

LUND UNIVERSITY

MASTER'S THESIS

The impact of delivery lead time on customer conversion

Quantitative impact of change in delivery lead time within e-commerce

Author:

Jame HANNA
Olle JOSEFSSON

Supervisor:

Peter BERLING

February 11, 2020



LUND UNIVERSITY

Abstract

Master's Thesis

The impact of delivery lead time on customer conversion

by Jame Hanna and Olle Josefsson

Academic supervisor: Peter Berling, Department of Production Management**Company supervisor:** Erik Berggren, Operations Specialist

Delivery lead time (DLT) is seen as one of the most important service factors affecting the consumers willingness to fulfill a purchase within online retailing (Esper et al., 2003). The purpose of this thesis is to investigate the effect variations in the offered DLT have on customer conversion rate within e-commerce. This is done by analyzing historical online customer demand data from a case company within the furniture industry. Further, two other factors are studied in relation to DLT, delivery charge and consumer commitment. The purpose was to further understand how these factors influence consumers behaviour in relation to the offered DLT. The research questions for the study related to the Swedish market and were the following: How does delivery-lead-time affect the probability of an fulfilled order for online furniture sales? and (2). How is the sensitivity for changes in DLT affected by the factors delivery-cost and consumer commitment?.

The analysis was done using a quantitative approach of logistic regression models. The generated models displayed statistical significance and could quantify the relationship between the variables DLT and conversion rate. The overall samples showed that when offered an DLT increase from three to ten days the probability of a consumer fulfilling the purchase decreases with 10.67 %, which for the case company studied, could be translated to a potential loss of sales of 68 million SEK per year. Further, the conducted study indicate that a high consumer commitment make consumers less sensitive to changes in DLT, while delivery charge have the opposite effect. That is a high delivery charge make consumers more sensitive to longer DLT.

Historically research related to the topic of DLT has been done using surveys or interviews to study consumer preferences. This is what makes this study different as it is based on actual sales data enabling the study of consumers actual behaviour, rather than their experienced preferences. The work of this thesis contributes to the research by quantifying the relationship of DLT and conversion rate.

Acknowledgements

We would like to express our gratitude to our supervisor Peter Berling, associate professor at the Division of Production Management in Lund, for his support throughout the process of this thesis. Further we would want to thank Erik Berggren, Operations Specialist at the case company, for the opportunity to conduct this research on data from their company, as well as his support throughout the period of writing this thesis.

Contents

Abstract	iii
Acknowledgements	v
Abbreviations	ix
1 Introduction	1
1.1 Background	1
1.2 Scope and research questions	2
1.3 Focus and Delimitations	3
2 Theory	5
2.1 Consumer behaviour	5
2.1.1 Consumer involvement and commitment	6
2.2 Service quality factors	7
2.2.1 Delivery lead time	7
2.2.2 Delivery charge	8
3 Method	11
3.1 Research methodology	11
3.2 Research approach	11
3.3 Research strategy	12
3.4 Research design	13
3.5 Logistic Regression	14
4 Case study	17
4.1 Delivery configuration	17
4.2 Empirical data	19
4.2.1 Validity	20
4.2.2 Reliability	21
4.2.3 Data analysis	22
5 Results	23
5.1 Preliminary assessment	23
5.2 Regression analysis	24
5.2.1 All LSCs throughout Sweden	24
5.2.2 Large cities: Stockholm, Gothenburg and Malmo	25
5.2.3 All areas excluding Stockholm, Gothenburg and Malmo	25
5.2.4 Selected areas	26
5.2.5 Delivery charge ratio impact on conversion rate	27
5.2.6 Consumer commitment impact on conversion rate	28

6	Analysis	31
6.1	DLT's impact on conversion rate	31
6.1.1	All LSCs	31
6.1.2	Three largest cities compared to the rest	32
6.1.3	Selected areas/LSCs	33
	City 1	34
	City 2	34
	City 3 and 5	34
	City 4	34
6.2	Purchasing factors impact on DLT sensitivity	35
6.2.1	Delivery charge	35
6.2.2	Consumer commitment	36
7	Discussion	39
7.1	Discussion and Reflection	39
7.2	Future research proposals	40
8	Summary and Conclusion	43
8.1	Conclusion	43
8.2	Summary	43
A	Underlying conversion rate	45
A.1	Underlying conversion rate in demand data	45

List of Abbreviations

CCD	C entral- C ustomer- D elivery
CDC	C ustomer- D istribution- C entre
DLT	D elivery- L ead- T ime
LCD	L ocal- C ustomer- D elivery
LDC	L ocal- D istribution- C entre
LSC	L ocal- S ervice- C enter
3PL	3 rd- P arty- L ogistics

Chapter 1

Introduction

In this chapter, the background of this thesis will be presented and the choice of topic explained. Further the scope covered in the thesis and the research questions to be answered are presented. Finally, the delimitation's are listed and discussed.

