial supply chain management, consistently from inventory point of view. Theoretical base supports the decision on parameters to be examined as potential inventory drivers and guides the data collection.

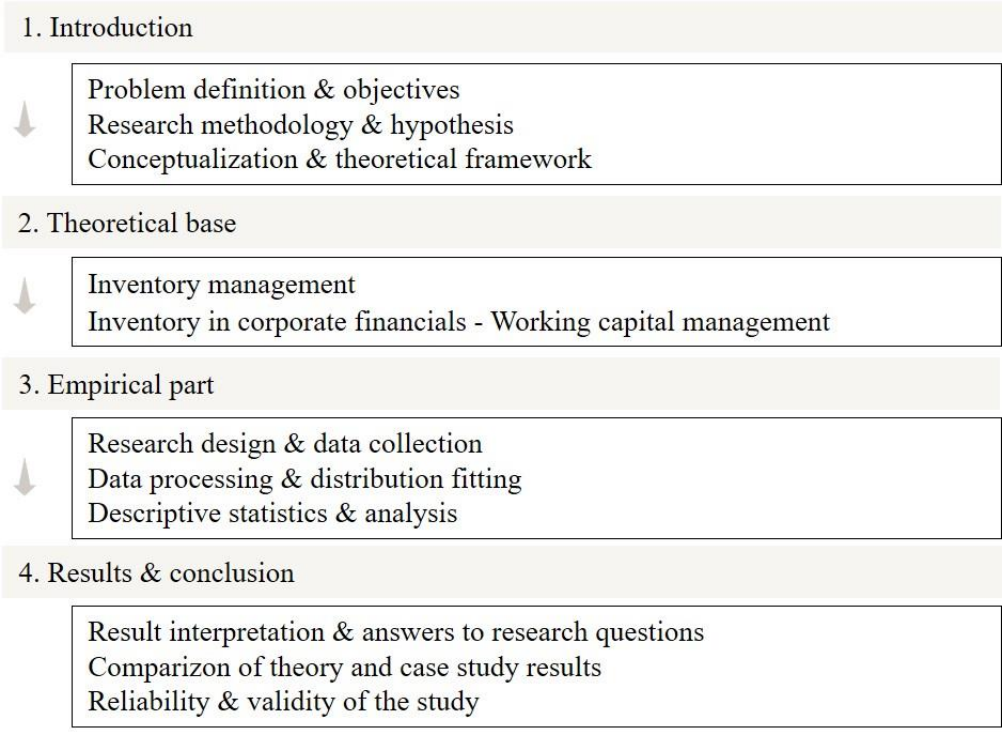

Figure 3. Research content and structure

The third section consists of the empirical part of the study. In this part, the case organization will be shortly introduced, and the collected data will be presented and described in detail. Furthermore, case specific inventory drivers will be explained. The next chapter will focus on the data analysis and interpretation. First exploratory analysis and distribution fitting will be presented, followed by a discussion on analysis approach, including multivariate regression analysis and analysis of variances (ANOVA) analysis.

The fourth section presents the results of the analysis, the outcome and concludes the case study. This section summarizes the research, reflecting the outcome to the theory, supporting and developing the existing theory with new empirical evidence. The final chapter summarizes the study and presents the main contributions provided for literature and for the

case organization and assesses the reliability and validity of the study results. Finally, suggestion for further research will be presented.

1.3 Theoretical framework

Typically, quantitative research applies a deductive approach, which tests the existing theory with a new sample. Theoretical framework provides relevant background information of the study and guides the empirical research in terms of data collection and data analysis. (Halinen & Törnroos 2005.) Figure 4 resumes all the literature parts examined prior to the empirical study as well as the focus areas of each section. In this case study, the theoretical framework consists explicitly of inventory management, supported by necessary aspects of supply chain structuring from inventory point of view as well as the impact of inventory on organizations financial performance.

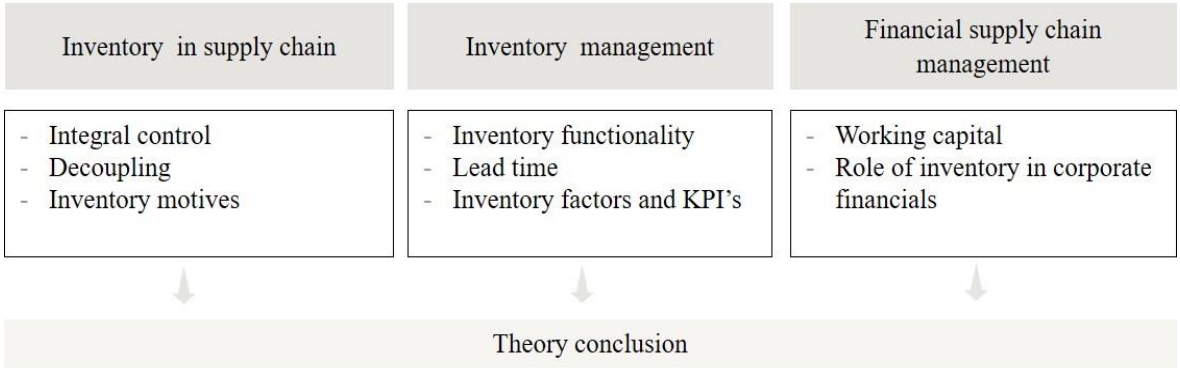

Figure 4. Theoretical framework (KPI: Key Performance Indicator)

The first aim is to understand the complexity of supply chain and where inventories are placed in different business environments. Then, by researching the theory of inventory management, the purpose is to understand inventory functionality in detail, to find the theoretical drivers for inventory, and finally to examine the discussions of lead time as an inventory driver. Also, in order to understand the significance and the effects of capital tied up to inventory, the working capital management as a relevant financial concept will be discussed.

1.4 Research key words

Main key words used in this study include inventory, lead time and working capital. These key words will shortly be introduced in this chapter thus their definitions will be discussed

more explicitly later on in the theoretical part. The key words have been used as the base for the theoretical framework in this research.

Inventory has the purpose of balancing supply and demand. Inventories are required for geographical and decoupling reasons, as well as to buffer any uncertainties in supply chain, caused by the variation of demand or disruptions in supply. (Tersine 1988.) Shortages in material flows can disturb the manufacturing flows and out-of-stock (OOS) situations of products, consecutively resulting in added costs (Bowersox & Closs 1996, 243). Inventory is an essential contributing factor to organizations financial health and typically inventory figures compose a significant proportion of organization's working capital (Yang et al. 2005). In this case study the considered inventory consists only of finished goods.

Lead time typically refers to either manufacturing or transportation lead time. However, in supply chain context lead time typically consists of order preparation and order transit, supplier lead time, delivery time, and set up time. Reducing lead time allow companies to increase productivity, improve cost efficiency and effectiveness, and to realize quick response in supply chains. (Tersine & Hummingbird, 1995.) Lead times can be reduced by organizing working environment in a way, that different stations, plants and warehouses are closer to each other (Mueller 2011, 149). In this research lead time covers the time the finished good leaves from supplier and arrives to the warehouse. This includes transportation, handling and organizing in the warehouse.

Working capital represents the financial health of an organization and is closely connected to liquidity and profitability. Working capital (WC) typically refers to invested capital that a company needs to operate and to generate profit. WC consists of three segments; net working capital, operational working capital and financial working capital. Net working capital (NWC) is current assets from where current liabilities have been reduced. Operational working capital includes inventories, accounts receivables and accounts payables. Financial working capital consists of the parts of net working capital which are not connected to operational working capital, such as cash. (Kärri et al. 2016.) For this case study, operational working capital is crucial, as the focus is on inventory levels. The value of inventory is the finished good's material overhead costs, as well as transportation and duties till the point of warehouse.

1.5 Literature review process

A comprehensive review on existing publications and literature was completed and the systematic audit covers most relevant publications from the early 90's until the most recent papers of 2019. Existing publications were examined using Scopus, the abstract and citation database and platform for scientific publications. Relevance is measured by the citations, presuming high amount of citations referring to high relevance. To sustain the reliability of the sources, document types considered included articles, books and book chapters, while source types conjointly included only journals, books and book series. The language of all publications was restricted to English. The subject area was furthermore limited to contain only relevant contributions, including areas of "business, management and accounting", "decision science" and "social science".

Published material was examined with a two-level keyword approach, contemplating first-level keywords such as inventory, inventory level and lead time. Second-level keywords considered lead time, delivery time, safety stock, transportation time and working capital. First-level and second-level keywords were combined as reported in table 1.

Table 1. Literature review keyword combinations

Key word	AND	Documents in total	Papers selected
Inventory	Lead time	1714	11
	Delivery time	127	4
	Safety stock	42	4
	Working capital	199	6
Inventory level	Lead time	216	8
	Delivery time	19	0
	Safety stock	3	0
Lead time	Safety stock	185	5
	Working capital	13	4
	Transportation time	16	0

During the systematic review of paper abstracts and titles, it soon turned out that some of the keyword combinations provided same publications. The papers with highest relevance

to the case topic were reviewed and considered as a potential contribution to the literature review. The titles and abstracts of each potential paper were reviewed and the most interesting and relevant ones for this study were marked for complete reading. Publications with less than 10 citations were primarily neglected and observed as irrelevant for the context. Mainly papers investigating lead time and other relevant inventory drivers from a unique point of view were approved. Hereafter, 42 papers were selected and considered as relevant publications to construct the theoretical base for the literature review of this case study. The outcome of literature review outlines the defined research questions and hypothesis.

2 RESEARCH METHODOLOGY

This chapter discusses the selected research method, defined research questions as well as the hypothesis for the study. In addition, the selected analysis methods will be introduced and the limitations for the research will be defined.

2.1 Quantitative study approach

This research adopts a quantitative empirical analysis approach. Quantitative research is a distinctive philosophical research approach, which attempts to interpret numerical data and to explain a certain phenomenon (Saunders et al. 2016, 184; Apuke 2017; Kothari 2009). Quantitative research is applicable to phenomena which can be signified in terms of quantity (Kothari 2009, 3; Taylor 2007, 5). Therefore, quantitative approach is scientific from the nature and the research approach is non-flexible and linear. Quantitative research approach is typically based on research questions and defined hypothesis, which is followed by data collection, interpretation and conclusion of the results. (Eyisi, 2016.) Empirical research in turn indicates, that the research relies on observations and does not aim to develop a conceptual idea or model (Kothari, 2009, 3). It has been proven, that large-sample research approach have been used widely in strategic management of organizations (Ketchen et al. 2007). A quantitative analysis approach aims at supporting, falsifying or developing the existing theories.

There are various methods for quantitative research, among which case studies, surveys, public data studies and simulations. This research is conducted as a case study and more specifically a single case study, which is an in-depth inquiry into a phenomenon in a real-life business setting. (Apuke 2017; Saunders et al. 2016, 184.) The “case” in this specific study refers to a business organization. Using quantitative research approach allows the researchers to save time and resources due to the adoption of statistical data, which today can be analyzed utilizing computer power. Another advantage of quantitative research approach is, that the collection and analysis of data allows generalization. (Eyisi, 2016.) In this study, raw secondary data has been collected, which initially is collected for another purpose, in this case company’s inventory and supply management purposes and not processed at all. The data obtained is analyzed with the aim to provide new interpretations

and conclusions and to support or reject the existing academic studies. (Eyisi, 2016; Saunders et al. 2016, 316.)

Based on the existing evidence, an assumption and expected explanation can be concluded, which typically is referred to as hypothesis. Often it is not easy to recognize new insights nor better comprehensions of the phenomenon through already existing theories. The purpose of research is to test the hypothesis and to either support or reject them. (Saunders et al. 2016; Hoy 2010, 70.) As quantitative research typically relies on hypothesis testing, it is rarely replicated of earlier studies. Afterwards the empirical research design can be conceived, which includes a detailed clarification of the approach to data collection and data processing. A suitable data for a quantitative research is a large quantifiable dataset. Data analysis typically consists of descriptive statistics and analysis, data interpretation, measurements and calculations. (Saunders et al. 2016.) The challenge in quantitative research approach typically is the fact that the researcher is an external observer, which may mean that it can be difficult to interpret and explain the data as well as to make reasonable conclusions of a phenomena (Eyisi, 2016). Analysis of data is typically done by using a statistical software (Saunders et al. 2016). In this case study Excel, Minitab and Analycess Procurement software from Process Bench have been used. The analysis uses multivariate regression analysis and ANOVA analysis. Finally, the addressed data reveals results, which may be presented in various ways including tables and diagrams.

2.2 Research questions

Based on the aim and purpose of this case study, the following research questions have been consequently defined to guide the research process and to be answered to:

> ***RQ1: What impact does lead time have on inventory levels and can the capital tied up to inventory be reduced by reducing lead time?***

In order to comprehensively answer the main research question, sub research questions have been set as following:

> *RQ2: What are the main drivers that determine inventory level and how significant are their impacts?*

RQ3: What is the role of inventory in corporate financials, why is it important to comprehend the inventory drivers from financial point of view?

This report aims at responding these research questions justifiably. The combination of existing publications and empirical study will provide a comprehensive response to these given questions.

2.3 Hypothesis

Hypothesis is an assumption of the relationship between variables in the research and the hypothesis must be able to be tested (Kothari 2009, 19; Leik 1997, 4). Null hypothesis (H0) is a precise statement of testing the research question, expressed in a way which assume no relationship between the variables. For hypothesis, a dependent variable y must be defined. Dependent variable is explained with the research outcome with a selected variable of x, as shown in figure 2. (Hoy 2010, 70.) In a scientific research, extensive literature review should underlie for defined hypothesis which should be stated in clear terms. Hypotheses shall be tested after data analysis and either supported or rejected (Kothari 2009, 13-19).

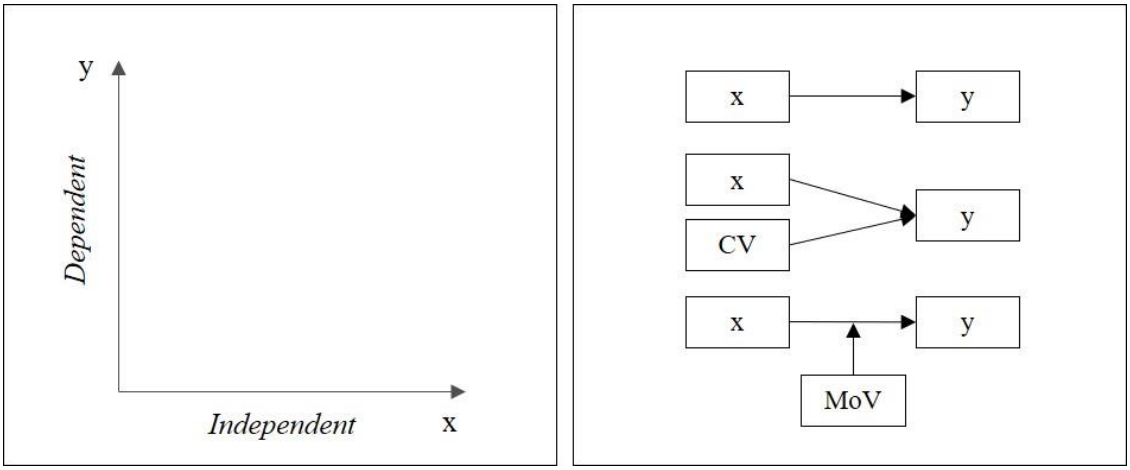

Figure 2. Hypothesis variables and impact (Hoy 2010, 70.)

The same figure shows, that in addition to an independent variable, the dependent variable can be impacted by other variables. Control variable (CV) is a variable that is not hypothesized but is known to have an impact on y. Moderating variable (MoV) also known as environment variable, defines a different relationship between x and y when MoV is

different. Null hypothesis is typically assumed to be true until further sufficient evidence is presented to reject it (Hoy 2010, 70; Leik 1997, 4). The null hypothesis in this research therefore assumes no relationship between lead time and inventory level. The hypotheses derive from the review of existing studies and publications. The hypotheses have been defined according to the statements and discussions of scientific authors discussed in the literature review part of this report. Based on that, the aim of the study and the defined research questions, this study established further hypotheses as following:

H1: Lead time has a significant impact on inventory level
H2: Decreasing lead time impacts inventory level positively by certain amount
H3: Lead time increases in a linear relationship with overstock
H4: Demand volatility has a significant impact on inventory level

2.4 Research limitations

This research will clarify the behavior of inventory in real business life. Factors affecting inventory will be investigated based on data from year 2019. Older data will not be considered. Especially the trade-off between lead time and inventory levels will be analyzed. Lead time in this research context considers transportation from manufacturing to warehouse and the goods receiving time. Lead time used in the analysis is the sum of those two mentioned variables. The research only considers finished goods inventory in the markets. Due to the complexity of the supply chain and time limitation for the research, this study will examine two product families, not all products of the company. Even though the aim is to examine the capital tied up to inventory, no further analysis of financial impacts will be considered.

3 INVENTORY MANAGEMENT IN THEORY

This chapter aims at reviewing the existing literature in the field of the research. Inventory management and related supply chain structure concepts as well as relevant aspects of supply chain financial management will be examined. Respective references have been used to get a general overview on the field as well as to collect focused literature relevant for the research. The theoretical base will be used as the basis for identifying the drivers for inventory which will be tested in the empirical part of the study.

3.1 Inventory's role in supply chain structure

Supply chain management is strategic and systematic coordination of traditional, as well as tactical, business functions across the businesses to serve and improve long-term performance of a particular organization (Templar et al. 2016, 16). Material and information flows are the two basis pipelines that supply chains are constructed around to. Integral control is a holistic control which aims at securing and managing continuous material and information flows in a supply chain. (Mason-Jones & Towill 1999a.) The purpose of the holistic control is to balance the costs between processes and to fulfill customer demand cost effectively by managing and planning the material flows of an organization. Therefore, integral control aims to find a balance between cost of producing and purchasing as well as the cost of warehousing and distributing. (Hoekstra et al. 1992, 3.)

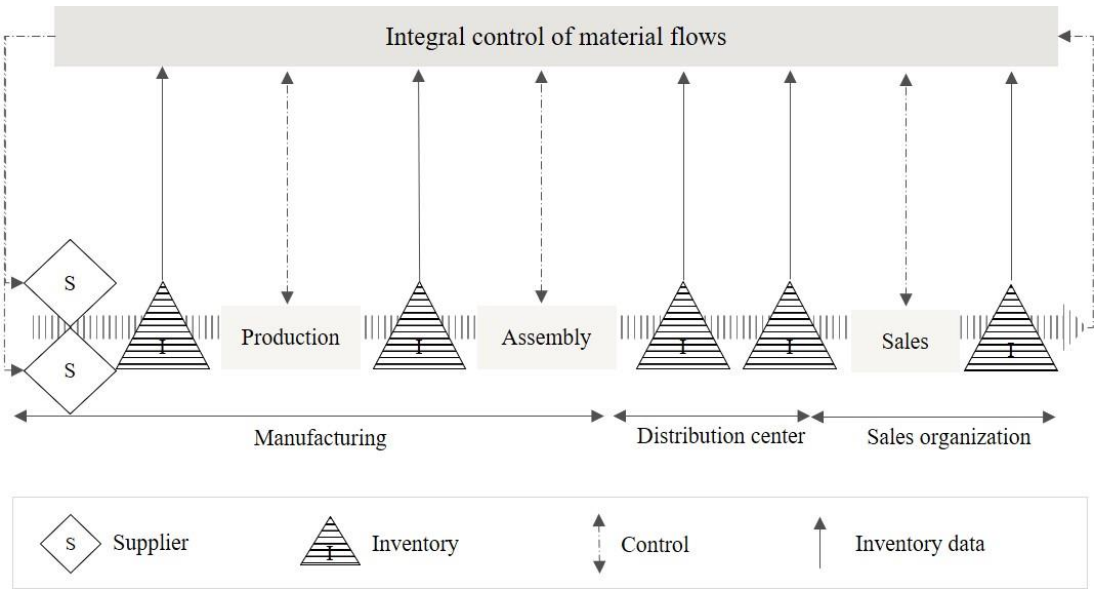

Figure 5. Integral control (adapted from Hoekstra et al. 1992)

Integral control covers managing and planning the material flows along the supply chain, as shown in figure 5. In manufacturing organizations, the inputs and outputs build up a complex and long supply and production system, whereas retail companies' supply chain typically is short and simple, as it mainly consists of warehousing and distribution. Organizational structure defines the number of aspects in the business, which is the basis for integral control system. (Hoekstra et al. 1992, 3.)

Along the supply chain, inventories typically consist of raw materials, components, work-in-process (WIP), finished goods, distribution inventory as well as inventory for maintenance and repair (Tersine 1988, 4). The design of an integral control system depends on the decoupling point (DP) of the business. DP is the basis for inventory management, as it separates the activities which are driven by forecast and the activities which are driven by orders, it determines where the main inventory is located and how to control each part of the supply chain. (Mason-Jones & Towill 1999a; Hoekstra et al. 1992, 66.) In general, there are five different decoupling point designs; (1) make and ship to stock, (2) make to stock, (3) assemble to order, (4) make to order, and (5) purchase and make to order.

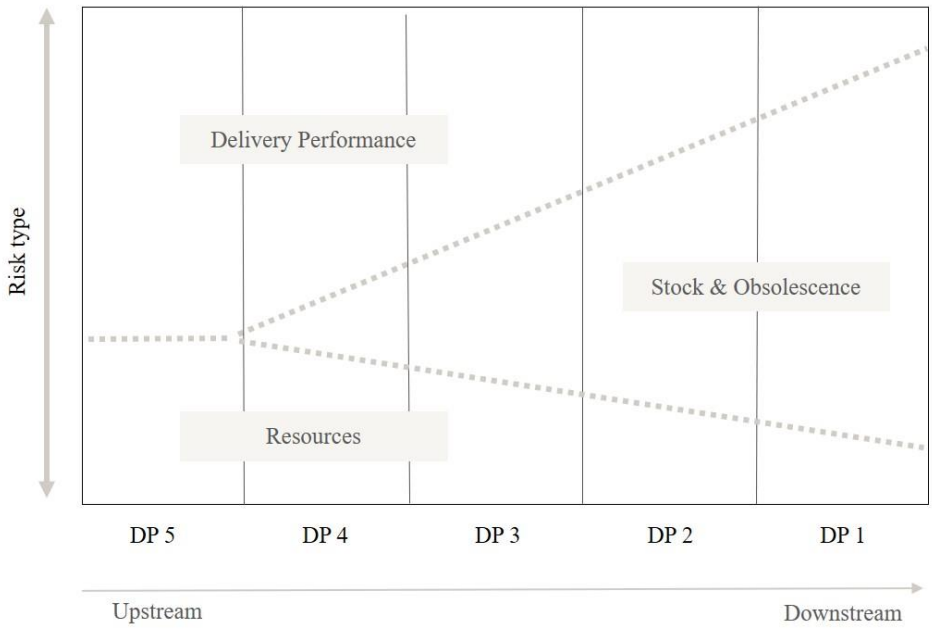

Figure 6. Risk types in decoupling (adapted from Hoekstra et al. 1992, 8).