1.1 Background

The e-commerce market is continuing to grow and according to Richter (2019) the global expected annual growth rate between 2019 and 2023 for retail online furniture sales is ten percent, with a final expected market totaling \$289.3 billion per year in 2023. These are huge numbers and in Sweden the actual growth in the 2nd quarter of 2019 was thirteen percent across all segments (PostNord, 2019b). As an e-commerce retailer it is important to offer the right products at the right price, but also the right level of service, in order to have an offer that satisfies the customer expectations (Ishfaq et al., 2016; Brynjolfsson, Hu, and Rahman, 2009). One important service that customers expect, is a short delivery lead time (DLT), consumers even state that a fast shipping increase the trust they have for a brand (MH&L, 2016). Other examples of services are delivery precision, delivery fee, assembly, return-handling and availability. The customers expectations on the service-level vary depending on factors such as product category, country, age and consumer commitment (Ishfaq et al., 2016; Smith and Bristor, 1994). An example of the relevance of product category can be derived from the report of (PostNord, 2019b). The average online shopper in Sweden expect a delivery time of 2.9 days for groceries, while for products in home furnishing and decor they expect 4.0 days, and considering all categories in general an average delivery time of 3.4 days is expected, based on survey responses. Some other characteristics of the Swedish e-commerce market that can be found in the report from PostNord (2019a) is that Sweden is the largest e-commerce market in the Nordics and has an estimated spending of SEK5800 per person and month. It also have the highest share of online customers in the Nordics, where 69 percent of residents state they purchased something online in the last month, compared to 62 percent on average in the Nordics. An interesting observation to note is the increasing interest for sustainability observed in the report regarding e-commerce. Sustainability is something that has become one of the most important social issues for consumers and companies in general (PostNord, 2019a).

The difference in customer expectations depending on factors such as product categories as described above, suggests that one should adopt different service-level targets depending on the products you offer and the characteristics of the market you operate in. Successfully meeting the customer expectations on these factors are complex, but very rewarding for the ones that do (Murfield et al., 2017; Ames, 2015). Hence, as an online-retailer it is in your interest to keep the service offer to your customers as good as possible. However there is a trade-off to be made between

increased customer satisfaction (and sales), and the cost of offering that level of service. An interpretation of this would be how much more or less one is expected to sell depending on the level of the service. This is what this thesis will try to answer.

1.2 Scope and research questions

The search for a correct level of service is an ongoing quest for many organizations and companies. This thesis aim to quantify the relationship between DLT and conversion rate, which is the same as answering the question of how the service level in terms of DLT, impact sales. This thesis is written in corporation with a furniture retailer operating with both physical and online stores, usually refereed to as omni-retailer (Ames, 2015). It will be refereed to as "the retailer", "the company" or "the partner/case-company" moving onward in this thesis. In recent years the company has been working to expand their service offering to customers. Moving from traditionally only offering furniture in physical stores, to also offer surrounding services such as assembly, home delivery and waste management, among other services, as well as the option to order online in several markets. As just described above, DLT is an important factor for customer satisfaction and customer conversion (MH&L, 2016). Today online sales make up for roughly fifty percent of the companys overall sales in Sweden. It is this online-operation in Sweden that is the topic of this thesis, and how their service offer regarding DLT affect their online sales performance. Or put in other words, how changes in delivery lead time impact the demand of their Swedish e-commerce. In the report from PostNord (2019a) one find that furniture and home decor is the category with the second highest average amount spent on each purchase, after home electronics. Further, the report state that ten percent of consumers shopped furniture and home decor in the last month. Both of these are example of factors that make it relevant for the company to further focus resources on better understanding the behaviour of their online customers and how to determine the correct level of service.

Previous research on DLT has shown a strong connection between DLT and sales for a brick-and-mortar furniture retailer in Italy. A study performed by Marino and Montagna (2018) at the Italian retailer were examining consumer sensitivity when it comes to changes in DLT for their customers. The researchers concluded that although the importance of DLT have been researched by many, most of this research has been viewing the service factor of DLT qualitatively, usually through surveys or interviews with customers. The purpose of their study was to quantify the relationship between DLT and demand through a data driven approach. Their study showed that an increase in DLT from two to seven days, reduced the demand by 37.5 percent for an average selling case in the Italian case company (Marino and Montagna, 2018). The Italian study also examined how other variables such as price, distance to competitor and in store display, affected the impact of change in DLT (Marino and Montagna, 2018). Similar to this we aim to further research the relation between sales and DLT quantitatively, but for online consumers and focusing solely on DLT as the significant factor, and less on individual product characteristics. As discussed previously there are several factors affecting the expected service level and in this research we will consider delivery charge and consumer commitment in relation to DLT to understand how these affect the sensitivity of changes in DLT.

As mentioned, there are limited research that quantify the relationship between sales and DLT, which makes this thesis relevant and contributing to an increased understanding of DLTs magnitude as a service factor for online consumer behaviour.

The purpose of the thesis is to study how changes in the delivery lead time, affect the conversion-rate for furniture e-commerce customers, and how these are affected by delivery charges as well as the estimated commitment of the consumer. Which is summarized as research questions below.

1. How does delivery-lead-time affect the probability of a fulfilled order for online furniture sales?
2. How is the sensitivity for changes in DLT affected by the factors delivery-cost and consumer commitment?

1.3 Focus and Delimitations

The focus and target group of this thesis is primary the case company and it's employees working with last-mile operations. The secondary focus of the thesis is academics and other stakeholders interested in consumer behavior of the e-commerce industry and especially concerning logistics service quality.

There are several aspects that this thesis and study will not cover, some are very specific for the case company in question and some are more general. The limitations that relates to the specific case company of this thesis is mainly in relation to the delivery-setup described extensively in chapter 4.1. In short, the case company adopt two different delivery-flows. The first one called local customer delivery (LCD), which refer to delivery's made from the warehouses or brick-and-mortar stores around the country, and is not considered in this thesis. The second flow is called central customer delivery (CCD), which refer to delivery's made from the central warehouses known as CDC (Central Distribution Centers). Today there are two CDCs, one in Stockholm that serve the region of Stockholm and its surroundings, and one in Torsvik (outside of Jönköping) which serve the rest of the country. The CDCs send the deliveries via Local Service Centers (LSC) that is run by third-party logistics providers (3PLs) who are responsible for the last-mile delivery to the customer. This thesis will only study the online customers and only the CCD-flow mentioned, and no investigation will be made for DLT for either the LCD-flow or offline customers ordering home delivery in physical stores. The following list aim to summarize the major delimitation's that has been made for this thesis and the implications of them.

- The thesis will cover the current setup for the case companys online-orders and deliveries. The implications of this is for example that the customers are not allowed to select another delivery-window than the earliest date for delivery. The company have plans to change this in the future but as stated this will not be covered in this thesis.
- Parcel-orders, which refer to smaller orders and is handled by a postal-carrier (which is not subject to the same type of capacity restrictions) is not covered. The same goes for Pick-up orders or orders to be collected in store, these are not subject to any analysis in this study.
- The thesis study how the DLT affect the demand/sales. It is not meant to examine how the operational modification of DLT is made. So in other words the analysis will not cover whether the company should add another permanent delivery-window or simply increase the capacity-constraint. This operational challenge is left for the department in charge at the company to solve, or for further thesis's to investigate. The implications of this is that throughout the

thesis we consider that the DLT can increase/decrease incrementally for all customers.

- The thesis will be analyzing data for all customers and regions in Sweden, but the partner company has requested to consider some specific areas of interest that will be analyzed separately. These areas are identified by their respective LSC and prioritized due to their attributes in regards of sales volume, location, physical store availability and minimum lead-time. One important attribute among the selected areas are that they offer seven days DLT as minimum. There is a variation in the minimum offered DLT between the three largest cities (Stockholm, Malmo and Gothenburg) who have three or four days minimum and the rest of the country which have seven days minimum DLT. Which is elaborated more in the chapter covering the delivery setup, section 4.1.

Chapter 2

Theory

In this chapter, relevant theory will be presented based on a literature review. There are many research areas that relate to our research topic, however as the focus is on the impact that delivery lead time variations has on demand, hence the focus will be on literature relating to this. Starting with general consumer behaviour and the underlying assumptions of it, moving on to the factors in the service offer. The theory is used as basis for segmentation of the data as well as indicating what results can be expected, and a foundation for the analysis and discussion of the result.