Decoupling point is the point of balance between requested delivery lead time from customers and the lead time of procurement, production and distribution processes. DP is typically determined for each product or product group separately, considering the earlier mentioned factors of demand and lead time in upstream. In supply chains where lead time is shorter, the DP usually can be placed further in upstream. This way large stocks in far downstream can be avoided. (Hoekstra et al. 1992, 5-8.) The placement of DP allows to optimize the upstream operations to a certain degree independently from the volatility in customer demand (Hoekstra et al. 1992, 66). The decision of the placement of DP is therefore strategic for every business, as keeping the stock in the right position of the supply chain is not only cost effective but also allows geographical flexibility and as shown in figure 6, can mitigate different types of risks. Furthermore, strategic decision of DP strengthens the position of being able to respond to varying demand. (Mason-Jones & Towill 1999a; Hoekstra et al. 1992, 64-65.)

3.2 Motives of holding inventory

In order to remain competitive in the markets, businesses must provide sufficient service to their customers. The function of inventory in general is to balance supply and demand. Proper inventory assortment is not crucial just for the sake of responding to customer demand, but also critical for manufacturing. Shortages in raw material flows can disturb the manufacturing flows which, consecutively, results in added costs. (Bowersox & Closs 1996, 243.) Holding inventory is necessary for geographical reasons, for decoupling and to buffer any uncertainties in supply chain. Yet inventory ties up space and working capital of an organization and can in time suffer from obsolescence or other risks, like deterioration or shrinkage (Bonney 1994). Holding high inventory levels may improve customer relationships, reduce delivery interruption risks, and may protect from price fluctuation or product scarcity. However, earlier studies have proven that organizations may improve their profitability when managing inventory effectively. (Lind et al. 2012.)

According to Tersine (1988), there are three motives for holding inventory; transaction, precaution, and speculative motive. Transaction motive refers to inventory being hold in order to smoothen the production and ensure uninterrupted production. Precaution motive in turn refers to inventory holding approach, where a company is prepared against

unpredictable changes in demand or supply. Precaution is therefore a way to manage risk of interrupted supply or demand peaks. Speculative motive takes place when a bulk of items is purchased due to quantity discounts. (Tersine 1988, 7-8.)

According to Tersine (1988, 7-8) inventories can be further divided into different functionalities, depending on the purpose of use. For example, anticipation inventory is used to respond to seasonal demand peaks, safety stocks to cover the buffer between demand and supply, transportation inventory covers inventories that are transported between production steps, and maintenance, repair, and operating (MRO) inventories. Rumyantsev and Netessine (2007) on the other hand argue that companies hold inventory to manage the lead time between production and demand, to cover rigid production capacities, due to the advantage of the economies of scale, or to cover nonstationary such as seasonality or stochasticity in either supply or demand.

However, inventory binds significant amount of organizations' capital and unnecessarily high stock levels introduce increased cost through further warehousing, handling, insurances, taxes and even obsolescence. (Bowersox & Closs 1996, 243.) Therefore, managing stock levels is essential to minimize the capital tied up to redundant inventory, to minimize added costs and to improve profitability. In fact, reducing the capital tied up to inventory just by a few percentages can impact the profit improvement dramatically. (Blinder & Maccini 1991.) Chen et al. (2005, 2007) report evidence that companies in manufacturing and retail industry have successfully reduced inventory levels between years 1981 and 2001 by yearly 2%. Besides, managing inventory is also an approach to mitigate risks that come along with the capital investment, whilst maximizing the service level on customer orders and keeping up with the sales orders. (Blinder & Maccini 1991.)

3.3 Inventory functionality

There are various internal and external factors that affect inventory levels. It is essential for businesses to understand the impact of each factor in order to manage inventory effectively while tying up the minimum possible capital in it. Typically, inventory behavior is characterized by order placement, deliveries and demand. Inventory level is at its peak when delivery arrives. (Bowersox & Closs 1996, 253.) The level decreases as demand pulls items out to the customers. At a certain point a new order is placed – this is called re-order point

(ROP). (Blinder & Maccini 1991.) The order placement may take place also at the peak or even later, when average inventory level has been consumed (Bowersox & Closs 1996, 253). Typically, the most optimal behavior of inventory consists of order delivery and consistent demand, as figure 7 shows. The model describes the inventory behavior with demand at two companies' stocks; company A and B. Ideally, inventory process consists of make-to-order operations, where a product is produced as a customer places an order. In such case, an organization is not holding stocks of raw material and finished goods based on demand forecasts. (Bowersox & Closs 1996, 247.) Unless the ideal process is possible to be implemented, companies are forced to keep certain level of inventory to respond to demand and to sustain desired service level (Van Jaarsveld & Dekker 2011).

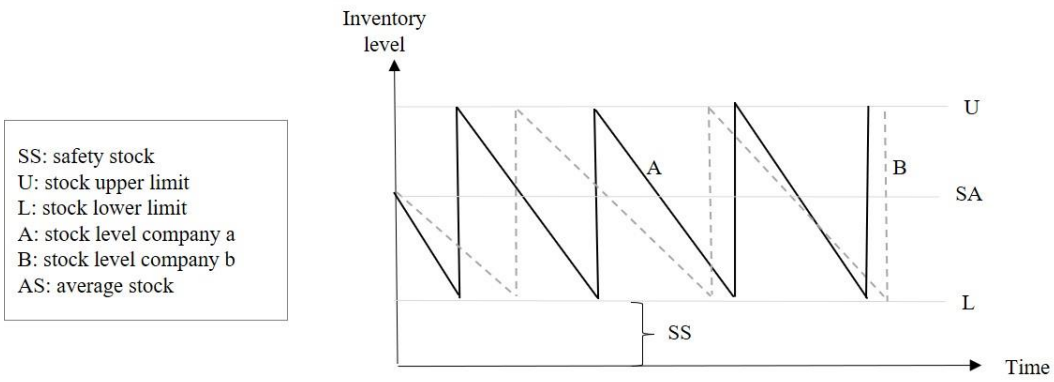

Figure 7. Optimal inventory behavior model (modified from Blinder & Maccini 1991; Bowersox & Closs 1996, 253)

The optimal lot size, which represents the quantity to order, depends on variables such as purchase price, fixed cost, interest rate and sales distribution. In the optimal inventory behavior, the optimal lot size typically is calculated with a formula of upper stock limit (U) minus lower stock limit (L). However, depending on the business strategy, a company might not have an optimal level of inventory at all, but instead has an optimal range of inventory. In this case, a reaction is made as soon as the trigger point of inventory level is hit – otherwise there is no reaction. (Blinder & Maccini 1991.) The optimal inventory model describes average inventory as half of the order quantity. The average capital invested into inventory can therefore be calculated as in equation 1.

Avg. capital invested = (min. stock + max. stock) / 2 * unit value (Eq .1)

In fact, the typical inventory models do not always reflect to business reality, because they do not take into account competition, cycles, trends, industry typical factors, and company's financial distress. In reality, the complexity of supply chains is higher than the typical inventory models are planned for. Different factors can impact the inventory levels in different organizations and impacting factors might be other than the models account for. (Rumyantsev & Netessine 2007.)

3.3.1 Cycle stock and safety stock

In theory, inventory consists of two variables; cycle stock and safety stock. Cycle stock is the portion of inventory which results from a replenishment. Customer demands are served from cycle stock until the point of new replenishment arrival. Safety stock is part of inventory which is devoted to respond to demand uncertainty in short-term. (Sitompul et al. 2008.) If safety stock does not exist and demand unexpectedly exceeds the replenishment size, a stockout will be encountered. Stockout situation is not preferable, as it results in loss of revenue, customers, and market share. Therefore, safety stock has an essential role in customer satisfaction and increasing business revenue as it covers the business in replenishment cycle when the demand is higher than originally planned and an order quantity of cycle stock has been underestimated. (Bowersox & Closs 1996, 251.) Safety stock exists to tackle the burden of increased demand by customers and is an inevitably necessary function in today's inventory management. However, in the most optimal case with consistent demand, safety stock is not necessarily used at all, as shown previously in figure 7. (Blinder & Maccini 1991; Bowersox & Closs 1996, 253.) Cycle stock is driven by the order quantity, whereas safety stock is driven by the level of uncertainty, as shown in figure 8. Uncertainty covers unexpected changes in customer demand, incorrect forecasts and variability in product lead times. In theory, average stock equals one-half of the quantity ordered plus the defined safety stock, as shown in figure 8.

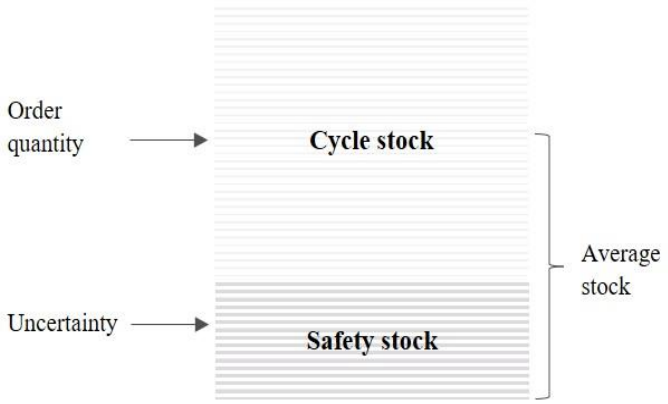

Figure 8. Inventory consistency and driving factors

Safety stock management is essential, thus one of the most challenging part of the work of supply chain managers. Decisions must be taken in regard to the location of inventory, which is related to the earlier discussed decoupling point concept, and corresponding level of inventory. Both decisions have a significant impact on not only service level, but also delivery lead-time, response time and total cost of the supply chain. All these interactions are present in various stages in supply chain, which makes the analysis and decision-making much more complex and difficult. The basic approach to safety stock calculations considers service level, lead time deviation and average demand. (Sitompul et al. 2008.)

Two main criteria of evaluating the efficiency of inventory management are service level and the inventory required to achieve the service level. Service level in inventory management is a performance target set by the management and it's typically expressed in percentage. (Barnes-Schuster et al. 2006.) Service level indicates the level of performance inventory function is achieving. Service level can indicate the performance in terms of order cycle time, order fill rates, or any other warehouse related fill rate. (Bowersox & Closs 1996, 250.) Safety stock has a significant impact on service level, which makes safety stock a must requirement to meet determined service level. Service level typically is between 90 – 99 %, meaning that large of a ratio of demand should be covered by the inventory available. Increasing service level will decrease the risk of stock out, thus requires a higher level of safety stock. Figure 9 illustrates inventory behavior when service level is determined at 95%. In 50% of the cases demand will we covered by cycle stock. The next 45% of demand will be covered by cycle stock too but supported by safety stock. In approximately 5 percent of the replenishment cycles a stockout is expected. (King 2011)

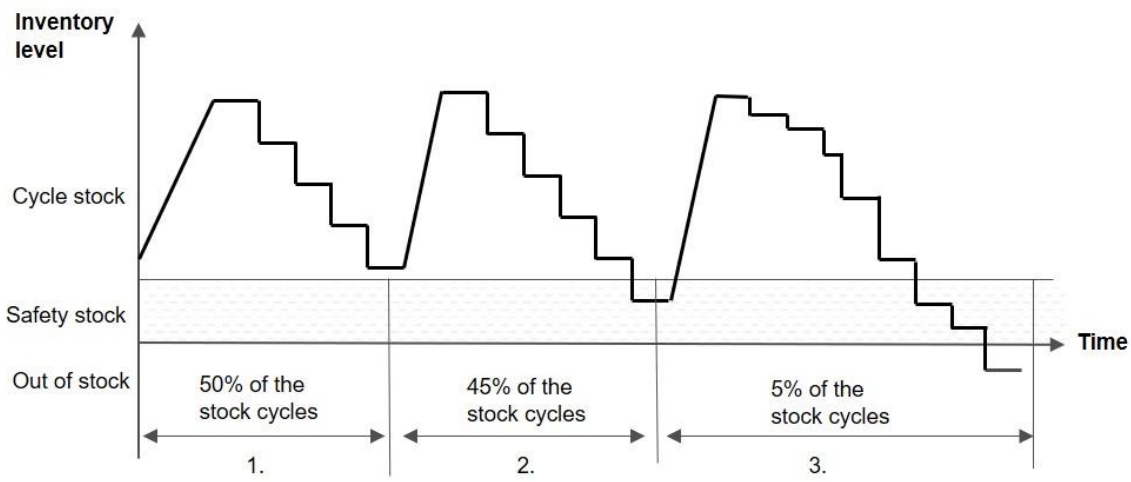

Figure 9. Inventory behavior with 95% service level (modified from King 2011)

In theory, there are various ways to calculate safety stock, in order to find a balance between inventory costs and service levels. In some businesses the safety stock is used to cover variability in demand and in some variability in lead time. If the aim of safety stock is to cover uncertain demand, the calculation approach typically considers service level factor, lead time, and standard deviation of lead time. If in turn, uncertain lead time is a concern, the calculation considers service factor, standard deviation of lead time, and average demand. If both demand and lead time are uncertain, the equations can be combined. Thus, this requires that the variables are independent, meaning they are influenced by different factors. (King 2011.) The equations for all three safety stock calculations are described below.

1. *When demand is uncertain:*

$$SS = Z\sqrt{\frac{PC}{T}}\sigma D \qquad \textit{Eq. 2}$$

2. *When lead time is uncertain:*

$$SS = Z \text{ x } \sigma \text{ } LT \text{ x } Davg \qquad \textit{Eq. 3}$$

3. *When both are uncertain and independent:*

$$SS = Z\sqrt{(\frac{PC}{T}\sigma \mathrm{D}^2) + (\sigma LTxDavg)^2} \qquad \textit{Eq. 4}$$

SS: Safety stock
Z: Service level factor

PC: performance cycle (lead time)
T: time used for calculationg standard dev of demand
σD: standard deviation of demand
σLT: standard deviation of lead time
Davg: average demand

However, safety stock has it cost and contributes to not only in terms of capital it employs along the goods, but also contributes to inventory holding costs (Woerner et al. 2018). In business environment where two main variables are lead time and demand volatility, safety stock helps to assure that products can be shipped continuously without stock-outs. In manufacturing environment, safety stock plays another type of role, since the purpose is not to directly ship to customer, but to ensure continuous production and timely delivery of final product. (Ruiz-Torres & Mahmoodi 2009.)

Typically, safety stock is placed in downstream, at the final stage of the supply chain for instance at the storage of a retailer. This way, ideally, the rest of the supply chain can be saved from the impacts caused by demand volatility. Nevertheless, in reality demand variability cannot be only addressed by the retailer and the consequences will be visible also on the upstream of the supply chain, at the production stage, as well as raw material supply actions. A potential way to approach this issue and to prepare the supply chain for demand volatility is to place safety stock along the supply chain in several stages. However, the challenge is to find the most optimal stages for safety stock and the right amount of inventory to obtain the desired service level at the lowest possible cost. (Sitompul et al. 2008.)

3.3.2 Lot sizes and order quantities

Inventory management should be distinguished between retail and manufacturing industries. Retailing organizations work with finished goods whereas manufacturers work with raw materials and components. Therefore, deciding the order quantities and timing differ in these two environments. (Mueller 2011, 127.) Earlier studies have proven, that determining optimal order quantities allows businesses to realize significant cost savings. In fact, the most ideal situation is when balance between supply and demand exists, and items are consumed at the same pace they are produced. (Degraeve & Roodhooft 1999.) Inventory management focuses on having the right products, at the right place, and at the right quality.

However, to meet these requirements, some companies simply increase safety stocks. Though increasing safety stock involve higher capital on inventory and additionally takes space in warehouse, increasing the inventory cost. (Mueller 2011, 127-128.) To optimize the inventory level and to serve the demand, companies are utilizing methods of reorder point (ROP) and economic order quantity (EOQ).

Inventory management defines reorder point by multiplying demand by lead time. ROP is a state where a new replenishment order should be placed in order to receive a new delivery when cycle stock level approaches zero. (Bowersox & Closs 1996, 258.) The basic reorder point calculation multiplies demand with performance cycle, also referred as lead time, as shown in equation 5.

$$ROP = D\ x\ LT \qquad (Eq\ .5)$$

$$ROP = D\ x\ LT + SS \qquad (Eq\ .6)$$

ROP: Reorder point
D: Average demand units / day
LT: Average length of performance-cycle
SS: Safety Stock

As long as the two variables are known, this calculation approach should be sufficient, but when either of the two are uncertain, the inventory will require a safety buffer to cover the uncertainty. Utilizing equation 5 as ROP calculation implies, that the replenishment is delivered just as the last unit leave the warehouse. If safety stock is necessary for the business conditions, it should also be considered in the calculation of ROP, as in equation 6. (Bowersox & Closs 1996, 258.) To illustrate this with an example, if daily average demand would be 50 units and lead time 14 days, reorder should be placed at 700 units (50 units/day x 12 days = 700 units). If safety stock is considered, assume it to be 300 units, the ROP would be at 1000 units (700 units + 300 units).

Harris (1913) has discussed the challenge and importance of defining the most economical quantity to order already early in the 20th century. The developed formula of economic order quantity allows inventory managers to determine the optimal quantity for their purchase in order to optimize the operations and inventories. (Harris 1913; Perera et al. 2017.) The

classical EOQ model assesses the tradeoff between inventory holding cost and fixed ordering cost.

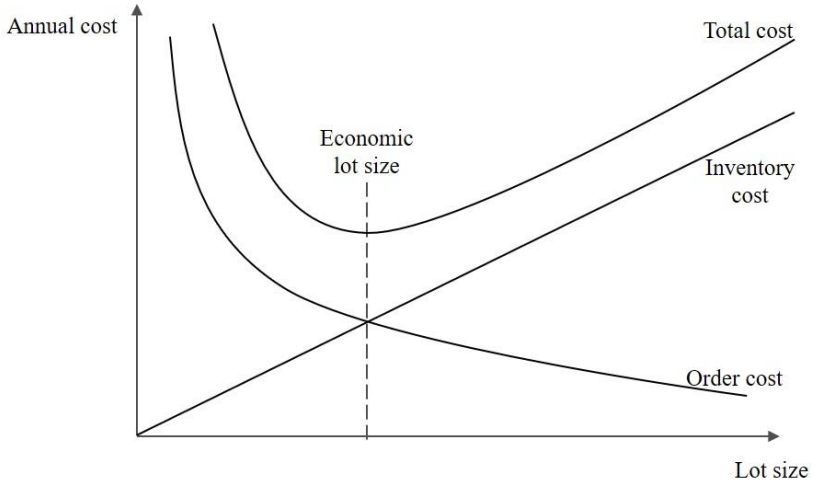

Figure 10. Relationship of inventory carrying cost and ordering cost (modified from Harris 1913)

Inventory holding cost, also called carrying cost, refers to the costs caused from holding the stock, such as capital costs, warehousing equipment and insurance costs. Inventory holding costs are expenses resulted from holding stock which at the moment generates no added value for the business. Ordering costs on the other hand encompass the expenses directly related to requiring the product. The costs include factors such as order placement, labor overhead costs and IT costs. (Mueller 2011, 136-137.)

The outcome of the tradeoff between inventory holding cost and order cost is the optimal order quantity. The classic model of EOQ is described in figure 10. (Harris 1913; Mueller 2011, 136-137; Sagner 2014, 117.) Generally, it is argued, that the classic EOQ model (Eq.7) is based on the assumption of demand rising continuously with a static rate (Perera et al. 2017).

$$EOQ = \sqrt{\frac{2\,A\,R}{K}} \qquad \textit{(Eq .7)}$$

A: Total Sales in Units Per Year
K: Carrying Cost of inventory per unit
R: Fixed purchase order cost

Also Mueller (2011) claims that the classic model is based on assumptions, where the demand rate is known without variations. Therefore, the classical EOQ calculations does not

take into consideration discounts on carrying or ordering costs, even if the quantity of order changes. In addition, the calculation requires that lead time must be known, and orders arrive at one batch without considering vendor stockouts. Surprisingly, Rumyantsev & Netessine (2007) claim, that the model has also been proven to be adjustable in business environments with stochastic demand and to be robust against varying parameters. Thus, several versions of this model are presented within existing publications. Nevertheless, the aim of the model is to define the tradeoff between inventory holding costs and procurement costs. However, suppliers typically impose a restriction on the size of the orders shipped and define a minimum order quantity (MOQ) to constraint the order batch size. (Perera et al. 2017)

3.3.3 Demand volatility and bullwhip effect

Various authors have presented evidence, that inventory levels are affected by volatility in demand (Rumyantsev & Netessine 2007; Chen et al. 2002; Ouyang & Li 2010; Hoffman 2017; Zhang 2004; Kok et al. 2005). The bullwhip effect is a supply chain variance phenomenon driven by minor changes at customer order sequence, which occurs as major reactions at supplier's order sequences in the upstream of the supply chain (Ouyang & Li 2010). The concept is well-known and typically the phenomenon has stronger impacts on component and raw material inventories than finished goods. The variability of demand does not only result in increasing inventory levels as one moves up the supply chain, but also makes equipment and personal planning unnecessarily difficult. (Kok et al. 2005.)

There are various causing factors to the phenomenon. Hoffman (2017) argues, that the phenomenon is a result of faulty forecasting based on aggregated data on demand, exaggerated orders, or lack of data points used for forecasting. Chen et al. (2000) present evidence that the bullwhip effect is commonly caused by demand forecasting and order lead times, shortages in demand, price variations, and batch ordering. According to Zhang (2004), demand volatility has five potential sources, including lead times above zero days, price fluctuations, promotions, processing demand signals, and order batching. To conclude the findings of all mentioned authors on the bullwhip effect, it is obvious that the main cause for the effect is inaccuracies in forecasting. The existing literature (Zhang 2004) suggests, that various forecasting methods should be used in order to take into consideration factors relevant to different business situations. The author states, that regardless of the method used for forecasting, increasing lead time will increase the effects resulted from bullwhip effect,

even though the volume of impact does not depend on the forecasting method. The outcome suggests that the bullwhip effect does not necessarily mean an increase in inventory, and it depends of the complexity and parameters of demand. (Zhang 2004.)

In order to mitigate the bullwhip effect in supply chain, several actions can be taken. Shortening lead times, having direct control over the downstream inventories, or restricting the flexibility at buyers are possible approaches to minimize the impact the bullwhip effect on inventory levels. (Hofmann 2017.) Chen et al. (2002) argue that centralizing transparently the demand data, the bullwhip effect can be mitigated although not completely eliminated. Some companies have integrated collaborative planning tools and actions in order to reduce the impacts of bullwhip effect. Cooperative demand planning and data sharing aims at reducing inventory and increasing service levels. Furthermore, actions like these can improve supplier flexibility and reliability, due to them being able to verify required quantities and delivery times virtually. Automatic sharing of data is especially beneficial in global supply chains where time zones and completely opposite working hours complicate the communication between all parties. (Kok et al. 2005.)

Many authors have demonstrated the existence of the phenomenon, determining the impacts it has on supply chain and proving methods to mitigate the impacts (Chen et al. 2000). Centralizing distribution systems can effectively stabilize variability in demand and furthermore to mitigate the impacts (Zhang 2004). Rumyantsev & Netessine (2007) agree on inventory levels increasing along with demand uncertainty, especially in retail industry. Nevertheless, they also prove that companies do not tend to increase inventories immediately when an increase in demand is recognizable (Rumyantsev & Netessine 2007). Zhang (2004) argues that reducing lead time as an action to mitigate the impacts of the bullwhip effect might be deceiving, in particular when the underlying demand is unknown and the impact of different demand forecasting methods are not understood.

3.3.4 Lead time

The relationship between lead time and inventory has been explored by numerous authors including: Karmarkar (1987), Fisher & Raman (1996), Henig et al. (1997), Enns (2001), Pan et al. (2002), Pan & Yang (2002), Barnes-Schuster et al. (2006), Rumyantsev & Netessine (2007), Glock (2012), and Marino et al. (2018). The premise is that any decision on operative

lead time, typically representing either manufacturing or transportation time, or both combined, will influence the inventory level of an organization (Glock 2012). Defined as the time elapsing between order placement and order arrival, lead time is a critical element in inventory management, playing an essential role in supply chain decisions. Lead time can be decomposed to contributing components, including time on setting up, processing, queuing, preparing orders and order transit, supplier's lead time, and transportation time (Karmarkar 1987; Glock 2012). Typically, in business environments, lead times are recognized with a certain distribution of variance. Lead time is a somewhat controllable decision variable which may be guided within certain boundaries (Pan & Yang 2002; Glock 2012). In some industries lead time is argued to be an independent variable from lot sizes, whilst some authors argue lead time to be dependent on manufacturing lot sizes (Glock 2012). However, improving lead time always comes with a certain cost (Pan & Yang 2002). The length of lead time is argued to have a direct impact on service levels, inventory costs, as well as capital tied up to safety stocks. Additionally, lead time has been proven to correlate with financial performance parameters, such as return on investment (ROI). (Pan & Yang 2002; Glock 2012.)

In theory, long lead times typically increase stock levels. High inventory levels are inadequate for financial performance and long lead times harmful for market response and service levels (Enns 2001). In theory, long lead times impose increased costs due to higher inventories of, for example work-in-process materials, larger safety stocks to respond to increased uncertainty of requirements, and finally poorer performance to meet due dates. (Karmarkar 1987.) Reducing lead time is a potential action of increasing the competitiveness of every company (Marino et al. 2018) and improving productivity (Glock 2012). Evidence has been provided, that reducing lead time is beneficial especially when demand uncertainty is high. When lead times are longer, companies put themselves under greater risk of running out of stock, while waiting for the next order to arrive. (Glock 2012)

Enns (2001) provides evidence that finished goods inventory level is influenced by planned lead times and lot sizes. Thus, his study focuses on lead time from lot size and MRP (material requirements planning) point of view, the outcome is explained by stating that increasing lead time results in earlier accomplishment of finished goods in regard to actual date of requirement. Also, increasing lot sizes have an identical impact on inventory levels, due to

lot size rounding resulting in MRP creating larger orders for production, which leads to higher remnant finished goods inventories. Therefore, increasing lot sizes has a long-term impact on inventory levels, if from period to period the remnant finished goods inventory increases. (Enns 2001.) Henig et al. (1997) studied lead time and its variability reduction initiatives from supply contracting point of view. According to the authors, the frequency and volume of future demand is specified while the demand is still somewhat uncertain.

In supply chain management (SCM) context, delivery lead time has been explored in strategies that aim to either improve production efficiency or to achieve desired service levels. In fact, lead time should be considered as a contributing factor on competitiveness, as it impacts the responsiveness of the company. The relevance of lead time in supply chain management is widely recognized, although much of an adequate evidence of the impact of different lead times is not available. (Marino et al. 2018.) The research conducted by Rumyantsev and Netessine (2007) proves that inventory levels in manufacturing industry are associated with demand uncertainty, lead times, margins and economies of scale. Their analysis prove, that increasing lead times impact inventory levels, since companies end up holding inventory buffer against long lead times. (Rumyantsev & Netessine 2007.) Sufficient shortening of lead times allows companies to schedule production in response to actual demand (Fisher & Raman 1996). Also, Karmarkar (1987) has recognized already in 80's that lead time has an impact on order sizes. The tradeoff between ordering small batches often reduces the capital tied up to inventory however, typically increases ordering costs. Long lead times tend to increase the risk of unavailability of products which leads to disruption of business – either in manufacturing standby's or missed customers' orders. (Karmarkar 1987.) Furthermore, forecasting and planning actions are directly impacted by lead times, because planning is required well in advance. This reduces the flexibility to respond to any changes in demand and manufacturing capacity requirements. For this reason, companies store safety stocks to protect against longer lead times and against greater forecast inaccuracies resulted from long lead times. According to Karmarkar (1987), safety stocks typically increase more than proportionally as lead times grow. Increasing inventory as a result of long lead times might also lead to deterioration or obsolescence of products and materials, which equals to loss in business profit. Coordination of supply chain is consequently more challenging when lead times are long and any delays that might occur, will have a major impact on many factors of the chain. (Karmarkar 1987.)

By shortening total lead times, companies are able to get along with lower safety stocks, reduce financial losses caused by stock outs, improve service levels and to reduce the total costs in supply chain (Pan & Yang 2003; Glock 2012). Since lead time is somewhat controllable, it can be reduced, thus with an additional extra cost. Typically, shorter lead times lead to larger number of orders and smaller quantities per order. Generally faster transportation methods are more expensive than slower methods, and faster transportation method is often the option to reduce lead time. The associated costs of quicker transportation methods are generally proportional to the size of the shipped order. In addition, administrational costs related to smaller order sizes and more frequent deliveries should be considered. Vendors might have to cope with increased inventory holding costs when order sizes are smaller, which will be added to the price customers eventually must pay. (Pan et al. 2002.)

An increasing trend shows, that suppliers are relocating activities closer to the buyers aiming at reducing their lead times close to zero. Also, earlier studies prove that reducing lead time brings savings to organizations. More than that, it is not only a single player in the chain that benefits from reduced lead times, but the efficiency of the complete supply chain is argued to increase. (Barnes-Schuster et al. 2006.) A research by Mason-Jones & Towill (1999b) reveal that in some industries organizations prefer to aim for short lead times due to the significant loss caused by stockouts. The authors mention Benetton from fashion industry as an example, which transports half of the sold products by air due to the fact that the cost of air freight is not nearly as significant as the cost savings achieved with less inventory. (Mason-Jones & Towill, 1999b.) Another initiative to secure reliable delivery lead times is to establish long-term single supplier relationships with vendors. If a supplier is offered a business to deliver all orders, they can be insisted to guarantee reliable delivery. Productivity improvements will improve the business on both sides. In practice, lead time can be reduced although with additional cost and requires a certain level of collaboration between supplier and buyer. (Pan & Yang, 2002.)

3.4 Financial supply chain management

Various authors have discussed supply and supply chain management having a significant financial impact on an organization (Ellram & Baohong 2002; Hofmann & Kotzab 2010;

Templar et al. 2016). It is proven, that organizations with excellent supply chain management operations have consequently also strong financial performance (Hofmann & Kotzab 2010). The impact of supply management exceeds the aim of cost reduction (Ellram & Baohong 2002) and influences multiple aspects in organizations financials, such as credit risk and payable extensions (Hofmann & Kotzab 2010). The decisions taken on inventory management level have a significant impact on an organization's balance sheet and income statement, as well as on shareholder value. Critical performance areas such as business growth, profitability, liquidity, and asset utilization are impacted by purchasing activities. (Ellram & Baohong 2002; Templar et al. 2016, 15-17.) Balance sheet consists of two halves, the other half indicates where the money to fund the operations was raised from, and the other half consists of total net assets, meaning where the company has spent the funds. Total net assets are fixed assets, which consist of tangible and intangible assets and working capital. (Templar et al. 2016, 21-22.)

A supply chain is typically comprised by non-current assets, such as plant and equipment, and by working capital, which can be comprehended as current assets minus current liabilities (e.g. Knauer & Wöhrmann 2013; Hofmann & Kotzab 2010). Both elements contribute to the balance sheet of an organization. Classic current assets consist of inventory, cash and account receivables, while in turn current liabilities typically include for example accounts payable to suppliers or dividends to be paid to shareholders. (Templar et al. 2016, 21-22.) It is proven, that a shifting cost to supplier by extending and negotiation payment terms may result in short-term benefits on organizations balance sheet. However, long payment extensions may turn to a struggle also at the buyer's side, as a supplier with unstable financial status may lack the capital for instance to acquire raw material which may trigger production downtimes, delays and quality matters. Eventually, a supplier would add the costs of these incidents into the purchase price. (Hofmann & Kotzab 2010.)

3.4.1 Working capital management

Working capital represents the financial wealth of an organization and is generally understood as the capital available for daily operations and short-term finance of an organization (Sagner 2014; Lind et al. 2012; Knauer & Wöhrmann 2013). Effective working capital management aims at ensuring the availability of necessary funds to run day-to-day business operations, while simultaneously securing the investment of organizations assets in

a productive manner. Efficient management of working capital releases funds for strategic objectives, improves profitability and reduces financial costs. (Lind et al. 2012.) The need for working capital is influenced by internal and external factors. Internal factors include for instance company size, growth rate, organizational structure and investment capacity. External factors on the other hand include the economy, competitors and business environment, as well as interest rates and technology innovation. (CFA Institute 2020.) Working capital is calculated by deducting the current liabilities (accounts payables, dividends and taxes) from the current assets (inventory, cash & account receivables). (Knauer & Wöhrmann 2013; Templar et al. 2016, 21-22.)

According to Talonpoika et al. (2015) working capital consists of three sections; net, operational, and financial working capital. With this division, *net working capital* refers to working capital as known by Templar et al. (2016); current liabilities deducted from current assets. In addition, Talonpoika et al. (2015) introduce *operational working capital* which consists of inventories, accounts receivables and payables. The third section, *financial working capital* includes the factors of net working capital, which are not included in the operation working capital, such as cash. Operational working capital has exclusively been under recent studies, which mainly have focused on the impact on profitability as well as financial constraints. (Talonpoika et al. 2015.)

Decisions taken on the supply chain side predominantly concern the total net assets, rather than where the funds for the operations coming from. The cause and effect chain flow is following; capital tied up to inventory directly impacts working capital, which consequently has an impact on total net assets, which finally appears in the in balance sheet. Therefore, inventory can be recognized in balance sheet as an asset that the organization has spent capital on. (Templar et al. 2016, 21-22.)

3.4.2 Working capital indicators

Income statement is the profit and loss statement, which derives the profit gained after expenses have been reduced from sales revenue. Return on total net assets (ROTNA) is financial ratio which measures the earnings as a percentage of the total net assets (denominator). Supply chain decision can positively impact ROTNA, as decisions have direct impact on cost of goods sold (COGS) which when reduced has a positive impact on

earnings before interest and tax (EBIT) - the numerator. Improving inventory management by reducing inventory often has an impact on both, EBIT as well as total net assets. Just by decreasing inventories, the current net working capital can be reduced. (Templar et al. 2016, 22-23.) Figure 11 represents the breakdown of ROTNA and clarifies the role of inventory in organizations financials.

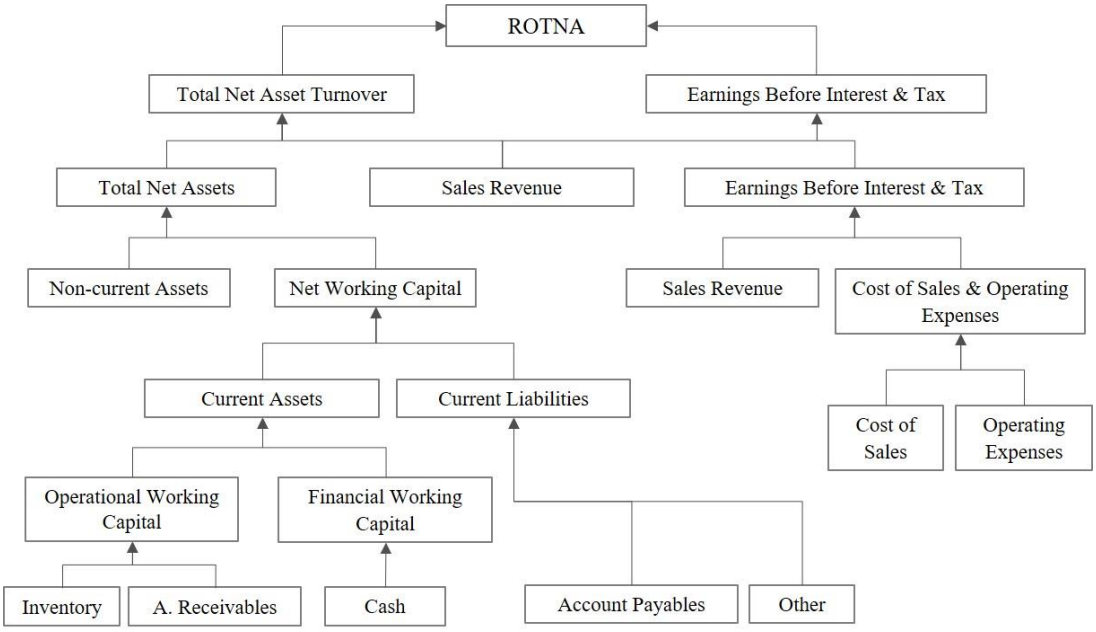

Figure 11. Return on total net assets; A: Account (modified from Templar et al. 2016; Talonpoika et al. 2015)

The study conducted by Enqvist et al. (2014) indicates that retrieving for working capital efficiency on routine basis in businesses has a significant impact on corporate profitability. Inventory is an essential factor in working capital management, and it is considered as an asset, and therefore also appears as an asset in the balance sheet of every organization.

Table 2. Inventory volumes in global companies (respective financial statements 2018)

Company	Inventory 2018 (in m EUR)	In original currency	Original currency	Conversion rate
Apple Inc.	265,151	289,000	USD	1 EUR = 1.0899 USD
Bosch	11,015	11,015	EUR	-
Hilti	643,170	678,600	CHF	1 EUR = 1.055 CHF
HM Group	3,445	37,721	SEK	1 EUR = 10.927 SEK
KONE	648,300	648,300	EUR	-
Marimekko	22,1	22,1	EUR	-

As table 2 shows, large global businesses hold millions of euros on inventory yearly. For example, the balance sheets of selected organizations reveal that at the end of the fiscal year 2018, the companies were holding inventory worth of million euros as following: KONE 648 million EUR, Hilti 643 million EUR, and Apple Inc. 289 million EUR. (Financial statement Kone 2018; Financial statement Hilti 2018; Financial statement Apple 2018) These figures prove the significance of inventory management as part of the corporate financials and explain the cruciality of successful inventory management in profitability.

Reducing inventory is a potential action to reduce current assets, subsequently improving cash flow, reducing the expenses of operations, positively impacting the profit and finally reducing the total net assets in the balance sheet. Inventory reduction can be achieved through for example reviewing procurement strategy or improving demand forecast accuracy, which may impact the cost of holding inventory as well as to able reduce order quantities. (Templar et al. 2016, 24.) Furthermore, excessive inventories can be difficult to liquidate especially in case of economic downturns (Enqvist et al. 2014). The factors of PSM and inventory management that impact the financials and working capital of an organization, include purchase prices and pricing concession, as well as volume purchasing and delivery timing (Sagner 2014, 123). Enqvist et al. (2014) state that when managing working capital, managers must consider the tradeoff between profitability and liquidity, as keeping low inventory levels may result in stock-outs, consequently increasing the account payables.

3.5 Literature conclusion

The literature review has highlighted the significance of inventory management for corporate efficiency, liquidity and profitability. The significance of inventory management as a contribution to financial health of the organization has been emphasized. The evidence states that inventory has a significant influence on working capital, which corporations use to fund short-term operations. Therefore, researchers and practitioners are keen to understand the inventory drivers and the influence of single parameters on inventory. Evidence has been collected and various earlier studies prove that there is a large set of driving factors in different business environments. A summary of the inventory drivers discussed in the literature review is presented in figure 12. The inventory drivers have been categorized based on motives of holding inventory discussed by Tersine (1988).

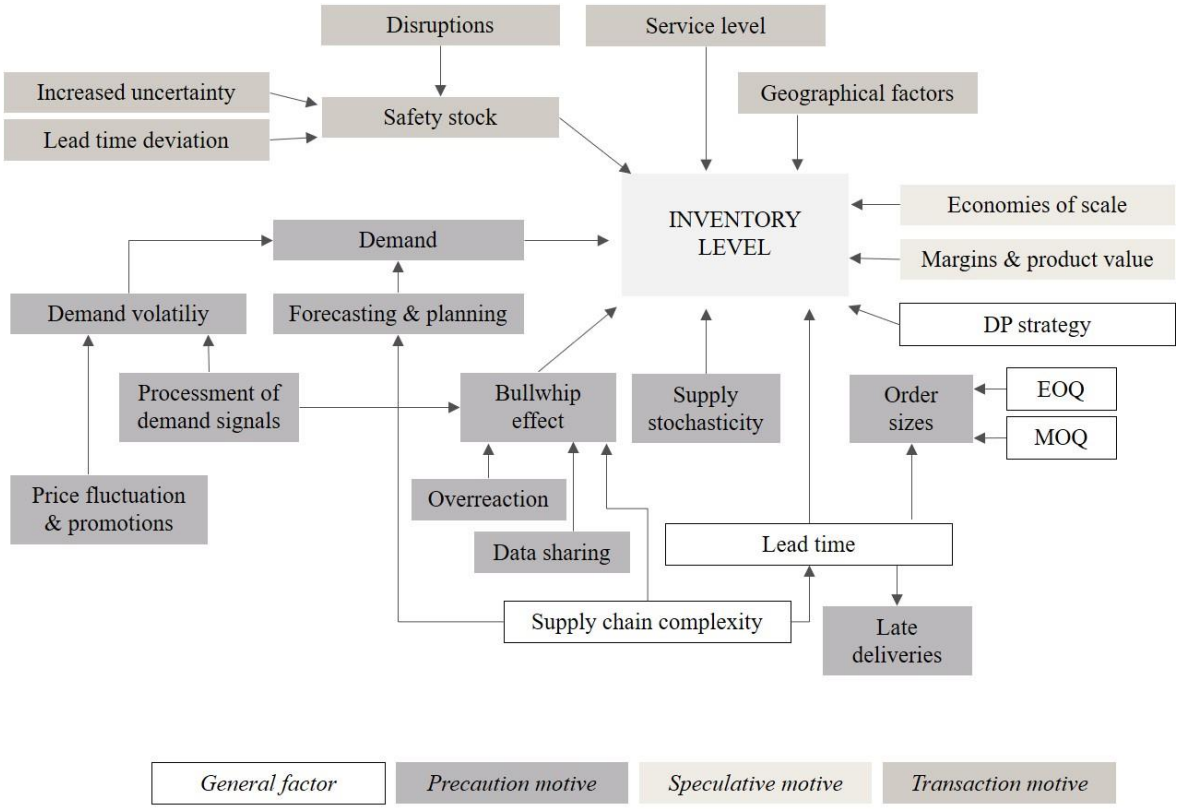

Figure 12. Inventory drivers defined by the literature review

As the figure 12 summarizes, various inventory drivers have been identified. The cause and effect chain of these factors is a complex entity and the factors defined are influencing not only each other but also the level of inventory either directly or indirectly. Motives of holding inventory allows some interpretation for categorization of each factor. For example, from manufacturing business point of view, safety stock would surely be placed under transaction motive, as the safety stock would support continuous manufacturing in case of supply interruptions. But, in a retail company, safety stock would surely be placed under precaution motive, where the purpose of safety stock would only be securing the product availability in case of sudden demand peaks or delivery issues. For this case study both placements would be suitable, as the case organization is a manufacturing firm as well as a sales company. Nevertheless, the purpose of the figure is to summarize the factors discussed in the literature review, not to interpret and describe the complete cause and effect chain of inventory management. Multiple drivers from the figure 12 have been selected to be tested and analyzed in the empirical phase of this case study, which will be described in the paper next.

4 EMPIRICAL CASE STUDY

Globally operating manufacturing company provides an excellent opportunity for a case study, where the relationship between lead time and the current assets on inventory can quantifiably be studied in a real business environment. The empirical part of the research proposes evidence of the classical parameters influencing inventory levels, that were defined in the literature review by examining various academic papers. This chapter introduces shortly the case organization, describes the data and defines the case study specific inventory drivers.

4.1 Case organization

Hilti Corporation is a family-owned company and has been founded in Liechtenstein in 1941 by brothers Martin and Eugen Hilti. Today, the company operates as a global market leader in demolition and fastening technology in the construction industry. Since the beginning, Hilti has been reaching increasing sales and successful growth, reaching in the fiscal year 2018 annual net sales of 5’659 million Swiss francs. With 30 000 employees the organization operates in more than 120 countries and has been recognized as a great place to work in Europe and worldwide (Great place to work 2020).

Hilti is divided into two business divisions; fastening & protection (F&P) and electric tools & accessories (ET&A). These two divisions together buildup 11 business units. Production facilities are located in nine locations globally. In addition to the production plants, further facilities that contribute to the supply chain of Hilti include local, regional and central warehouses, decoupling points, Hilti stores, and containers on customer construction sites. The company operates with a direct sales model, not using any third-party retailers for sales purposes. Suppliers produce components and finished goods and therefore the material flows and the lead time between suppliers and the organization depend on the type of the product. In addition, some products are classified as dangerous goods, which create an extra challenge for supply chain management. Procurement decision-making is operated in a harmony of centralized and decentralized decision-making, although global decisions are taken in the central function. Inventory management is carried out by materials management and logistics. Highly sophisticated models are utilized in order to optimize the inventory control, including the company specific safety stock models.