2.1 Consumer behaviour

To understand how service quality factors affect the decision of a consumer to fulfill or not fulfill a purchase, it is relevant to first look at consumer behaviour in general. Consumer behaviour is a discipline studying how and why consumer purchase, or do not purchase a goods or service (Peter, Olson, and Grunert, 1999). It has been researched by many, especially within marketing, psychology, behavioural and ecological economics, but is also being subject to more perspectives from various cross-fertilized disciplines (Solomon, 2010).

According to Katona (1968) the principal assumptions of traditional theories on consumer behaviour is characterized by rational decision making and expenditures on income, or as put by Katona (1968):

- (1) the consumer chooses the best alternative among the conceivable courses of action open to him, and (2) the primary determinant of consumer expenditures, aside from tastes, is income (absolute or relative) or, according to more recent formulations, the normal or permanent income of the household.

The idea that humans are acting rational has been a major topic for academia for a long time and some recent indication of its relevance is the award to Richard H. Thaler of "The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2017" for his contributions in understanding the decision making of individuals and how they are not always rational (Nobelprize, 2017). An example of the challenge with rational behaviour is how to define a rational decision. In the traditional sense it refers to a well informed decision based on weighting alternatives of action to reach a maximum value for the individual (Thaler and Ganser, 2015). However, consumers change taste and preferences and what was the "best" decision one day might differ from the same person making the decision another day (Katona, 1968). The assumption of human rationality were challenged already by Katona (1968) in his paper which construct the low-level theory of the adaptive behaviour, arguing that humans are part of an interacting and changing environment and hence consumer behavioural

theories must consider this. A consequence of rational decision making is the need to seek and gather information in order to make a well-informed decision. Research show that this behaviour is true in some cases but in others the consumer does not go through the time-consuming process of information gathering, and hence act more upon habits or impulse (Smith and Bristor, 1994). It is also an ongoing research question whether traditional consumer behaviour theories applies when transitioning from the offline to the online environment and maybe even more relevant today, the omni-channel-environment (Patwardhan and Ramaprasad, 2005). The changes in environment imply that some factors that are highly relevant in the offline environment are replaced or complemented with others in the online environment. An example is the change from face-to-face customer interaction to the face-to-screen interaction online, which affect the customers perceived availability of services (Immonen, Sintonen, and Koivuniemi, 2018). Both of the aspects discussed above, of consumer rationality and expenditure relative to income, affect the consumer purchasing behaviour. In this report the major focus is evaluating the impact of the service quality factor delivery lead time and how it is affected by consumer commitment and delivery charge. The current theories on consumer behaviour of these factors are further explained in the upcoming section.

2.1.1 Consumer involvement and commitment

An important factor to consider in regard to consumer behaviour is the commitment or involvement the consumer have in relation to the product or service being purchased (Robertson, 1976). Traditionally, within service marketing literature the term commitment is referring to the strength of the individuals belief system with regard to a product or brand, but it can also refer to the economical commitment of the purchase, or the engagement from the consumer to search for information before the purchase (Robertson, 1976; Gronroos, 1990; Smith and Bristor, 1994). The idea of the latter definition regarding information search, is that consumers seek information when faced with uncertainty, which is in line with the idea of rational behaviour. However, as described by Smith and Bristor (1994) there can be observed that not all consumers act this way, and one explanation to this is the degree of involvement or commitment the consumer have for the specific purchase-decision. As outlined by Smith and Bristor (1994) purchase involvement can vary across individual consumers for the same purchase, higher levels of involvement implicate higher motivation to search for information before the purchase (Schmidt and Spreng, 1996). This relates to another important factor in the level of involvement, which is the perceived financial sacrifice, that in short can be translated to the price of the goods or service. However, different consumers have different perceptions of what is an expensive or trivial purchase (Smith and Bristor, 1994). One categorization of low and high commitment is by product category, for example automobiles can be considered as a high commitment purchase for a majority of consumers as it is has a high price in relation to income, while consumables can be considered low commitment. Studies do however show that variations within the same product category is also applicable (Smith and Bristor, 1994). This implies that also within the same product category, one can divide purchases into high and low involvement. This thesis covers the furniture industry and according to Ponder (2013) furnitures are considered as central to ones self-concept and hence viewed as a high involvement product category, with variations within the segment. In this report the terms involvement and commitment will be used synonymous to describe the perceived personal relevance of the product or service for the individual consumer.