4.2 Data collection

In quantitative studies, data is typically collected from either public or private databases. The quality of the data must be proofed, and necessary modifications must be done in order to improve the quality of the data. Data with high quality is modified in order to consider the correctness, completeness, and objectivity of the data. Correctness of the data refers to careful examination of details such as parameters like unit or currency. Completeness in turn refers to modifying the data in a way that only complete data observations remain. This would include for example removing uncomplete rows due to missing data. Objectivity refers to the reliability and pureness of the data, meaning the data must not be modified by the system or other third party prior to the data collection. (Pipino et al. 2002.)

Prior to the data collection, it was necessary to understand the supply chain design and inventory set up of the organization. While the study was ongoing, it became obvious that various different warehouse types exist globally; global distribution centers, national distribution centers, regional distribution centers, Hilti-store warehouses, and Hilti-cars (on-site inventories). Knowing this, it was decided to look at a data set for a view items prior to the main empirical study, in order to comprehend the level of data available.

The data collected was quantitative, gathered for the purpose of this research and was collected between January and February 2020 from the ERP system of the case company. The first test sample was collected from the SAP system already end of December 2019. The purpose of the first sample was not to generate results but to help to understand what the data represents and what parameters should be considered when aiming for results in regard to the defined research questions. Challenges in the data from SAP included for example various interpretations of demand and understanding the differences between different values for demand.

Consequently, it became clear what parameters should be considered for the all-encompassing analysis to examine the impact of lead time on working capital invested in inventory. The final data sample included all products from two product families. After investigating and learning the purpose of each inventory indicator in the system, it was decided to utilize average monthly inventory and inventory coverage level A (ICLa), which

indicates the inventory days on hand (DOH). These allow to examine the monthly average inventories both in Swiss Francs (CHF) and in pieces on an item level at the selected warehouse. It was decided to exclude from the beginning the smallest global warehouses because it was known that in these warehouses the demand is small and in comparison, inventory levels very high. For this reason, smallest warehouses were considered as high disturbance risk for the analysis results. In addition to mentioned inventory insights, the data sample included information such as safety stock method, actual safety stock, lead time, EOQ and service level.

4.3 Data description

This study uses a representative sample of secondary data obtained from the ERP-system of the case company. The sample consists of annual data from 2019 containing monthly figures and values. Because no absolute historical daily figures were available, average monthly figures were collected. Utilizing monthly data allows to account for seasonal inventory fluctuations. The study accounts solely finished goods inventories, no raw materials or WIP items. Two largest product families of the respective business unit were considered. Furthermore, the focus was decided to set on major markets, where also inventory levels are the highest. In this study case, this meant the largest warehouses, which included 26 warehouses globally.

Although the holistic literature review resulted in a rich identification of all parameters impacting inventory level, not all identified factors will be considered in the extensive analysis. The parameters selected will be presented later and the drivers not included can be rationalized with following reasons:

- Some parameters, such as ordering cost and carrying cost, have an indirect impact on inventory, thus all these factors should be considered by the lot sizes rather than inventory level directly.
- Some parameters are suitable for analysis only in specific situations. Type of inventory management is relevant for studies where different control environments are compared, such as lean or ROP based inventory management.
- Some parameters are difficult to be quantified, e.g. strategic decisions such as economies of scale.

Although the comprehensive literature review suggests large number of inventory drivers to exist, a reduced set of drivers was selected based on the research limitations as well for the fact that not all information was necessary nor possible to obtain. Through discussion and validation later in this paper, many drivers will be excluded whereas a view will remain till the end. A set of drivers was selected and proposed for exhaustive analysis for the case context. The collection of drivers should include all basic inventory drivers, such as demand and demand volatility, but also all variables which potentially could be considered relevant in inventory level determination based on the results of literature review process.

Since the aim of this study was exclusively to define the impact of lead time as a determining factor of inventory level, it was crucial to obtain required lead time inputs. The literature review has stated that also various other variables are influencing inventory level. All the available inventory driver parameters can be classified by the following categories:

- **supplier/plant-related:** such as delivery lead times, lead time deviation or minimum order quantities
- **customer-related:** such as demand and demand volatility
- **strategy-related:** such as service level and business environment (push or pull), human decisions (e.g. management and orders from experience and gut feeling)
- **logistic-related:** such as forecasts, forecast accuracy, inventory control type (e.g. JIT or ROP), ROP, safety stock and EOQ

A set of potential variables was selected based on the literature review to be tested on this case analysis. These variables presented in table are supposing determining drivers of the level of inventory, therefore their causal relationship with the response variable was tested. Clarified terminology and specific measures of each variable is described in table 3. These are case company specific factor descriptions and can vary from company to company. A detailed case organization specific description of each factor follows below the table.

Table 3. Set of tested inventory drivers in the case organization

Factor	Description	Unit of measure
Value	Purchase price of the product from a supplier	CHF/piece
Demand	Average monthly demand (182d)	pieces
Demand volatility	Average monthly variation in demand (182d)	pieces
Lead time	Time elapsing between the order and the delivery of goods to a named warehouse	days
Lead time dev.	Deviation of lead time over lead time in 182 days	days
Safety stock	The level of additional stock to cover unplanned demand or disruptions	pieces
Service level	Level of which the existing demand is satisfied with the stock on hand	percentage
MOQ	The minimum quantity to be shipped by the supplier	pieces
EOQ	The calculated quantity that should be ordered in order to minimize costs while satisfying the demand	pieces
Forecast accuracy	Deviation of estimated demand from real remand	-

Value represents the purchase price of a finished good, including the material and overhead costs. Purchasing price has a direct impact on the capital employed, as inventory is one of the assets that company must invest capital into in order to operate and generate profit. Unlike the other parameters, it is assumed to have an inverse correlation, as theoretically the higher the value, the lower the stock should be.

Demand represent the average customer demand of the finished goods at item level. From its nature it represents the main driver for inventory since it is the base for cycle stock as well as safety stock calculations. As the case company operates on a business environment with highly seasonal demand, an average figure is sufficient to be considered. By default, SAP provides the average demand of the past 6 months (182days), which will be used and considered as a reliable time period.

Demand volatility represents the variation in monthly demand along the past 6 months. This is compared to identify the level on variation in customer demand.

Lead time is the time elapsing between the order creation and the delivery of the order to a named warehouse. This study does not consider manufacturing lead time, thus focuses only

on delivery lead time. According to literature review lead time is an influencing factor just like demand, as it is used to calculate the cycle stock as well as safety stock.

Safety stock represents the extra level of inventory maintained in order to mitigate the volatility in demand as well as any unforeseen changes or disruptions in supply. The case company has developed six different safety stock methods, which are meant to serve different product and business environment characteristics. An overview of the safety stock methods is depicted in figure 13. Some of the safety stock methods consider lead time as a factor while some do not. This means, in some formulas lead time is a variable while in SBB and SB1 formulas lead time is not a variable in the formula. Therefore, safety stock is determined without considering the lead time at all. Out of the safety stock methods only SB1 and SBB does not consider lead time in calculations, the rest of the methods do.

The basis for the safety stock decision relies on the accuracy of historical demand forecasts. If the historical demand forecasting has been accurate and forecasting for the product is considered a reliable approach, then forecast based method can be used. However, if forecasting has not been accurate in the past, the safety stock method will be selected based on demand statistics. SBA is the only method which balances both approaches – forecast and statistical based.

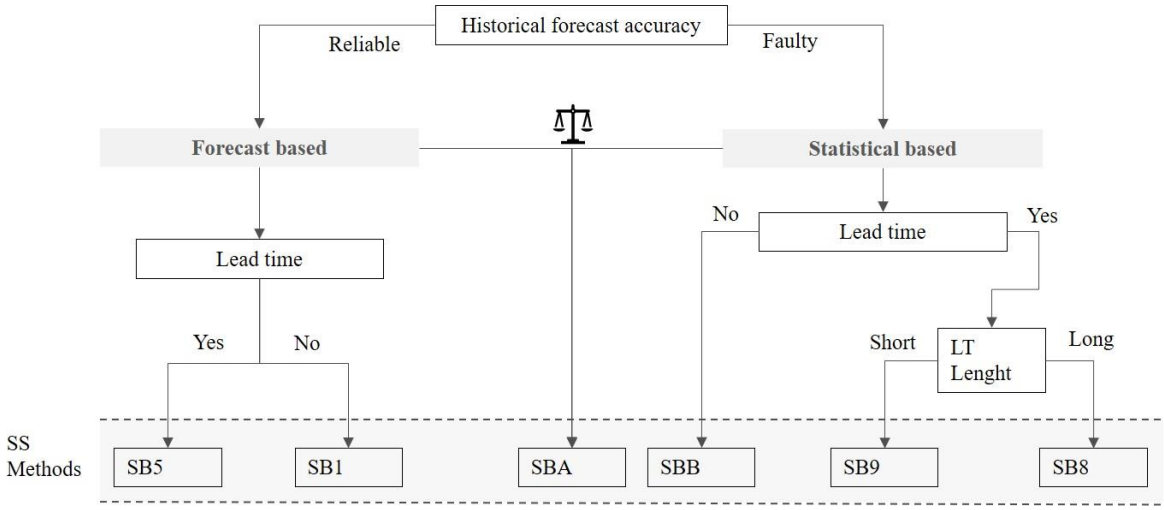

Figure 13. Safety stock method determination at Hilti

Instead of a safety stock method, occasionally also reorder point (ROP) method is used instead. In total there are three different ROP methods at Hilti, one for statistical determination of ROP, one for consumption dependent ROP, and the last method takes the

largest of the two earlier methods. All ROP methods consider lead time as a variable in the calculation method.

Service level represents the level of the demand the warehouse is able to satisfy with the current stock on hand. In this case, the service level only refers to customer demand, as no raw materials are considered, but finished goods. Service level relates to company's strategy and with a few exceptions, the company aims at serving with 95 – 99% service level.

MOQ represent the minimum order quantity imposed by the supplier. Therefore, it is the minimum lot size that must be ordered by the company from its suppliers. MOQ does not define an upper limit for an order, thus does not consider any inventory related costs.

EOQ represents the most appropriate economic quantity of which the company places order deliveries from a supplier. EOQ is a calculated lot size to optimize certain inventory related costs, such as handling and ordering costs, while satisfying the demand as a certain service level. However, MOQ overrules the EOQ, if MOQ quantity is higher than the EOQ.

Forecast accuracy is defined as the level of forecasted demand meeting the actual demand. Instead of demand parameter, often inventories are based on forecasted demand, particularly in the push-environments.

5 ANALYSIS METHODS

This chapter discusses the analysis approach and the quantitative methods of analysis used in this case study. First, the analysis approach will be presented and supported with a short overview on the analysis methods. Multi variate regression method will be discussed more in detail as well as the method of ANOVA analysis.

5.1 Analysis approach

There are various techniques and methods to analyze and process quantitative data among which statistical analysis, data visualization, data harvesting and KPI measurements. In this case study approach of statistical analysis and visualization of data were applied. The data was processed by three statistical analysis methods; exploratory analysis, multivariate regression analysis, and analysis of variance (ANOVA). According to Ketchen et al. (2007), the methods to analyze data for the purpose of strategic management expanded in the 90's, and the in the beginning of 21st century when regression and ANOVA analyses became common approached on quantitative data analysis. These two methods were dominantly used in analysis aimed for strategic management. (Ketchen et al. 2007.) In this study, the outcome relies on these analysis methods.

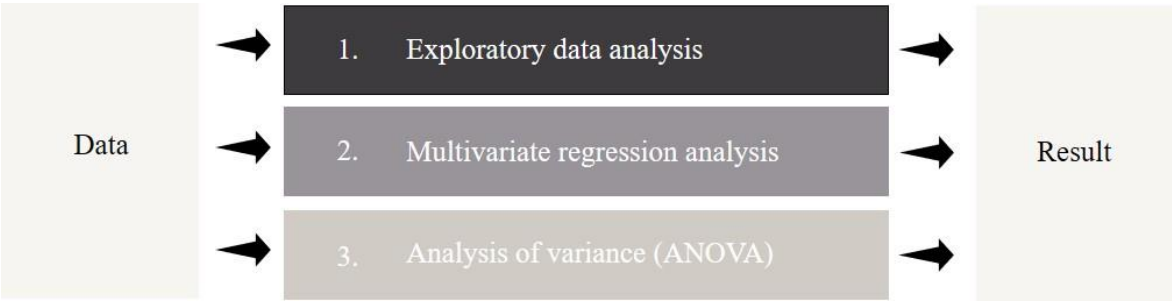

Figure 14. Case study analysis approach

The inventory drivers considered as relevant factors in measuring the quantitative effects on inventory included lead time, lead time deviation, demand, demand deviation, forecast accuracy, service level, minimum order quantity (MOQ) and economic order quantity (EOQ). As figure 14 shows, the analysis flow initiated with exploratory data analysis (1). Exploratory analysis allows to examine the first insights of the data, explaining the characteristics of the sample. Exploratory, also called descriptive, statistics were completed using Minitab. Prior to the first analysis, the data set was processed by removing all

incomplete rows, meaning the rows that were missing any data on the selected variables. The data samples described in this report are already processed in this matter.

This research aims at explaining the dependent variable stock value (y) with an independent variable (x). A variable is an object of measurement. A dependent variable is the variable assumed to respond to the values of independent variable (typically denoted by x). Dependent variable (typically denoted by y) represents the output and is impacted by the independent variables, which are not impacted by other variables. For example, an age of a person is an independent variable, while the health of a person may be an dependent variable. When looking for relationships, the process typically contains the aim to recognize the independent variables that impact the dependent variables. (Mason & Perreault, 1991.) The independent variable must include lead time and was expected to include also other factors. Therefore, multivariate regression analysis was selected as the main method for the analysis, as it allows to examine various impacting variables. Multivariate regression analysis was completed using Analycess Procurement. As a further analysis method ANOVA was applied in order to confirm and strengthen the results and to create better understanding of the impact of lead time on inventory. ANOVA was completed using Minitab.

5.2 Multivariate regression analysis method

As justifiably discussed in the literature review part, inventory is typically driven by various parameters. Hence the most suitable analysis method to explain the level of inventory is an approach which allows to consider not only single, but multiple parameters to explain the dependent variable. Multivariate regression analysis predicts the dependent variable (y) with two or more independent variables (x). In fact, it is one of the most commonly adopted statistical procedures. (Mason & Perreault, 1991.)

The accuracy of the multivariate regression model is quantified with the magnitude of the r square (r^2). In a reliable model, the value of the r^2 must be high and the corresponding p-value must be low. Each independent variable is also assigned an individual p-value, which in multiple regression modelling means, that the lower the p-value of an individual variable, the higher the impact of the variable to fit and improve the model. Multiple regression results may appear paradoxical in some cases. Even the p-value of the complete model would be

low, the individual drivers might represent a high p-value. This should not be interpreted as a negative sign, as it would mean that the given data fits the model well, but none of the independent variables contribute significantly to the fitness of the model. The reason for a low p-value of the model is the strong correlation between the independent variables. Therefore, the data would fit the model well, although individual x-variables contribute no extra value to create a better fit of the model. Linear relationship between independent variables is called multicollinearity. (Kumari 2008.) Typically, the assumption in regression modelling is, that there is no linear correlation between x-variables. In addition, there are two further basic assumptions, firstly the residuals follow a normal distribution, and secondly, there is no autocorrelation between the variables. Multicollinearity may cause an error in the forecasting model and make the assessment of the significance of each individual variable problematic. (Mason & Perreault 1991; Kumari 2008.)

5.3 ANOVA analysis method

Analysis of variance (ANOVA) is a statistical technique and a common approach to compare observation groups with each other by their means. The purpose of ANOVA is to determine whether the means of two or more groups are significantly different from each other and to define the extent to which the independent variable is a significant component. (Turner & Thayer 2001.) ANOVA test was used in order to validate whether the analysis results of descriptive and multivariate analysis are significant. ANOVA analysis also helps to figure out if null hypothesis should be rejected. As a recap, null hypothesis expects no relationship between the variables. (Girden 1992; Turner & Thayer 2001.) ANOVA can be used to analyze either experimental or nonexperimental data, but it is commonly used to analyze especially experimental data. As ANOVA is using the means in order to determine the differences between groups, the result can be manipulated by adjusting observations, which is considered as a main problem in ANOVA analysis. (Leik 1997, 2-4.)

6 DATA ANALYSIS AND INTERPRETATION

This chapter analyses the case study data by the three earlier discussed methods; exploratory analysis, multivariate regression analysis and ANOVA analysis. The data will be processed, analyzed and interpreted thus the discussion of the results will follow later in the next chapter. The inventory drivers discussed in the previous chapters will be analyzed in detail in two product families.

6.1 Exploratory data analysis

The analysis was conducted for two different data sets, which both represent one product family; product family N (PFN) and product family C (PFC). The product families were selected based on their relevance in terms of revenue and these two product families generate majority of the revenue in the business unit. Other product families were not included due to their minor proportion of revenue. An observation in data sets represent a product in a warehouse. Globally 26 largest warehouses were selected for the analysis in order to exclude smallest warehouses which might hold excessively more inventory than the actual demand due to lot sizing and minimum shipment volumes. However, the smallest warehouses contribute very little to the overall inventory volumes in a global scale and comparing to other markets. Furthermore, those observations could consequently contribute with false interpretations in the analysis if considered parallel to the main warehouses of the leading markets.

The data set PFN consists of 1841 observations, representing 278 products of the product family and their inventory data in 26 warehouses. Table 4 shows the descriptive statistics of the PFN sample. As described in the table, average monthly stock (*Avg. Stock [CHF]/m*) varies from three Swiss Francs to 224’168 revealing a large scale of inventory values within the product family. Stock rotation, also referred to as months on hand, varies from 2 months up to 92 months. The table points out that not all observations have safety stock, as the minimum is zero. The lead time for these observations vary from 1 day to 96 days, whereas the lead time might deviate up to 21 days, as seen from the table 4. Demand deviation is a factor describing the level on demand volatility in comparison to the average monthly demand. As the table shows, demand is deviation at maximum of 13.5 times the monthly demand, which reveals a high volatility in demand, although it may represent only one observation. Forecast precision is a factor which compares forecasted monthly demand with

the actual demand. The closer the factor is to zero, the closer the forecast has been to the demand. EOQ and MOQ appear to have same maximum and minimum of both quantities vary with only 20 pcs.

Table 4. Descriptive statistics for product family N (PFN)

Product family N							
Variable	N	Mean	SE Mean	StDev	Minimum	Median	Maximum
Avg. Stock. [pcs]/m	1841	117307	10416	446910	67	17458	9981600
Stock rotation	1841	3.402	0.143	6.136	0.061	1.826	91.633
Avg. Stock. [CHF]/m	1841	1631	172	7387	3	384	224168
LC [CHF]/m	1841	956.9	87.7	3764.4	1.1	189.3	77033.8
Act. SS [pcs]	1841	58428	5631	241592	0	6000	5266307
Leadtime	1841	17.28	0.454	19.462	1	5	96
LT dev.	1841	0.9196	0.0428	1.8379	0	0	21
Avg. Dmnd. [pcs]/m	1841	93183	8542	366506	116	8768	8035260
Demand deviation	1841	3.7215	0.0492	2.1129	0.8544	3.2296	13.4532
Forecast precision	1841	1.487	0.115	4.948	0	0.988	173.172
EOQ [pcs]	1841	32707	1136	48724	100	12000	388800
MOQ [pcs]	1841	32775	1151	49395	80	12000	388800

The descriptive statistics in table 5 describe the insights of the other sample, product family PFC. As the table indicates, the product family is significantly smaller than the PFN, as there are only 310 observations in this data set. The lead time varies from 3 days to 103 days, similar scale as in the PFN sample. Stock rotation has a minimum of zero whilst a maximum of 91 months, which indicates a large scale also within this data set. The result is not surprising, as PFC consists of dangerous goods which might reveal a very random inventory behavior, due to customs and other dangerous goods related transportation limitations and effort.

Table 5. Descriptive statistics for product family C (PFC)

Product family N							
Variable	N	Mean	SE Mean	StDev	Minimum	Median	Maximum
Avg. Stock. [pcs]/m	310	289539	44296	779912	292	52942	8740667
Stock rotation	310	5.592	0.624	10.989	0.072	2.161	90.561
Avg. Stock. [CHF]/m	310	10231	1717	30231	7	2015	368653
LC [CHF]/m	310	4394	475	8370	2	865	63750
Act. SS [pcs]	310	128043	26188	461092	0	20823	7000000
Leadtime	310	24.31	1.48	25.99	3	20	103
LT dev.	310	1.633	0.278	4.892	0	0.388	44.5
Avg. Dmnd. [pcs]/m	310	217393	35590	626618	16	25351	7633260
Demand deviation	310	3.445	0.135	2.37	0.851	2.851	13.464

Forecast precision	310	1.0776	0.0778	1.3692	0	0.9589	9.5269
EOQ	310	44170	3017	53036	100	21000	240000
MOQ	310	55428	4180	73470	100	30000	588000

For PFN the high value of months on hand is more of an interesting aspect. In addition, if comparing the two product families, it is obvious that the maximum MOQ in PFN is almost 50% lower than the maximum MOQ in PFC. This can also be an indicator of high stock rotation maximum for the PFC data set. In further analysis, variable *stock rotation*, also referred to as *months on hand*, will be considered as the output variable, the dependent variable, y.

6.2 Data distribution fitting

Descriptive statistics have shown that a large scale of values in *months on hand* (MOH) exists. The minimum MOH value for the PFN sample is 0.06 while maximum is 91.63. For PFC the respective values are from 0.07 and 90.56. To understand the distribution of the observations within this scale further distribution analysis were done. Practically all researchers must understand the statistical distribution of the sample and it is fundamental almost without exceptions in all research methods. It allows to define which statistical distribution does the data set best fit to. In addition, distribution fitting allows to comprehend the probability of a random variable occurring on the acceptable space (Taylor 2007, 20; Thomopoulos 2017, 3).

In order to process distribution fitting, the outliers shall be examined first. Outliers are frequent concurrences in statistical data analysis and may impact the reliability of the analysis and to significantly degrade the efficiency of the sample data. Outliers impact specifically the estimating statistics, such as standard deviation and mean values. For this reason, outliers must be processed as the results of analysis will depend considerably on the art of processing the outliers. (Sang & Jong 2017) The data samples of both product families have relatively many outliers, as visible in boxplots in figure 15. Both boxplots indicate that most of the observations belong to a cluster where stock rotation is below 10. Despite the outliers, a distribution fitting for complete data sets was created, without processing the outliers yet.

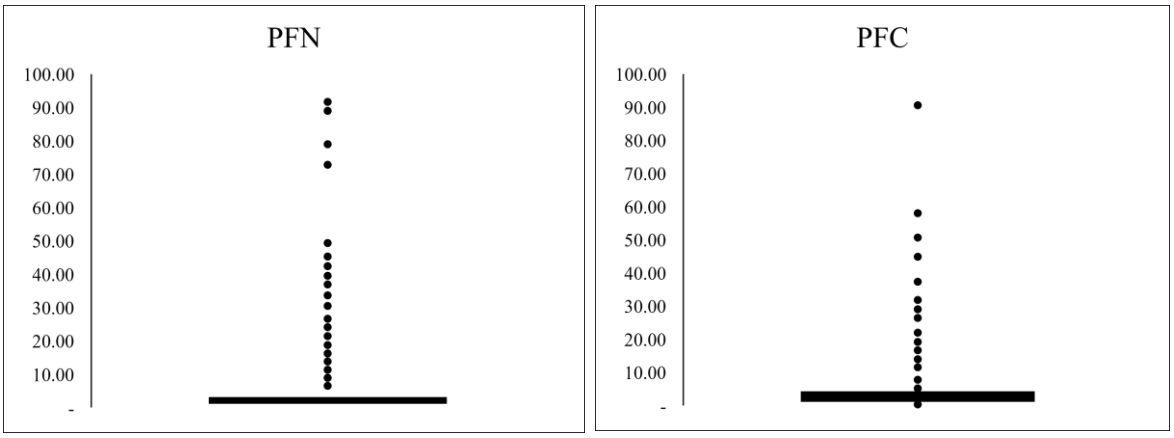

Figure 15. Boxplot of variable *Months on hand* - PFN & PFC data sets.

Distribution fitting was executed using excel, on the variable *months on hand*, which in addition to *average monthly inventory* was defined as a suitable dependent variable in this case study. The distribution fitting was executed in three steps; histogram, probability plot, and as a third step a test for clarification of either exponentiality or lognormality of the data. Table of descriptive statistics has shown the median, maximum and minimum of the sample. In addition to these, distribution fitting is based on 1st and 3rd quartile. As figure 16 shows, the histogram and the probability plot of the raw data of PFN both suggest a right skewed distribution for either exponential or lognormal distribution. In right skewed distribution, the data is positioned to the left, typically following a long tail to the right (Taylor 2007, 20), which in this sample appears to be rather short.

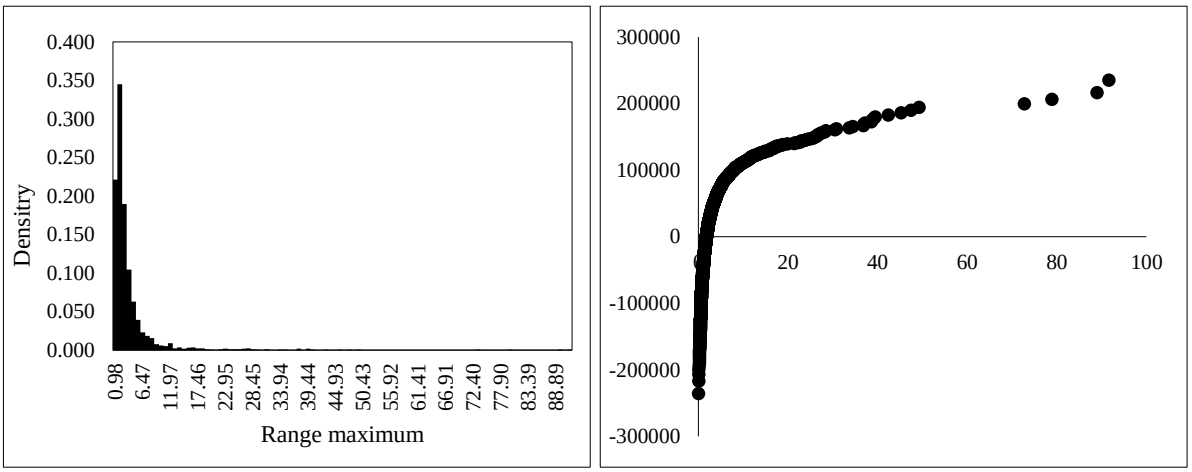

Figure 16. *Months on hand* data distribution histogram & probability plot - PFN.

Consequently, it was be verified, whether the data follows exponential or lognormal, by examining the logarithm of the variable. In the research sample, the distribution after logarithm on *months on hand* -dependent variable appears normally distributed. This is verified by the bell shape in the histogram in figure 17. Normal distribution is the most commonly occurring distributions in statistical studies and natural phenomena typically follow normal distribution, such as human characteristics or manufacturing, where typically majority of the product are approved by set quality standards, and only a few fail (Taylor 2007, 83). In a bell-shaped distribution the normal has a variable x and two parameters; the mean and standard deviation (Thomopoulos 2017, 69).

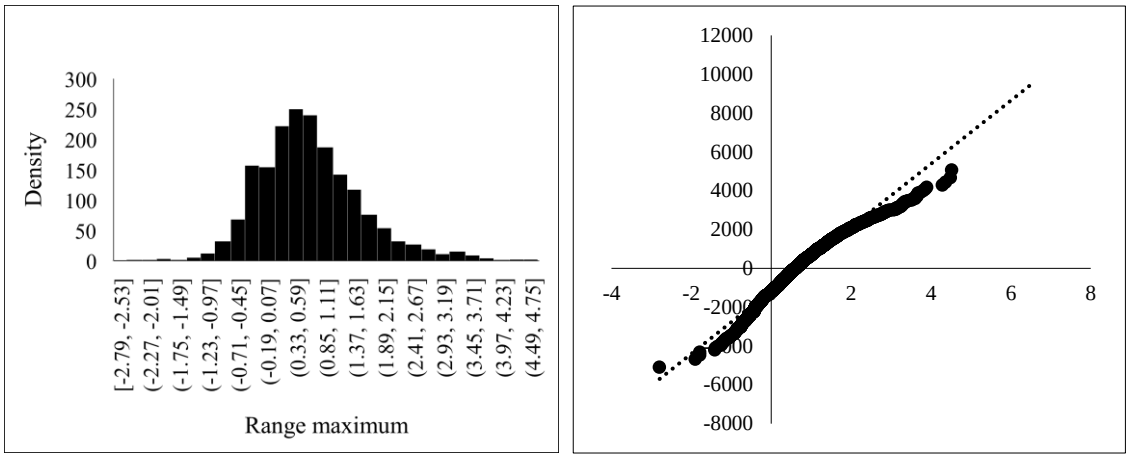

Figure 17. *Months on hand* lognormal distribution - PFN.

As a result, the probability plot on the right side in figure 17 suggests a lognormal distribution. As the plotted line follows roughly a straight line, it interprets that the result follows a lognormal distribution instead of exponential, as exponential distribution would result in a curvy outcome (Taylor 2007, 20; Thomopoulos 2017, 75). Lognormal distribution exists when the variable begins at the value of zero and the peak of density follows immediately, followed by higher values of x which tail down. Lognormality of variable x can be stated if another dependent variable becomes normally distributed when formed by the logarithm of variable on x. (Thomopoulos 2017, 77) Based on the outcome, it is fair to state that the data follows a normal distribution and it is therefore likely for a new observation to represent a value in the area of the bell shape in figure 17.

However, as seen in the boxplots earlier, both samples include outliers. On account of the outliers, another distribution fitting was done with a processed data set, excluding five percent of the outliers of the original data set. The purpose was to assess if the linear model of the probability plot sharpens when removing outliers. Figure 18 shows the outliers after removing 5% of the outliers in the PFN sample. These 5% represented randomly high *months on hand (MOH)* values and are unusual compared to the rest of the data set. Other than the MOH-value, there was no recognizable factor that would appear common for these 5% of the data, no common alliance with the warehouse location or any other driving factor.

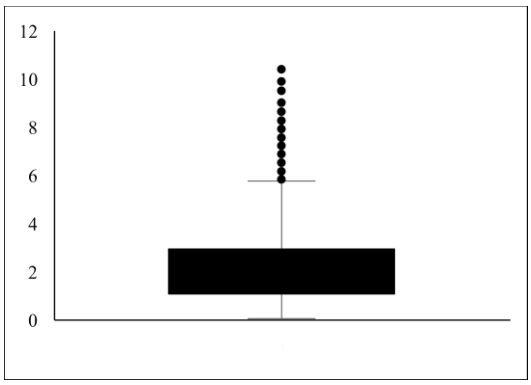

Figure 18. Boxplot of PFN data after removing 5% of outliers

As shown in figure 19, data distribution appears to follow similar pattern as with the earlier PFN data set with outliers. Probability plot curve has smoothened as a result of removing outliers, and the data appears more consequent with this approach. Furthermore, the right skewed distribution can be recognized more clearly after having removed majority of the outliers and the typical long tail to the right is well to be recognized in figure 19.

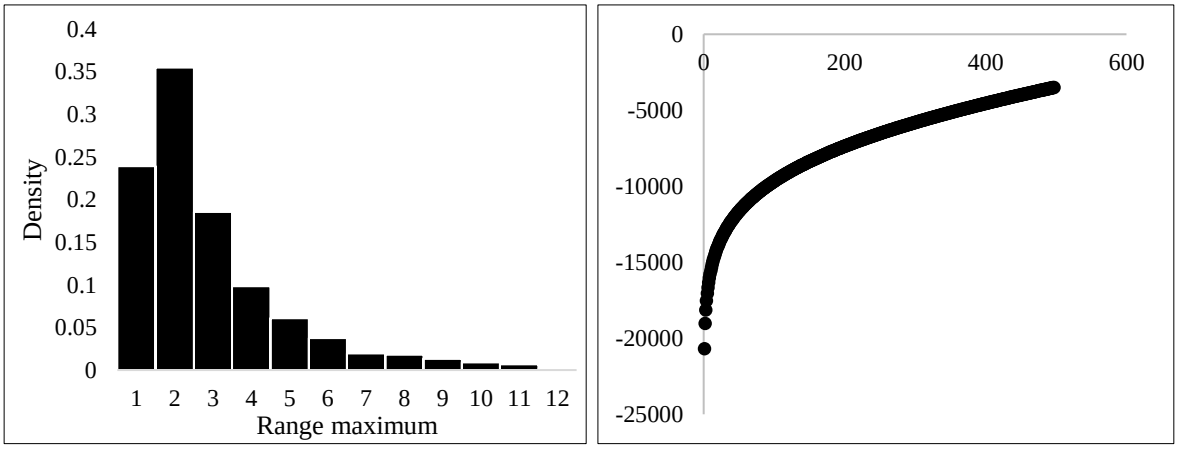

Figure 19. *Months on hand* data distribution after 5% outlier removal - PFN.

Thus, the significance of outliers can more relevantly seen in figure 20. The data appears further to follow lognormal distribution which indicates the data being consequent, even when excluding part of the sample. Furthermore, the probability plot in figure 20 has barely changed, which can be interpret as a positive sign. The number of outliers in the beginning appeared large and indicated that the existence could disturb the overall results. However, distribution fitting proves that the original complete data, with outliers included, follows lognormal distribution, therefore the analysis was further continued with the complete data set. The distribution fitting results are similar within the both product families. All graphs describing data distribution analysis of the product family C can be seen in detail in the appendix.

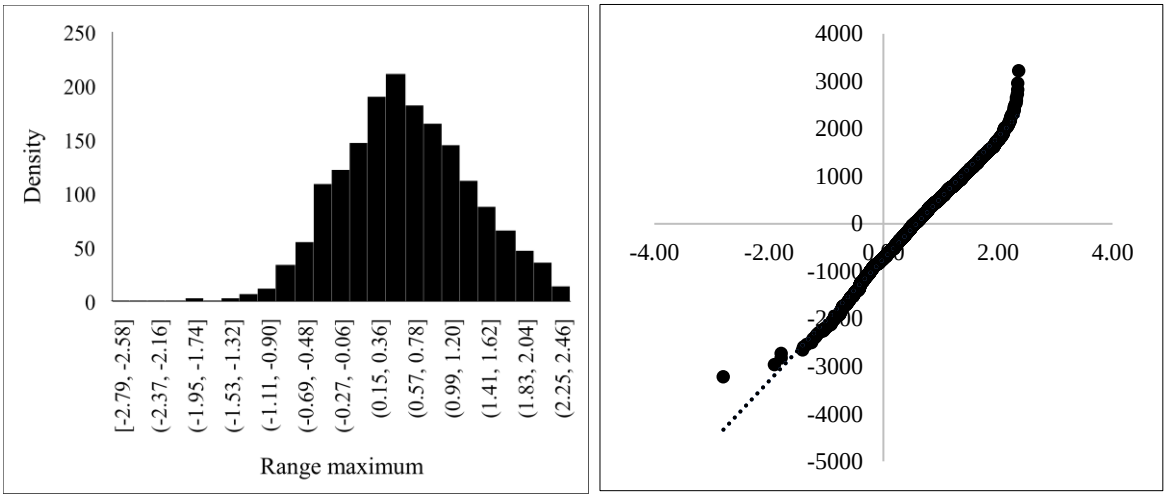

Figure 20. *Months on hand* lognormal distribution after removing 5% outliers - PFN.

6.3 Inventory levels at Hilti

In order to comprehend the volumes of inventories and the amount of capital tied up to inventories at Hilti, a closer examination was conducted. The two samples have proven that within the selected two product families, the case organization holds in average 70% (PFN) and 133% (PFC) more monthly inventory than the average monthly demand is. This outcome is visualized in figure 21. The organization invests monthly in average more than 6 million Swiss Francs of capital into the inventories of these two product families only. Although it's an average monthly value and only in 26 largest warehouses, it proves that the capital invested into inventories is significant.

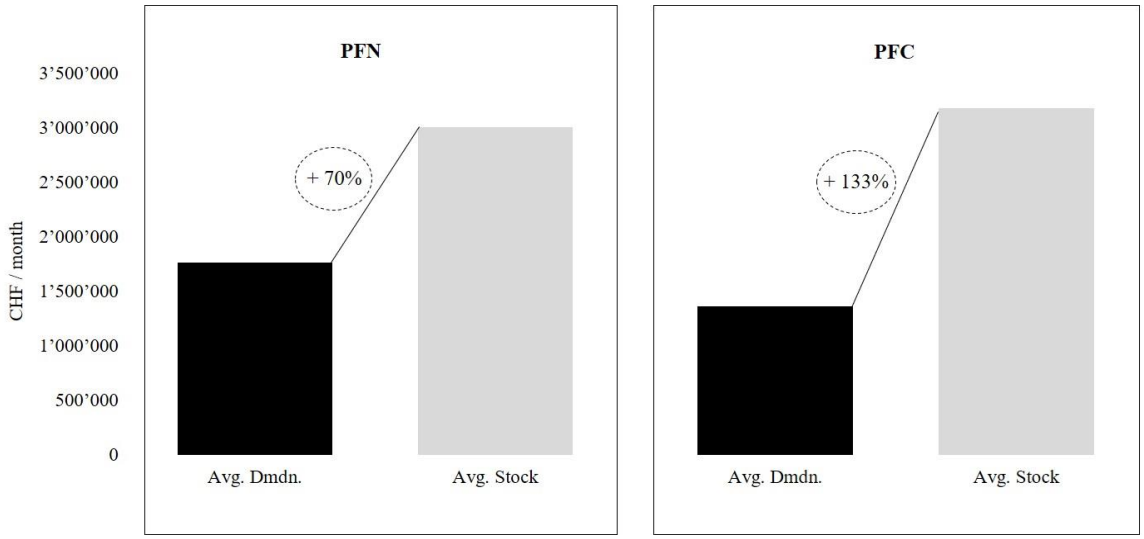

Figure 21. Average monthly demand vs. average month stock

Figure 22 shows the distribution between low and high runner products in the PFN sample. Low runners are defined as products which have monthly demand less than 1000 CHF and high runners in turn are the products covering demand of above 1000 CHF. As the chart in figure 22 presents, 82% of the observations in the study sample are covered by low runners, whilst 18% left to be covered by high runners. The outcome has been similar with sample PFC. As high runners are the products that have the highest demand, they can be considered essential part of the portfolio. The analysis reveals that high runners cover 86% of the monthly average stock. The outcome confirms the rule of pareto, also known as "80:20", where 20% of the sample typically covers 80% of the value. According to the law of pareto, a relatively low amount of the causes is responsible for majority of effects. In inventory management pareto rule is typically a common approach, as it is logical to fill the stock with product that generate most of the revenue. (e.g. García et al. 2015)

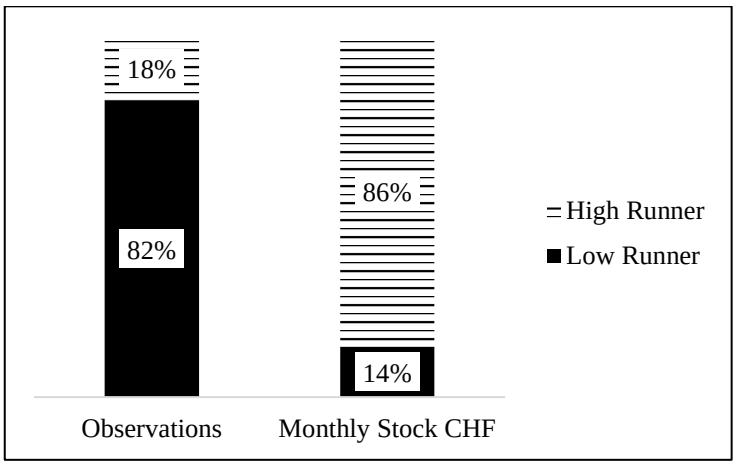

Figure 22. Visualization of high and low runners in PFN

Figure 23 shows two scatter plots describing the relationship between average inventory level and demand in both product families. Logistic consumption is an indicator of the value of the items that leave the warehouse. Consistently, both plots reveal similar relationship between the factors. Consequently, first indication of an inventory driver may be determined, and it appears obvious that demand should be a considered as an inventory driver. However, the relationship is not linear, as the observations do not appear all in the same line. The pattern is similar in both product families, although both samples include noise around the trendline. Based on these graphs it would not be suitable to claim the exact level of stock even if the demand would be known, however, it gives rather valid direction for the inventory level – especially in these two product families.

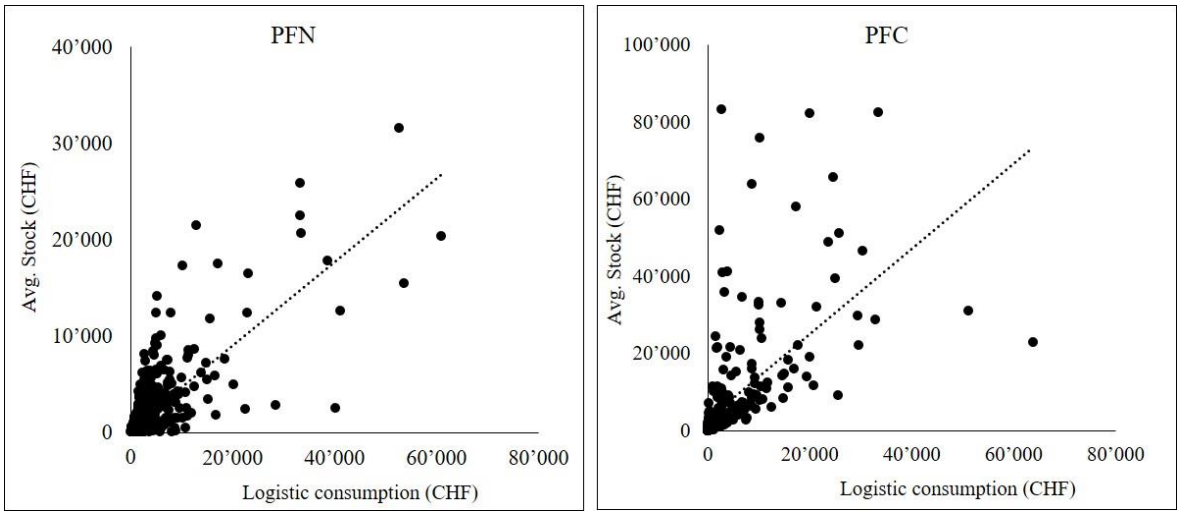

Figure 23. Scatter plot of average inventory and demand in PFN and PFC

The plots in figure 24 describe the relationship between months on hand and lead time in both product families. Analyzing lead time purely against inventory level in Swiss Francs does not allow to see the impact of lead time, as the level of inventory should theoretically be built as the consequence of demand. Therefore, the lead time is more logically examined as an influencing factor on months on hand, which describes the level of inventory without considering the value of inventory.

The plots in figure 24 indicate no clear relationship between lead time and MOH, as the observations are widely spread. However, the plots reveal same results as the histogram in figure 16, where it has been clearly described that most of the observations belong to the

group of *months on hand* less than 10 months. From the scatter plots it can be clearly seen that there is no sign of months on hand increasing as lead time increase. Therefore, an obvious pattern between lead time and inventory level can by now not be recognized.

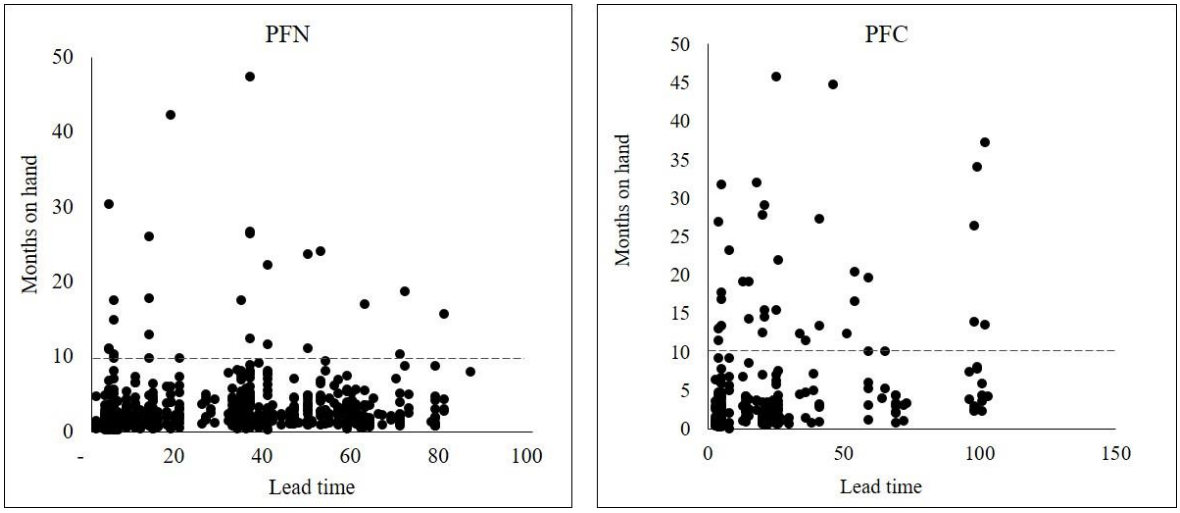

Figure 24. Scatter plot of months on hand and lead time in PFN and PFC

In order to investigate the impact of lead time on inventory, it is necessary to understand the behavior of inventory within different lead times. Therefore, the lead time was divided into two categories and the sample divided according to the lead time. The two categories are lead time below 15 days and above 50 days. The purpose was to recognize any significant pattern between inventory level and demand, typical for both or either one of the lead time categories. Figure 25 describes the monthly average inventory level as well as the demand in Swiss Francs for both product families for lead time below 15 days.

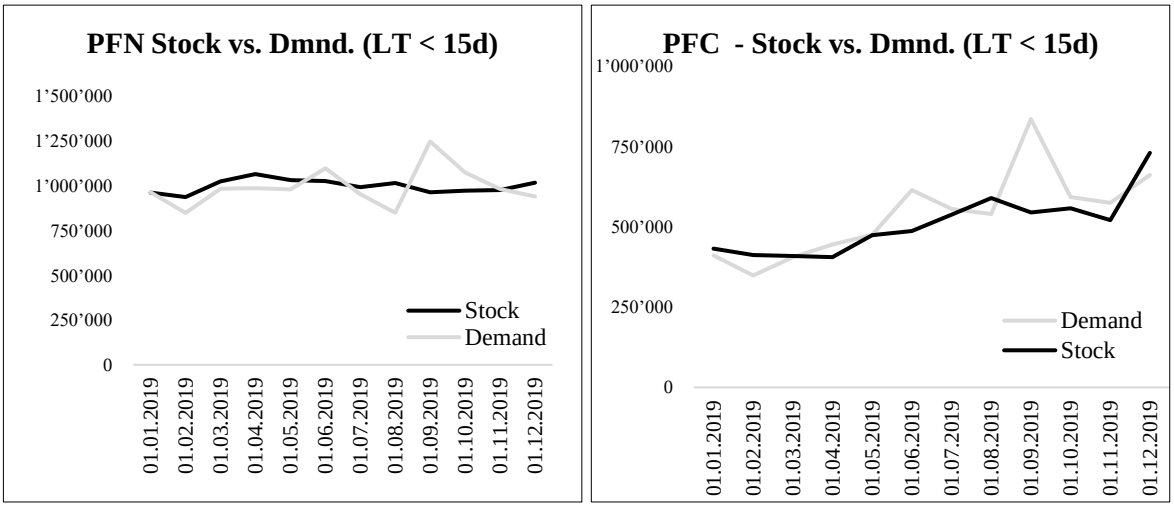

Figure 25. Average inventory and demand in CHF with lead time below two weeks

As visible in both linear plots in figure 25, inventory (black line) and average demand (grey line) are throughout the year almost aligned with a few exceptions in the autumn months. As noted earlier, the PFC product family is smaller, which explains the inventory and demand volume on average half of the volumes in PFN figure. However, it can be concluded that the demand and inventory level seem to be aligned when lead time is less than 15 days. Therefore, the inventory level is well in alignment with the actual demand, which is clearly one of the main aims of inventory management.

Expectedly, higher lead times reveal contrasting results. As figure 26 shows, a notable gab between inventory and demand exists, when lead time is above 50 days. Nevertheless, in the PFN sample the gap, also referred to as overstock, represents roughly 400’000 CHF on average. For the quantitatively significantly smaller product family PFC, the overstock is around and above 1 million CHF, which certainly is significant amount of capital. Based on these graphs it is obvious that most of the PFC items have a longer lead time, as majority of the stocked items are presented in the graphs with lead time above 50 days.

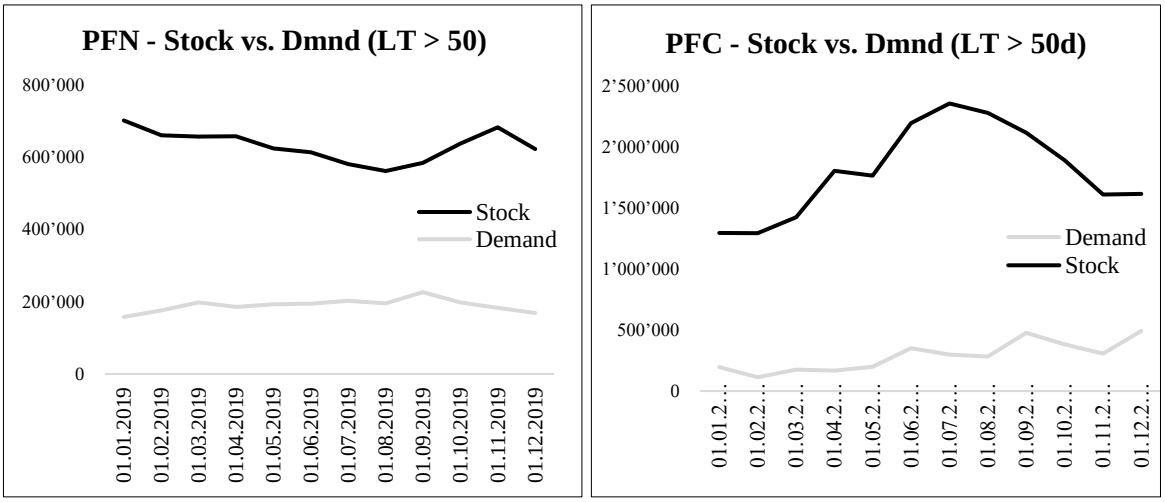

Figure 26. Average inventory and demand in CHF with lead time above 50 days

PFC is a product family which consists of products purchased from suppliers. PFN on the other hand consists of mainly low-cost products produced inhouse. To conclude, these two aspects may explain the relatively large overstock for items with high lead time for PFC – as the suppliers are external partners and therefore demand planning may be challenging, costs higher than for inhouse products, and the earlier mentioned aspect of dangerous goods may contribute to high level of overstock especially in case of long lead time.

Considering the unquestionably long lead time of 50 days, the safety stock might furthermore be a partial factor for increased inventory. Other notable reasons for overstock might be earlier in descriptive statistics defined high MOQs. The distribution of MOQ volumes for both of the product families reveal that the MOQs for the PFC items are indeed often high as shown in both bar charts of figure 27. The data indicates clearly that especially PFC items have rather high MOQ.

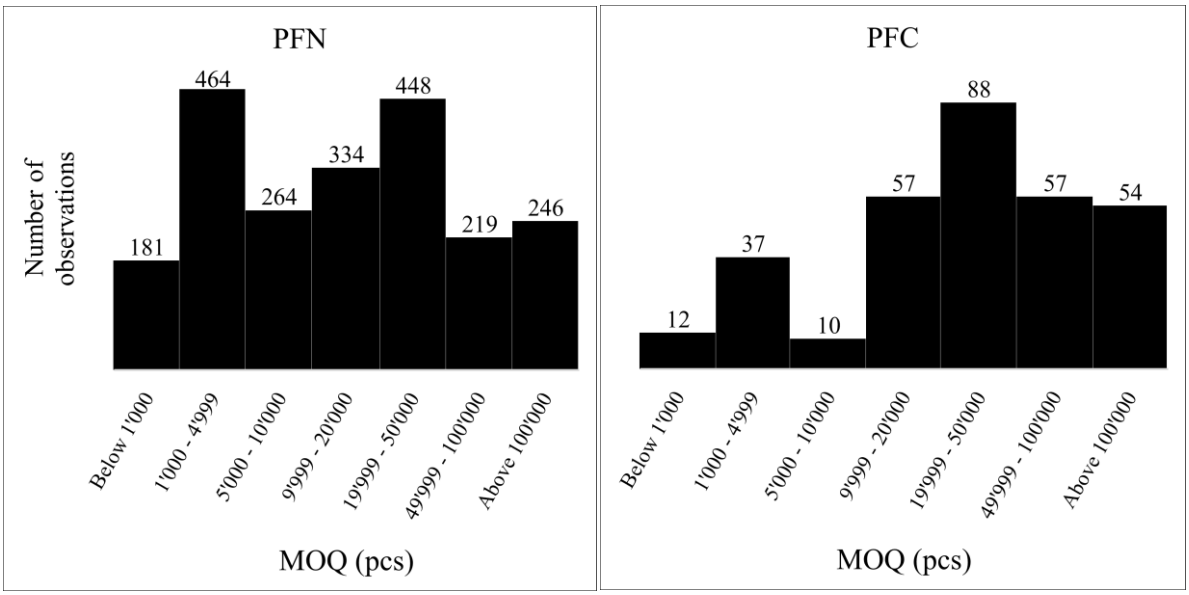

Figure 27. Distribution of minimum order quantities in both samples

As the table 6 shows, in PFN sample, 87% of the observations have smaller or equal size of MOQ and EOQ. Surprisingly, in PFC sample, 50% of the observations possess higher MOQ than the EOQ. This indicates, that in half of the cases, the organization is forced to order more than what economically would be optimal.

Table 6. MOQ and EOQ distribution

Rule	PFN observations	%	PFC observations	%
MOQ < EOQ	1604	87%	119	54%
MOQ > EOQ	237	13%	101	46%

In fact, the data reveals that the items that contribute to the most on the inventory level of PFC have all consistently higher MOQ than the EOQ. Therefore, it can be concluded that the MOQ certainly is one cause for the extremely high overstock levels of product family C.

6.4 Inventory driver correlations

Correlation indicates the relationship between two variables. Correlation matrix reveals, that there are correlations between different variables in both samples. In the Pearson correlation matrix in table 7, a correlation value as well as P-value for the correlations are presented. P-value is the probability of an observed result occurring under the null hypothesis, also referred to as the significance level. The higher the correlation value between two items, the stronger the correlation is.

Table 7. Correlation matrix for PFN including P-values

Correlations

	Avg. Stock. [pcs]	Stock rotation	Avg. Stock. [CHF]	LC [CHF]	Act. SS [pcs]	Lead time	LT dev.	Avg. Dmnd. [pcs]	Dmnd. Dev. [pcs]	Avg. Fcst. Dmnd. [pcs]	Forecast precision	EOQ	MOQ
Stock rotation	-0.044												
	0.104												
Avg. Stock. [CHF]	0.688	-0.037											
	0	0.167											
LC [CHF]	0.568	-0.087	0.807										
	0	0.001	0										
Act. SS [pcs]	0.934	-0.062	0.565	0.523									
	0	0.022	0	0									
Leadtime	0.217	0.197	0.161	0.065	0.223								
	0	0	0	0.015	0								
LT dev.	-0.02	0.079	-0.001	-0.022	-0.004	0.074							
	0.457	0.003	0.961	0.421	0.895	0.006							
Avg. Dmnd. [pcs]	0.81	-0.091	0.715	0.689	0.747	0.103	-0.034						
	0	0.001	0	0	0	0	0.2						
Dmnd. Dev. [pcs]	0.836	-0.101	0.734	0.698	0.784	0.144	-0.021	0.974					
	0	0	0	0	0	0	0.428	0					
Avg. Fcst. Dmnd. [pcs]	0.786	-0.087	0.595	0.623	0.737	0.11	-0.03	0.93	0.911				
	0	0.001	0	0	0	0	0.258	0	0				
Forecast precision	-0.033	0.206	-0.029	-0.04	-0.035	-0.04	0.014	-0.039	-0.047	-0.008			
	0.221	0	0.287	0.14	0.198	0.099	0.6	0.144	0.082	0.774			
EOQ	0.512	-0.176	0.307	0.381	0.496	0.135	-0.024	0.575	0.614	0.555	-0.087		
	0	0	0	0	0	0	0.368	0	0	0	0.001		
MOQ	0.496	-0.105	0.299	0.36	0.477	0.153	-0.011	0.542	0.578	0.528	-0.063	0.945	
	0	0	0	0	0	0	0.69	0	0	0	0.019	0	
Service Level	-0.011	-0.05	0.014	0.031	-0.037	-0.27	-0.019	0.018	0.012	0.018	0.013	-0.05	-0.025
	0.693	0.065	0.612	0.255	0.167	0	0.482	0.499	0.645	0.513	0.631	0.063	0.354
Cell Contents													
Pearson correlation													
P-Value													

The matrix in table 7 suggests, that inventory level (*Avg. St. [pcs]*) has a strong correlation with five factors. These include the following variables in the corresponding order:

1. Actual safety stock in units (*Act. SS [pcs]*)
2. Demand volatility (*Dmnd. Dev. [pcs]*)
3. Average demand in units (*Dmnd. [pcs]*)
4. Average forecasted demand (*Avg. Fcst. Dmnd. [pcs]*)
5. Average stock in Swiss Francs (*Avg. St. [CHF]*)

The outcome is not especially surprising as the strongest correlations include all variables of demand. Furthermore, safety stock as the strongest correlation is logical, as inventory typically consists of two parts – cycle stock and safety stock. Logically, also the monetary value of the stock correlates with the units of inventory. Surprisingly demand volatility has the second strongest correlation with inventory level. Furthermore, the correlation matrix reveals that lead time (LT), economic order quantity (EOQ), and minimum order quantity (MOQ) likewise have a correlation with the volume of units in stock, although less significant as the earlier mentioned variables. Interesting observation further is, that months on hand (*Stock Rota.*) seems to have the most significant relationship with lead time, although negative correlation as well as very weak correlation. The correlations were tested multiple times by dividing the data set into high and low runners and to different markets. In addition, a categorization based on safety stock methods were done, in order to create groups with safety stock methods that does not consider lead time (SBB and SB1) and the safety stock methods that do consider lead time. The results were continually consistent, indicating similar correlation values for both samples – product family N and product family C. The correlation matrix for the whole sample of PFC is visible in appendix at the end of this report.

6.5 Multivariate regression analysis

In order to agree, disagree and strengthen the findings gathered from the correlation matrix, multivariate regression analysis was conducted. The dependent variable was tested with multiple options including inventory in CHF and inventory in units, from which the last option was selected as the dependent variable for this analysis. Both variables provided the same results, which was considered a reliable outcome and therefore one of them was selected. As earlier analysis suggest, demand appears to be the strongest driver for inventory based on the correlations. However, multivariate regression analysis allows to select and investigate various variables and analyze their impact on inventory level simultaneously.

A multivariate regression analysis was run with a statistical regression software Analycess Procurement. As potential influencing factors on inventory level the following drivers were considered;

- **average demand** (pcs)
- **demand deviation** (pcs)
- **lead time** (days)
- **lead time deviation** (days)
- **forecasted demand** (pcs)
- **safety stock** (pcs)
- **minimum order quantity** (pcs)
- **economic order quantity** (pcs)
- **service level** (%).

For multivariate regression analysis, the data was optimized in order to exclude the items which had monthly average demand less than 100 CHF. These excluded items were considered as extreme low running products which may disturb the analysis but in reality, were not relevant products in the portfolio. Remaining observations represent 1147 data points for PFN and 239 observations for PFC, which both can still be considered as a relevant and large enough of a sample. The results of multivariate regression analysis are shown in table 8. “Range” describes the relevance of corresponding variable in the given sample and adjusted R^2 determines the significance of each factor. The higher the range, the higher the statistical significance for the regression is the factor. The analysis suggests year quantity to possess the strongest significance. This is due to the statistical system set up and year quantity represents purely the monthly stock multiplied by 12 months. Therefore, this shall be ignored and not considered as a driving factor. Second strongest driver appears to be safety stock, which is not surprising for the same reason discussed earlier, as similar result was seen in the correlation matrix. Further in alignment with correlation matrix is the occurrence of the third strongest driver, which is suggested to be demand deviation. According to the R^2, demand deviation as a variable seems to explain 69% of the sample. Almost as significant driver appears to be average demand and forecasted demand. Again, the results are nearly identical with the results from the previous correlation matrix.

Table 8. Multi regression analysis on inventory drivers PFN & PFC

Name	Range PFN	Adjusted R^2 PFN	Range PFC	Adjusted R^2 PFC	Type
Part Description (SAP)	-	-	-	-	categorical
Warehouse	-	-	-	-	categorical
Average Monthly stock 12m [pcs]	-	-	-	-	numeric
Average Monthly stock 12m [CHF]	6	0.48	2	0.94	numeric
EOQ	8	0.28	8	0.34	numeric
Logistical consumption [CHF]	7	0.29	7	0.45	numeric
Actual SS [pcs]	2	0.85	6	0.81	numeric
Leadtime [days]	10	0.05	10	0.1	numeric
Leadtime deviation [days]	13	R^2: 0	12	R^2: 0	numeric
Average demand [pcs]	4	0.66	4	0.83	numeric
demand deviation [pcs]	3	0.69	3	0.84	numeric
average forecast demand [pcs]	5	0.59	5	0.82	numeric
year quantity	1	1	1	1	numeric
MOQ	9	0.27	9	0.33	numeric
Service level	11	0	11	R^2: 0	numeric
Stock rotation	12	0	13	R^2: 0	numeric
Plant	14	R^2: 0	14	R^2: 0	numeric
Safety stock method	-	-	-	-	categorical

Surprisingly, lead time, lead time deviation as well as service level appear to have no influence on inventory level at all. In addition, the origin ("plant") appears to be no significant factor for inventory level either. However, as table 8 shows, EOQ and MOQ appear to have an impact on inventory in both samples, although a minor one. Comparing PFN and PFC further, it is can be interpreted that demand and demand deviation have significantly stronger impact in PFC than in PFN. This suggests, that PFC is strongly driven by demand and its volatility, whereas PFN appears to have wider distribution among the weights of each tested inventory drivers.

As the first attempts of multivariate regression approach on original data samples seem to interpret that lead time has no influence on inventory level, further analysis was conducted by dividing the sample according to lead time into two categories; lead time below 14 days and above 28 days. The purpose was to recognize if this would create significantly different result. However, the outcome was nearly identical to the original sample and no changes in the position of the inventory drivers was recognized. Further set ups were tested, reducing the items with demand less than 1.000 CHF per month. In both product families, the outcome

indicates similar results to the original findings – lead time has no weight at all. Therefore, a test for the major market, United States of America (USA), was conducted. Again, the outcome indicates similar results and lead time remains irrelevant inventory driver. The result of multivariate regression analysis of various set ups can be seen in the appendix of this report.

6.6 ANOVA analysis

Previous analyses have proven that demand unhesitatingly is the main inventory driver at Hilti. Demand and the volatility of demand appear to have such a strong weight that other inventory drivers could not been proven to have a significant influence by correlation matrix or multivariate regression analysis. Nevertheless, correlation matrix has shown that lead time and MOQ also minorly correlate with inventory level. Also, as earlier proven, the size of overstock appeared to be significantly larger when lead time is extremely long (>50 days). Based on these results, further analyses were accomplished in order to verify any common factors or major differences between defined lead time categories. The method for further analysis was chosen to be ANOVA because the method represents valuable alternative for regression analysis and allows to examine interesting characteristics of inventory data by dividing lead time into categories instead of using absolute values.

In order to define the categories, the sample was tailored and divided according to lead time into three groups; low lead time (<9 days), mid lead time (14-21 days), and high lead time (>30 days). The categorization was defined based on the distribution of the observations, dividing the groups systematically in a way, that each group have sufficiently observations. Furthermore, in each group a certain gab between values was intentionally left to remain in order to dissociate the three groups from each other. In addition to lead time, three other factors were categorized into further analysis; demand volatility, forecast accuracy, and minimum order quantity. The categorization details and number of observations in each category in both product families is visible in table 9. These three inventory drivers were selected based on the result from correlation matrix and multivariate regression analysis, as they appeared to have an influence on inventory level as follows; demand volatility major, forecast accuracy and minimum order quantity rather minor influence. The purpose of ANOVA analysis was to define whether these drivers together with lead time reveal any new indications from inventory behavior and lead time as an inventory driver.

Table 9. Inventory driver categorization for ANOVA analysis

			Observations per product family	
Inventory driver	*Category*	*Specification*	*PFN*	*PFC*
Lead time	Low	< 9 days	621	124
	Mid	10 - 21 days	170	44
	High	< 30 days	344	66
Demand deviation	90-200%	< 2	381	101
	200-350%	2 - 3,5	475	96
	350-500%	3,5 - 5	184	52
	>500%	> 5	108	48
Forecast precision	Accurate	0 - 1,6	796	186
	Moderate	1,6 - 3	137	25
	Not accurate	> 3	54	12
MOQ	Low MOQ	0 - 1,6	861	210
	Mid MOQ	1,6 - 3	208	42
	High MOQ	> 3	78	58

Demand deviation is a factor which is calculated by dividing *average monthly demand deviation* by *average monthly demand* of the past 182 days. This means, that if the factor is for example 2, the deviation has been twice the volume of demand. Therefore, the higher the factor, the higher the volatility in demand has been. *Forecast accuracy* describes the precision of the demand forecasting. The closer the factor is to zero, the closer the forecast has been to the actual demand. Observations with a demand forecast of zero was excluded from these analyses. Similar approach was leading the categorization of MOQ. The closer the factor is to zero, the closer the MOQ is to actual demand.

Figure 28 describes the inventory behavior in the three defined lead time groups in four categories of demand volatility. The graph remarkably suggests that months on hand tend to vary significantly especially between high and low lead times. The coefficient factors in the graph demonstrate the change in inventory months on hand between high and low lead time. A significant growth in inventory can be recognized as the volatility of demand increases. Low lead time does not indicate consistently low inventory level, as it is clearly demonstrated, that inventory level increases as a consequence of demand volatility. Interestingly, the coefficient between high and low lead time appears to increase as the demand volatility increases. Therefore, it can be concluded that increasing lead time together with increasing volatility in demand have an increasing impact on inventory level. Identical results were obtained from the PFC sample. However, surprisingly the coefficient in PFC

were significantly higher than in PFN. The interaction plots with coefficients for product family C are all visible in the appendix.

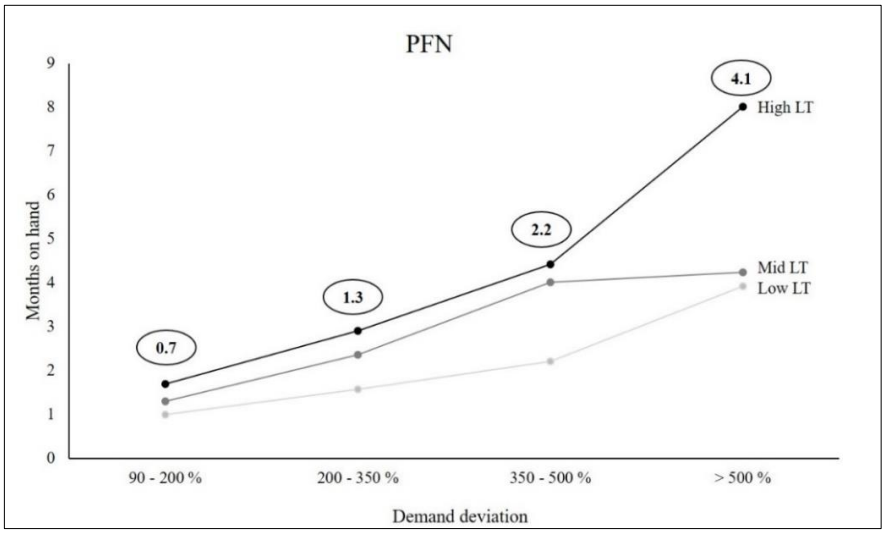

Figure 28. Interaction plot of lead time and demand deviation

Second tested variable was forecast accuracy. In alignment with the results from the earlier interaction plot of demand deviation, the inventory behavior appears to be remarkably similar with forecast accuracy. As figure 29 demonstrates, the higher the inaccuracy for demand forecast is, the higher is the level on inventory when lead time is high. Surprisingly, forecast accuracy seem to have minor influence on inventory level, as long as the lead time is low. In contrast, when lead time is above 14 days, the inventory level appears to significantly increase as the forecast inaccuracy increases. Identical results have provided the sample of product family C, although again the coefficients are remarkably higher than in product family N. The PFC graph is placed on the appendix.

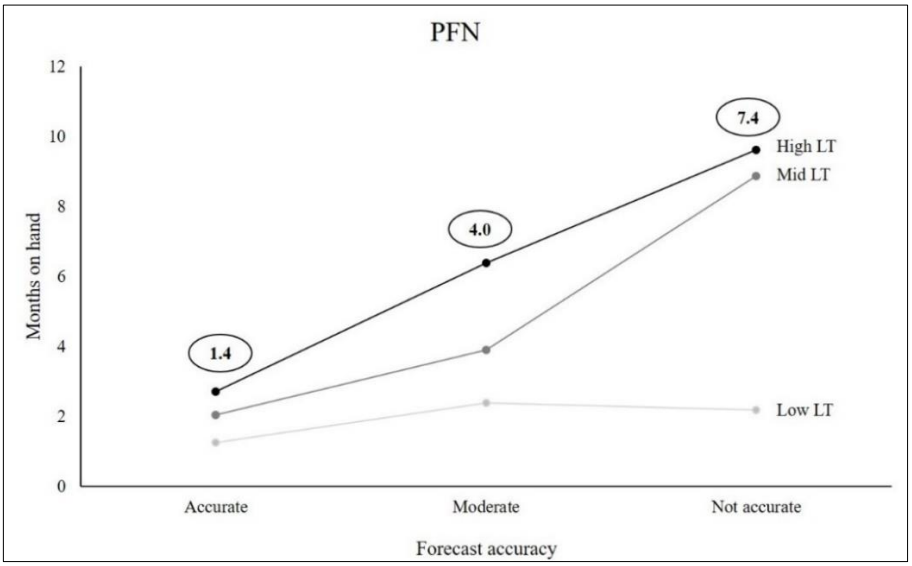

Figure 29. Interaction plot of lead time and forecast accuracy

The third tested variable was minimum order quantity. In addition to MOQ appearing to correlate with inventory level in the matrix earlier, it was also proven that in significant number of cases MOQ is higher than EOQ. Therefore, MOQ was considered as an interesting and valuable variable to be further analyzed. As figure 30 shows, inventory level appears to increase as MOQ increases. However, consistently to earlier observations, the length of lead time appears to significantly influence the level of inventory. The most expressive impact results from long lead time and high MOQ – the extreme categories of both variables. The results are similar in the product family C, for which the details can be seen in the appendix.

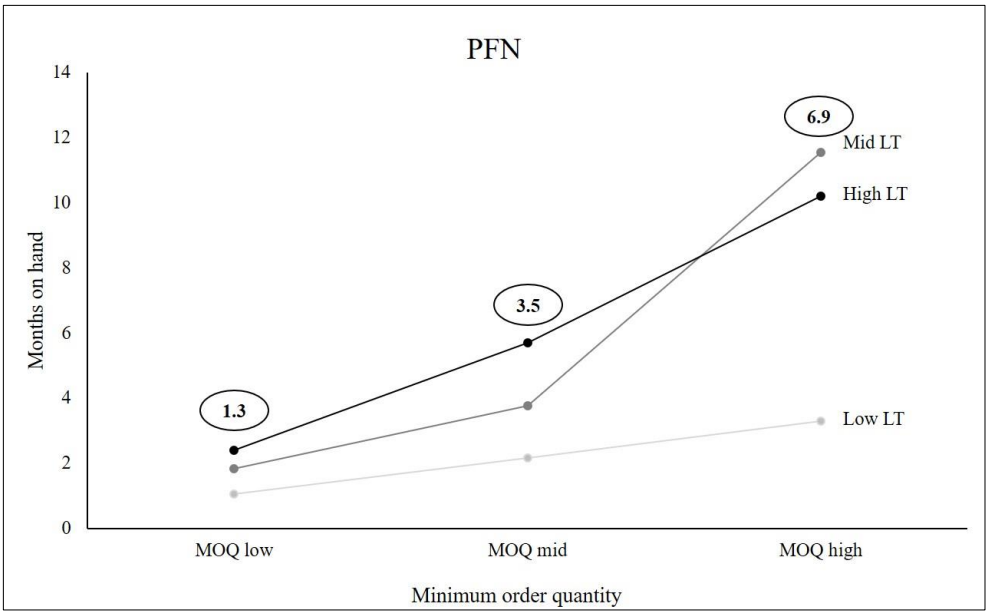

Figure 30. Interaction plot of lead time and minimum order quantity

Although the results for mid and high lead time appear to cross each other in the case of MOQ, all three tested inventory drivers indicate that when lead time is low the lowest inventory levels can be obtained. No significant difference was detected between mid and high lead time. Nevertheless, as far as lead time is concerned the analysis has proven that inventory levels appear to be the lowest when lead time is less than nine days. It is evident that the lower the months on hand is, the lower is the amount of capital tied up to inventory. This result is exclusively relevant to comprehend the inventory drivers and the mutual influence of the variables on the months on inventory.

7 RESULTS & DISCUSSION

The analyses have proven that inventory management at Hilti follows the rule of pareto, which is a common and natural approach to inventory management. Relevant evidence was found that the organization is holding stock of appropriate products, which are the ones that customers are mostly asking for. Unexpectedly, the analyses also have revealed that Hilti holds rather high inventory levels which requires major investments of capital. Fortunately, the products are not easily perishable, which liberates the company from financial losses through quick obsolescence rates. According to the analysis, the reason for high inventory levels potentially result from extensively varying demand volumes, which are difficult to forecast. In addition, the company appears to admire high service levels, although the influence of service level could not have been proven by the statistical analysis. Nevertheless, setting high service levels – which is a set target, not an actual "how did we do" -figure, indicates that whatever the customer is requesting for, it should be available for the customer in no time. In a complex global supply chain customer centric strategy requires high stocks in order to not disappoint customer expectations. It can be expected, that many organizations aim to find a balance between costs and customer satisfaction. As the competition is ever growing, it is not false to say that only Hilti would possess a customer centric strategy – it is today the case in majority of the organizations.

7.1 Inventory drivers at Hilti

This study has provided evidence that demand and demand volatility are the main inventory drivers at Hilti. It is not surprising, as based on the literature review it has clearly been claimed by various authors that inventory exists for the demand. In this study, demand was considered as a control variable, known to have an impact on inventory and was therefore not hypothesized. However, the analyses have proven that demand is indeed one of the main factors impacting the y-variable. More remarkably it is proven that demand forecasts and demand volatility are crucial inventory drivers. The outcome of both families in correlation matrix and multivariate regression analysis have indicated similar results. Both samples have suggested aligned outcome of the group of main inventory drivers – demand, demand volatility and demand forecast accuracy. Conducted multivariate regression analysis could not provide evidence in neither of the product families significant weight on lead time, EOQ or MOQ. However, the result only indicated that there is no linear relationship with these variables and inventory level. In contrast, correlation matrix has shown that MOQ, EOQ and

lead time have a minor correlation with inventory level. Therefore, the samples were approached with ANOVA analysis in order to examine variables that appear to have weak correlation.

The most remarkable result to emerge from the data is that lead time in combination with other inventory drivers have a significant impact on inventory level. No significant linear correlation between lead time and inventory level was observed but ANOVA analysis has significantly proven the importance of lead time as an inventory driver. The analysis has shown inventory months on hand increasing consistently when lead time increases – although not linearly. However, it is also obvious that lead time is significantly relevant when also other inventory drivers, including demand volatility, forecast precision and minimum order quantity, are extremely deviant from optimal values. This has been proven by ANOVA analysis, as the outcome obviously has shown, that long lead time alongside with high MOQ, high demand volatility or high forecasting error result in significantly higher inventory level, than when lead time is low. Interestingly, the analyses have shown that demand volatility drives the inventory level so significantly, that even with low lead times, inventory months on hand appear to increase significantly as demand volatility increases.

Even though the analysis in the previous chapter has provided coefficients for inventory levels between different lead time groups, it must be admitted that the influence of lead time on inventory undoubtedly is situation specific. Therefore, the coefficients presented in this report cannot be validated as a general influence behavior of lead time across industries. However, based on the analysis a conceptual model has been developed which gives guidance of the influence of lead time on inventory level. Figure 31 describes conceptually the impact of lead time on inventory at Hilti considering three additional inventory drivers. The steepness of the line describes the impact of short and long lead times in case of the three discussed inventory drives. As the model shows, the impact of different inventory drivers on inventory level is minor when lead time is low, demand volatility appearing as a minor exception. In the case of long lead time, the line is rather steep in the case of all three inventory drivers. In conclusion, the outcome reveals that when lead time is low, the inventory level is significantly smaller - also in cases of non-optimal values of other inventory drivers, such as inaccurate demand forecasts. Glock (2012) and Rumyantsev &

Netessine (2007) have all argued, that reducing lead time is beneficial especially when demand uncertainty is high, which has been proved also by this case study. Earlier studies have also stated that shorter lead times allow to reduce inventory in response to actual demand (Fisher & Raman 1996) which has been further proven by this study.

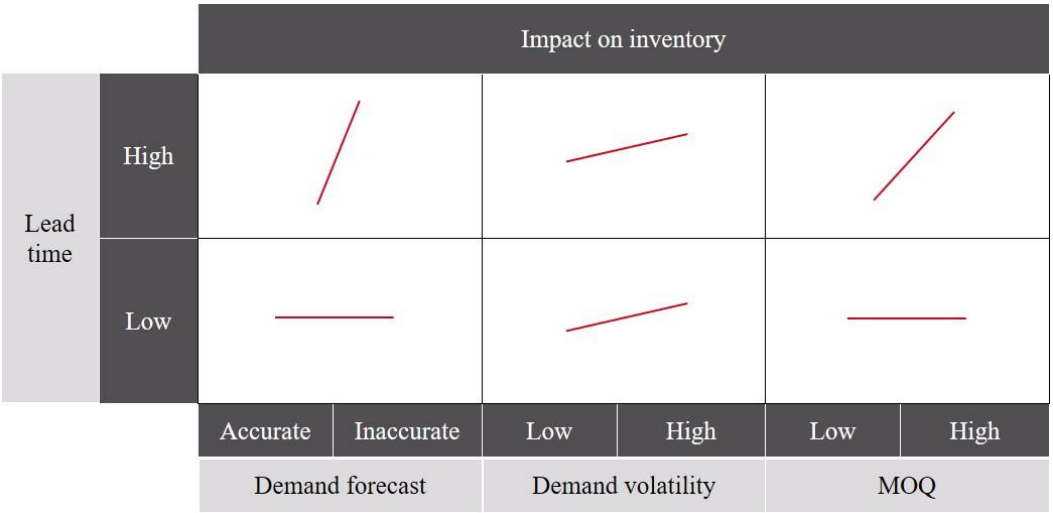

Figure 31. Conceptual model of the influence of lead time on inventory

The analysis allows to state that all these factors are relevant drivers for the level of inventory. Therefore, the study has statistically proven the following variables to possess a significant position as an inventory driver at Hilti:

- **Demand**
- **Demand deviation**
- **Demand forecast**
- **Lead time**
- **MOQ**

As stated earlier, not all variables are possible to be tested. Therefore, it is not argued that the five mentioned variables are the only drivers, however, these are proven to have a significant influence on inventory levels at Hilti. Also, the significance of service level has been discussed, however no evidence was found to support the statement of service level being a significant influencing factor.

7.2 Discussion

Examining the results of this study requires an understanding of the case study business environment. Hilti Group operates globally with a long supply chain with high complexity. By default, more complex supply chains are more challenging to manage, plan and operate than the smaller, more simpler ones. The supply chain of Hilti contains raw material supply base with hundreds of suppliers, production in various plants in three different continents, assembly operations, which necessarily does not always happen in the same place as component production, warehousing in hundreds of global warehouses and finally sales operations, which brings the products to the customers. Finished goods are partly produced in house and assembled to order, which excludes the possibility of high stock levels because of strategic decision to make to stock. When assembling to order, the risks of holding unnecessary stock of finished goods is lower, since the risk is partly shifted to delivery performance and resource management, as discussed earlier in literature review of decoupling point.

Hilti appears to follow a mixture of precaution and transaction motive of holding inventory of finished goods. Inventory is held to manage the demand peaks in highly volatile demand industry while considering disruptions and the long lead times. For product family C especially, the inventory levels appear much higher than the demand. In addition to covering the demand variances, the stock levels can be assumed to be high due to safety stock levels and surprisingly high MOQ volumes. PFC is classified as dangerous goods, which consequently results in longer processing times in customs and even cancellations due to ships not willing to take the risk to transport dangerous goods overseas. The complexity is certainly not the only cause for high inventory levels but based on the inventory data and case organization analysis it would be incorrect to dismiss the complexity aspect as an influencing factor to inventory.

The outcome of the study creates significant proof to the existing literature. The study has proven that demand volatility appears to be the strongest independent inventory variable, which has been also stated in earlier publications by various authors among which Rumyantsev & Netessine (2007), Enns (2001), and (Glock 2012). However, it should be considered that the business environment of the case organization is seasonal, follows project characteristics and demand varies significantly every month. As construction business is

based on projects, it is difficult for the organization to forecast the future demand. This could be one of the reasons for the outcome of demand volatility being the strongest driver. The analysis reveal that the impact of lead time is significant, however surprisingly the influence of lead time variation could not be proven. Thus, the impact of lead time alone was not proven either. The study has shown that lead time by itself indicates nothing for the level of inventory, however, as soon as other inventory drivers are considered, lead time becomes significantly important. This could also be the case with lead time variation. In addition, there was no significant evidence of the behavior of overstock and the influence of lead time on that. The reason for this rather contradictory result is still not entirely clear, but the significance of lead time was successfully proven on months on hand. Inventory months on hand basically is comparable to overstock as the higher the months on hand is, the higher must the overstock be. According to theory, inventory consist of cycle stock and safety stock. However, the functionality of inventory does not in reality follow the optimal function of re-order and demand. In reality, business environments are undoubtedly more complex and as the analysis have shown, very much noise appears in the data of inventory levels.

It is necessary to consider also the human factor in inventory management. The employees certainly use their experience when deciding when and how much to order. This among other mentioned factors impact the inventory level and therefore, it must be considered that this study only examines the inventory data of Hilti. Therefore, in other organizations and business environments the inventory drivers might appear completely vice versa, although demand most likely is continuously the main driver among industries.

The study provides further evidence to support the weight of demand as a driving factor of inventory. The data has inevitably proven, that demand indeed is the main inventory driver also in global and complex supply chain. The experiments confirm previous results by justifying lead time as an inventory driver. Although no proof of linear relationship with inventory level was obtained, the analyses have shown, that the lead time is a significant factor especially when other inventory drivers possess a nonoptimal and extreme value. The results extend the current understanding of lead time as an inventory driver and successfully proves the significance. Consequently, the null hypothesis can be rejected, which expected no relationship between inventory level and lead time. In contrast, the results allow to support the hypothesis 1, which expected a significant impact of lead time on inventory

level. However, no linear relationship between lead time and inventory was identified. H2 expected decreasing lead time positively impact the inventory level. Inventory appears to be rather case specific and depend also on other inventory drivers and therefore it cannot be proven that purely decreasing lead time companies could decrease inventory levels. Even though this study has proven coefficients for inventory months on hand for various lead time categories, the author believes that no clear evidence has been obtained in order to support the hypothesis 2. Therefore, hypothesis 2 must be rejected. Proof for linear relationship between lead time and overstock was further not observed. As a consequence, hypothesis 3 which expected linear relationship between lead time and overstock, must also be rejected. Fourth and the last hypothesis of the study expected the volatility in demand to have a significant impact on inventory. The study has provided sufficient evidence to support the hypothesis as it has clearly been defined in correlation, multivariate regression as well as in ANOVA analysis that volatility in demand is a significant factor on the high inventory levels of Hilti.

8 CONCLUSION

The main purpose of this study was to define the impact of lead time on inventory levels and to validate further inventory drivers. The aim for the study originated from the hypothesis of lead time being a significant factor that shall be considered in supply chain decision-making. The supply management function of the case organization assumes lead time being a significant factor and inventory level to be driven strongly by lead time.

Earlier studies proved that different factors influence the inventory in different organizations. This is for example due to different motives of holding the inventory, industry specific factors, financial and strategic aspects, competition, cycles and other trends. This case study has proven the factors that impact the inventory of finished goods at Hilti by examining selected product groups. The main research question was formed as follows: *What impact does lead time have on inventory levels and can the capital tied up to inventory be reduced by reducing lead time?* The multivariate regression analysis revealed that lead time has no linear impact on inventory level and consequently with lead time only it is not possible to explain the capital tied up to inventory. However, the analysis also proved, that the level of inventory was significantly lower when lead time was low even though when other inventory drivers possessed non-optimal values. In addition, the study has proven a similar impact from long lead time, proving that long lead time result in higher inventory levels. For instance, the results have shown that when demand is highly volatile and lead time is high, the overstock is consequently higher, as when the lead time would be short and demand less volatile. Therefore, unlike the case organization has expected, lead time on it's own has no impact on inventory but excessive inventory levels result from long lead times in combination with other inventory drivers. In conclusion, the capital invested in inventory can be reduced, thus not only by reducing lead time, but also decreasing the volatility of demand or the minimum order quantities, which may be negotiated with the suppliers.

The first sub research question was set as following: *What are the main drivers that determine inventory level and how significant are their impacts?* The literature review identified various inventory drivers from which selected variables were tested with the empirical data sample. The outcome of the study provides a clear understanding of the inventory drivers. In this case study specific business environment, the variables which have a significant direct impact on inventory were proven to be demand, demand forecast and

demand volatility. In addition, minorly identified factors were lead time, EOQ and MOQ. As discussed, the MOQ is essential factor also when considering lead time, as their combination was proven to impact the level of overstock. The study has shown that the minimum order quantity was in significant amount of cases higher than the economic order quantity. A strategy to reduce the MOQs could be an option to improve the inventory efficiency of Hilti supply chain operations.

The second sub research question aimed at defining *the role of inventory in corporate financials, and to importance to comprehend the inventory drivers from financial point of view.* Based on the literature review it is obvious that inventory has a significant impact on working capital, which is used to finance the daily business operations of an organization. The study has proven that Hilti holds unquestionably more of stock than the demand, which consequently reveals a significant amount of capital being tied up. In order to release that, the company must understand the inventory drivers. Based on this study, the company may take actions for instance to shorten lead times, improve demand forecasting or renegotiate MOQ's with suppliers, in order to reduce the level of inventories and release the capital.

To conclude, it might be well to state that the conceptual model given in the previous chapter might not be rigorously accurate, due to industry specific inventory drivers. Many minor parameters have purposely been left unconsidered in order to simplify the outcome and to guarantee user-friendliness of the conceptual model. Other refinements, while interesting, however too fine spins to keep the practicality of the model. The outcome developed in this research is reasonably correct and will be considered to give acceptable guidance when used in practice at the case organization. The results obtained in this case study offer invaluable and unique evidence for inventory drivers at Hilti and provide support to reconsider future decisions on lead time as it is significantly proven to have an impact on inventory. The outcome is indisputable and provides evidence for the importance of low lead times from the working capital point of view.

8.1 Validity & Reliability

Validity and reliability are research quality measures. In a quantitative study, validity is defined as the level of accuracy of a measurement of a concept in the research. Reliability is the other measurement which can be defined as the consistency of the accuracy of research.

A reliable study provides consequently the same outcome if the study approach is applied to another environment or sample. (Heale & Twycross 2015.) Existing studies have proven, that in different organizations different factors impact the level of inventory (Rumyantsev & Netessine, 2007). This study has supported the hypothesis of lead time being a significant inventory driver and therefore supports other existing theories. As this case study has provided evidence of inventory drivers in a specific business environment, the result may not be applicable nor relatable for other business environments, such as local, more simple supply chains. However, the approach to examine the drivers is versatile and applicable for any industry. This study can be considered as a reliable study due to the approved source of data as well as the amount of data. The number of observations is considered significantly high, which increases the reliability of the outcome. In addition, the study considered a whole fiscal year of 2019, which covers a wide time scale too. Analysis has proven that the results were multiple times verified by dividing the sample into smaller sets as well as analyzing the other product family. The results of inventory drivers were consistently aligned. This proves the stability of the results, which is one of the attributes of reliability (Heale & Twycross 2015). In addition, the dependent variable was considered as inventory in units thorough the study which supports homogeneity of the approach.

8.2 Further research

This study has focused on finding the drivers for inventory and determining the relationship between lead time and inventory level. The available data suggests that lead time is not linearly driving the inventory, however influence between different factors together on inventory were successfully defined. The conceptual model created is proven only to work in the case of Hilti. The model creates potential to be research among other companies in order to determine whether the result is consistent also in other organizations in the manufacturing industry. Furthermore, a comparison to local, more simple supply chain would be an interesting approach to a new study from lead times influence point of view. In addition, this study has not considered all possible inventory drivers and has not measured for instance human impact. Also, lead time could potentially have a significant impact on for example obsolescence, which causes loss of capital due to products not moving from stock and consequently even ending up to depreciation instead of to the markets. A further research idea therefore would be, to investigate the obsolescence, the volumes and the

influence of lead time on the depreciation in long and complex supply chains. Additional approach to an investigation would be the impact of lead time on disruption causes. What type of role does lead time play in case of disruptions in a complex supply chain and what are the costs of stock outs or unnecessary inventory increase. The cost impacts would be an interesting field to further examine and to investigate whether specific lead times have a relationship with the level of consequence of disruptions.

9 SUMMARY

This case study has successfully analyzed inventory data of a case organization in manufacturing industry. The organization is currently taking supply related decisions based on the purchase price mainly. The purpose of this study has been to examine the level of capital the case organization invests on inventory and more in detail, to investigate the influence lead time has on inventory. The aim of the study has been in an alignment with the future goals of the case organization, which intends to consider the capital invested on inventory in lead time related supply decisions.

Valuable outcome has been provided by examining the current state of finished goods global inventory data from 2019. More importantly, five inventory drivers have been defined and verified by various analysis methods. The analysis approaches applied in this study have included descriptive statistics, multivariate regression analysis, and ANOVA analysis. Based on these methods, evidence has been provided and successfully has been proven, that especially in this specific case organization, inventory levels are significantly driven by demand, demand volatility, demand forecasts, lead time, and minimum order quantities. A remarkable outcome has shown that unlike the case organization has expected, lead time on its own indicates no influence on inventory. However, when combining with any of the other defined five inventory drivers, lead time has been proven to be a significant influencer on excessive inventory level and consequently on the capital invested on inventory.

The study has provided a conceptual model to comprehend the impact of lead time on inventory. For future studies, the author has suggested to approach another company and industry to measure the impact of lead time with a similar statistical analysis approach in order to validate the universal qualification and competence of the model. By now, the model is proven solely to reflect an image of the inventory behavior in the selected case organization. Nevertheless, the study has verified, that there are various factors which drive the level on inventory and the influence weight of these factors vary between different business environments and product types. Therefore, it may be argued, that the behavior of inventory explicitly depends on the business strategy and the business case.

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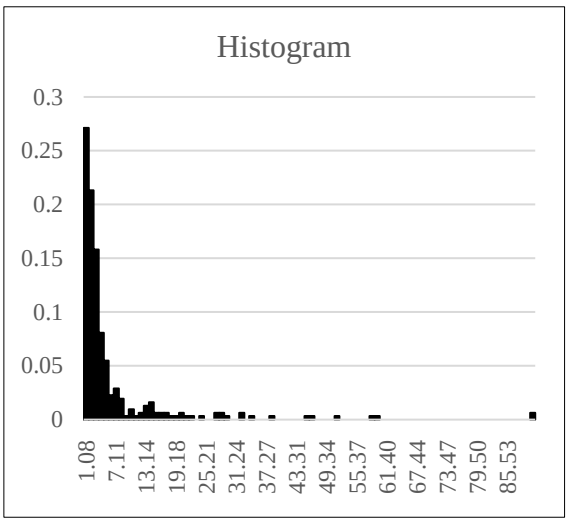
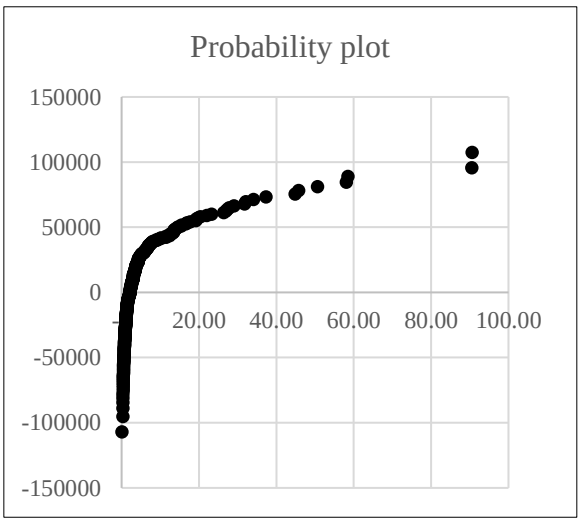
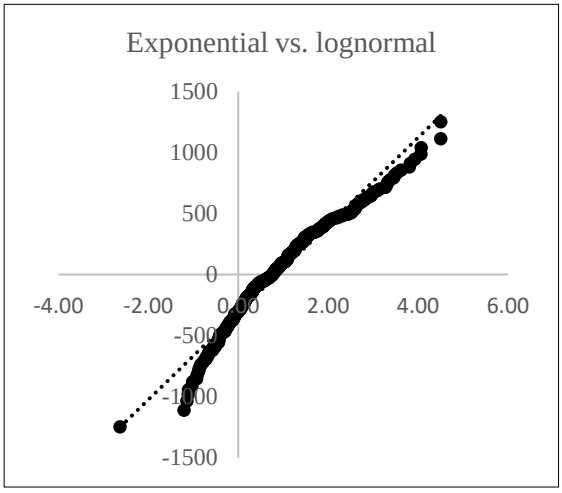
APPENDIX 1 Distribution fitting PFC







APPENDIX 2 Correlation matrix for product family C.

Pearson Correlations

	Avg. Stock. [pcs	Stock rotation	Avg. Stock. [CHF	LC [CHF]/m	Act. SS [pcs]	Leadtime	LT dev.	Avg. Dmnd. [pcs]	Dmnd. Dev. [pcs	Avg. Fcst. Dmnd.	Forecast precisi	EOQ	MOQ
Stock rotation	-0.037												
	0.583												
Avg. Stock. [CHF	0.973	-0.034											
	0	0.619											
LC [CHF]/m	0.696	-0.053	0.661										
	0	0.437	0										
Act. SS [pcs]	0.88	-0.026	0.89	0.621									
	0	0.706	0	0									
Leadtime	0.27	-0.038	0.254	0.037	0.154								
	0	0.573	0	0.585	0.022								
LT dev.	0.088	-0.022	0.037	0.024	0.029	0.237							
	0.19	0.746	0.582	0.726	0.666	0							
Avg. Dmnd. [pcs]	0.894	-0.033	0.855	0.763	0.926	0.117	-0.02						
	0	0.63	0	0	0	0.083	0.772						
Dmnd. Dev. [pcs	0.932	-0.036	0.905	0.756	0.934	0.165	-0.014	0.985					
	0	0.592	0	0	0	0.014	0.836	0					
Avg. Fcst. Dmnd.	0.885	-0.035	0.839	0.784	0.903	0.115	0.012	0.986	0.972				
	0	0.604	0	0	0	0.089	0.862	0	0				
Forecast precision	-0.039	0.845	-0.035	-0.054	-0.026	-0.07	-0.028	-0.034	-0.037	-0.036			
	0.566	0	0.603	0.426	0.696	0.299	0.679	0.62	0.581	0.596			
EOQ	0.57	-0.084	0.477	0.779	0.456	0.076	0.049	0.626	0.615	0.649	-0.086		
	0	0.213	0	0	0	0.262	0.471	0	0	0	0.201		
MOQ	0.528	-0.067	0.493	0.628	0.391	0.242	0.064	0.466	0.475	0.477	-0.072	0.745	
	0	0.322	0	0	0	0	0.34	0	0	0	0.286	0	
Service Level	0.054	-0.028	0.046	0.096	0.04	-0.055	-0.255	0.06	0.06	0.067	-0.005	0.141	0.112
	0.425	0.681	0.494	0.153	0.552	0.419	0	0.375	0.375	0.322	0.936	0.037	0.096

Cell Contents
Pearson correlation
P-Value

APPENDIX 3 Multi variate regression analysis set ups and results PFC.

Complete PFC data sample results				
Part Description (SAP)	FALSE	-	-	kategorial
Warehouse	FALSE	-	-	kategorial
Average Monthly stock 12m [pcs]	FALSE	-	-	numerisch
Average Monthly stock 12m [CHF]	FALSE	2	0.94	numerisch
EOQ	FALSE	8	0.34	numerisch
Logistical consumption [CHF]	FALSE	7	0.45	numerisch
Actual SS [pcs]	FALSE	6	0.81	numerisch
Leadtime [days]	FALSE	10	0.1	numerisch
Leadtime deviation [days]	FALSE	12	R^2: 0	numerisch
Average demand [pcs]	FALSE	4	0.83	numerisch
demand deviation [pcs]	FALSE	3	0.84	numerisch
average forecast demand [pcs]	FALSE	5	0.82	numerisch
year quantity	FALSE	1	1	numerisch
MOQ	FALSE	9	0.33	numerisch
Service level	FALSE	11	R^2: 0	numerisch
Stock rotation	FALSE	13	R^2: 0	numerisch

PFC, LC above 1000 CHF				
Part Description (SAP)	FALSE	-	-	kategorial
Warehouse	FALSE	-	-	kategorial
Average Monthly stock 12m [pcs]	FALSE	-	-	numerisch
Average Monthly stock 12m [CHF]	FALSE	2	0.93	numerisch
EOQ	FALSE	8	0.26	numerisch
Logistical consumption [CHF]	FALSE	7	0.38	numerisch
Actual SS [pcs]	FALSE	6	0.8	numerisch
Leadtime [days]	FALSE	10	0.14	numerisch
Leadtime deviation [days]	FALSE	12	R^2: 0	numerisch
Average demand [pcs]	FALSE	4	0.81	numerisch
demand deviation [pcs]	FALSE	3	0.81	numerisch
average forecast demand [pcs]	FALSE	5	0.8	numerisch
year quantity	FALSE	1	1	numerisch
MOQ	FALSE	9	0.23	numerisch
Service level	FALSE	11	0.03	numerisch
Stock rotation	FALSE	13	R^2: 0	numerisch

PFC, LC above 100 CHF				
Part Description (SAP)	FALSE	-	-	kategorial
Warehouse	FALSE	-	-	kategorial
Average Monthly stock 12m [pcs]	FALSE	-	-	numerisch
Average Monthly stock 12m [CHF]	FALSE	2	0.96	numerisch
EOQ	FALSE	11	R^2: 0	numerisch
Logistical consumption [CHF]	FALSE	5	0.78	numerisch
Actual SS [pcs]	FALSE	6	0.77	numerisch
Leadtime [days]	FALSE	7	0.09	numerisch
Leadtime deviation [days]	FALSE	8	0.01	numerisch
Average demand [pcs]	FALSE	4	0.86	numerisch
demand deviation [pcs]	FALSE	3	0.9	numerisch
average forecast demand [pcs]	FALSE	13	R^2: 0	numerisch
year quantity	FALSE	1	1	numerisch
MOQ	FALSE	9	R^2: 0	numerisch
Service level	FALSE	12	R^2: 0	numerisch
Stock rotation	FALSE	10	R^2: 0	numerisch

APPENDIX 4 Multi variate regression analysis set ups and results PFN.

PFN, dependend variable now SAFETY STOCK (pcs) and the data set of SS that include lead time				
Part Description (SAP)	FALSE	-	-	kategorial (deskriptiv)
Warehouse	FALSE	-	-	kategorial (deskriptiv)
Average Monthly stock 12m [pcs]	FALSE	2	0.76	numerisch
Average Monthly stock 12m [CHF]	FALSE	7	0.44	numerisch
EOQ	FALSE	8	0.32	numerisch
Logistical consumption [CHF]	FALSE	6	0.48	numerisch
Actual SS [pcs]	FALSE	-	-	numerisch
Leadtime [days]	FALSE	10	0.04	numerisch
			R^2:	
Leadtime deviation [days]	FALSE	13	0	numerisch
Average demand [pcs]	FALSE	4	0.72	numerisch
demand deviation [pcs]	FALSE	1	0.82	numerisch
average forecast demand [pcs]	FALSE	5	0.52	numerisch
year quantity	FALSE	3	0.76	numerisch
MOQ	FALSE	9	0.3	numerisch
Service level	FALSE	12	0	numerisch
Stock rotation	FALSE	11	0	numerisch

PFN, dependend variable now SAFETY STOCK (pcs) and the data set of SS that does not include lead time				
Part Description (SAP)	FALSE	-	-	kategorial (deskriptiv)
Warehouse	FALSE	-	-	kategorial (deskriptiv)
Average Monthly stock 12m [pcs]	FALSE	1	0.91	numerisch
Average Monthly stock 12m [CHF]	FALSE	5	0.68	numerisch
EOQ	FALSE	6	0.24	numerisch
Logistical consumption [CHF]	FALSE	8	0.23	numerisch
Actual SS [pcs]	FALSE	-	-	numerisch
Leadtime [days]	FALSE	9	0.03	numerisch
			R^2:	
Leadtime deviation [days]	FALSE	12	0	numerisch
Average demand [pcs]	FALSE	2	0.8	numerisch
demand deviation [pcs]	FALSE	4	0.71	numerisch
average forecast demand [pcs]	FALSE	3	0.77	numerisch
			R^2:	
year quantity	FALSE	13	0	numerisch
MOQ	FALSE	7	0.23	numerisch
			R^2:	
Service level	FALSE	11	0	numerisch
Stock rotation	FALSE	10	0	numerisch

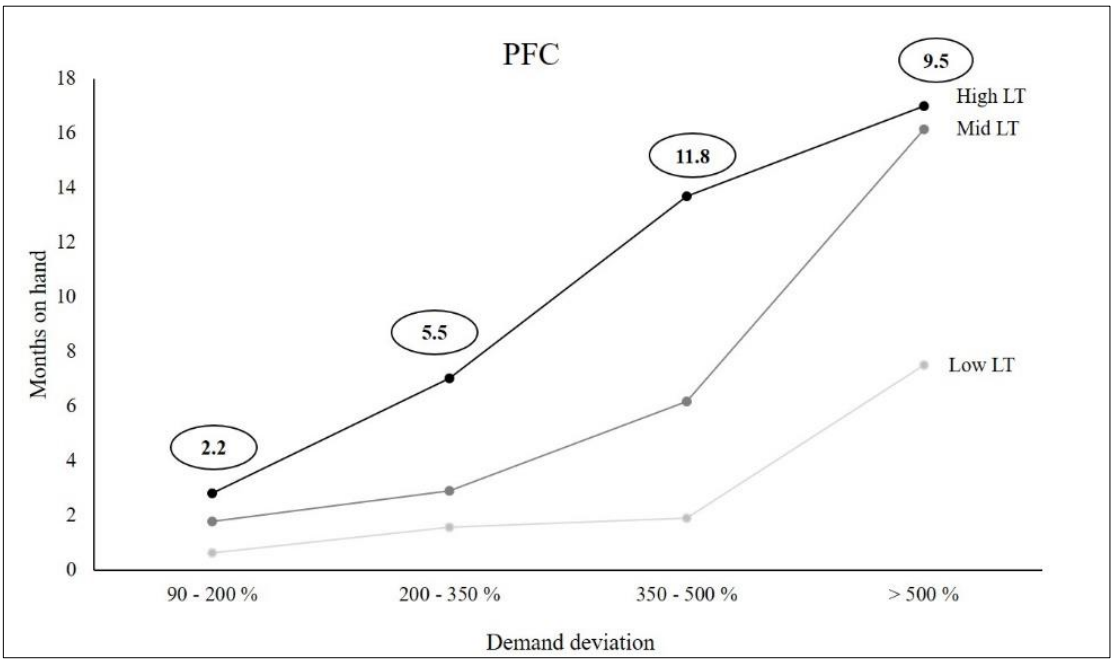
PFN, dependend variable inventory (pcs) and the data set include LC above 1000 CHF				
Part Description (SAP)	FALSE	-	-	kategorial (deskriptiv)
Warehouse	FALSE	-	-	kategorial (deskriptiv)
Average Monthly stock 12m [pcs]	FALSE	-	-	numerisch
Average Monthly stock 12m [CHF]	FALSE	6	0.42	numerisch
EOQ	FALSE	8	0.2	numerisch
Logistical consumption [CHF]	FALSE	7	0.2	numerisch
Actual SS [pcs]	FALSE	2	0.84	numerisch
Leadtime [days]	FALSE	10	0.08	numerisch

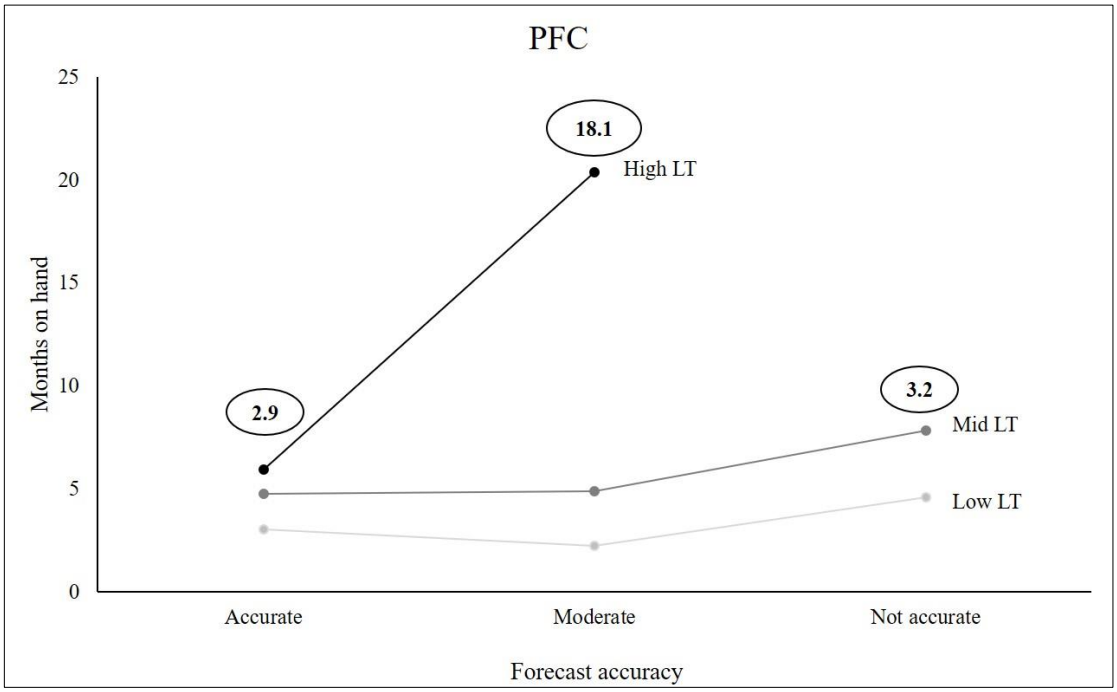
			R^2:	
Leadtime deviation [days]	FALSE	13	0	numerisch
Average demand [pcs]	FALSE	4	0.61	numerisch
demand deviation [pcs]	FALSE	3	0.63	numerisch
average forecast demand [pcs]	FALSE	5	0.54	numerisch
year quantity	FALSE	1	1	numerisch
MOQ	FALSE	9	0.19	numerisch
			R^2:	
Service level	FALSE	14	0	numerisch
Stock rotation	FALSE	11	0	numerisch

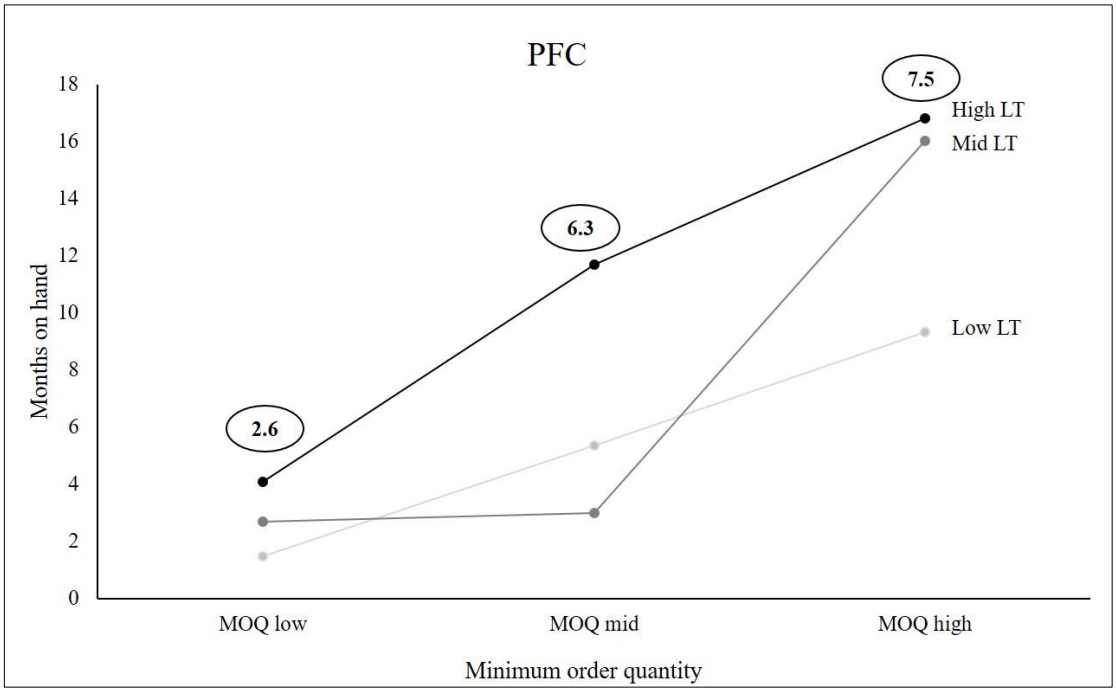
PFN, dependend variable inventory (CHF) and the data set include LC above 1000 CHF

Part Description (SAP)	FALSE	-	-	kategorial (deskriptiv)
Warehouse	FALSE	-	-	kategorial (deskriptiv)
Average Monthly stock 12m [pcs]	FALSE	4	0.42	numerisch
Average Monthly stock 12m [CHF]	FALSE	-	-	numerisch
EOQ	FALSE	8	0.03	numerisch
Logistical consumption [CHF]	FALSE	1	0.56	numerisch
Actual SS [pcs]	FALSE	7	0.26	numerisch
Leadtime [days]	FALSE	10	0.03	numerisch
			R^2:	
Leadtime deviation [days]	FALSE	14	0	numerisch
Average demand [pcs]	FALSE	3	0.47	numerisch
demand deviation [pcs]	FALSE	2	0.49	numerisch
average forecast demand [pcs]	FALSE	6	0.28	numerisch
year quantity	FALSE	5	0.42	numerisch
MOQ	FALSE	9	0.03	numerisch
			R^2:	
Service level	FALSE	13	0	numerisch
Stock rotation	FALSE	12	0	numerisch

APPENDIX 5 ANOVA analysis results PFC






PFC
18
16
14
12
10
8
6
4
2
0
Months on hand
7.5
6.3
2.6
High LT
Mid LT
Low LT
MOQ low
MOQ mid
MOQ high
Minimum order quantity