2.2 Service quality factors

Customer service has always been of great importance for retailers in order to satisfy customer expectation and achieve purchasing conversion (Brynjolfsson, Hu, and Rahman, 2009). As discussed in the introduction there are several factors that make up the service offer expected by the customer, and in this section the factors studied in this thesis will be highlighted and further explained. The presented factors are related to the available data-set for the specific case studied in this thesis. The authors acknowledge the presence of several other factors that are important for consumer behaviour, however for the purpose of this thesis the factors were chosen accordingly.

2.2.1 Delivery lead time

The absolute majority of marketing literature related to customer service do agree on customer satisfaction being negatively correlated with waiting time. From the customers perspective, waiting time is in many cases perceived as a lack of service quality or even service failure, and eventually leading to customer dissatisfaction (Bitner, 1990; Clemmer and Schneider, 1996; Tom and Lucey, 1995). In other words it can be expressed as the lower the waiting time is, the higher the customer satisfaction becomes, due to time being seen as a cost (Leclerc, Schmitt, and Dubé, 1995). In some rare situations it can though actually be on the contrary, e.g. when waiting for a future event which increases the customer's expectation of pleasure (Loewenstein, 1987).

Waiting time covers many different areas within customer service. In this particular study we narrow down the scope to specifically investigate the last mile delivery lead-time for online customer orders. In omni-channel retail the consumers delivery destination options are normally composed of: customers home, pick-up point or pick-up from store. The flow of online orders to customer's home is what falls within the term of last-mile delivery, being the last step of the entire delivery lead-time process. Due to the increasing customer expectations, it has over the years evolved to become a major challenge for omni-channel retailers to manage (MC, 2018). In supply chain management (SCM) context, delivery lead-time is often defined as: The time from the receipt of a customer order to the delivery of the product (DemandSolutions, 2019). For online customers, delivery lead-time is frequently considered to be one of the most important elements of customer service within retail (Esper et al., 2003). A study conducted by ICSC (2019) confirms that statement by finding that DLT is out of all listed service elements ranked the most important, whereas for in-store shopping it ranked only on eight place. Consequently, this confirms the literature suggesting that companies can use improvements in delivery lead-time service to gain competitive advantage over its competitors (Mak, 2018; Brynjolfsson, Hu, and Rahman, 2009). However, in order for online retailers to achieve this competitive advantage it becomes crucial for them to weigh the benefits against the cost of faster delivery (Fisher, Gallino, and Xu, 2019). In other words, this means that the correct setting of an appropriate delivery lead-time offering to consumers becomes highly relevant (Palaka, Erlebacher, and Kropp, 1998).

In a report conducted this year by Convey, entitled *"Last mile delivery wars"*, we can read about the significant effect that delivery time has on consumers purchasing decisions (Berman, 2019). The study performed surveys on more than 2500 consumers whereas 28,6 percent of these answered that they would be more likely to proceed with the order if it would arrive within a week. Comparing this to the 7.5 percent who answered that the delivery date doesn't impact their likelihood to buy (Berman, 2019).

Furthermore, yet another study, named *How Fast Delivery and Quality Packaging Drives Customer Loyalty* conducted 2016 by Dotcom Distribution, show in polls that delivery time is one of the key factors that affect customer behaviour. According to the study, delivery time influences 87 percent of online consumers purchasing decisions. The study also found that people are willing to pay more money in order to receive their products earlier (Parry, 2016).

Since the early 1990s the DLT has been one of the most studied areas within SCM literature. Much of the literature have focused on highlighting the advantages of reducing DLT (Tersine and Hummingbird, 1995) and the different ways to accomplish this (Goebel, Moeller, and Pibernik, 2012; Boon-Itt and Yew Wong, 2011). Meanwhile other authors have contributed with studies on strategies in setting an appropriate DLT in relation to demand (Palaka, Erlebacher, and Kropp, 1998). Most of these studies have conducted surveys in order to try to understand the consumer behaviour related to DLT. However, none or very few researchers have with historical data attempted to quantify this relation between DLT and customer demand for online retail. The only research paper that was similar to our thesis and of quantitative nature was the previously mentioned Italian study conducted by Marino and Montagna, 2018. Therefore, it is particularly interesting to present the results of that study in order to later in the analysis section compare these to ours. The study performed analysis for an offline retailer over a six month period and found that if the promised DLT changes from two to seven days, the probability of a consumer fulfilling the purchase decreases with 37.5 per cent Marino and Montagna (2018). Although we are studying the same type of phenomenon there are some big differences in our design set-ups that distinguish us from each other. The main differences are the following: This thesis investigate consumers for online retail whereas they study offline retail, we have DLT, cart-value and delivery charge as explanatory variables whereas they include DLT but also product display in store, competitor distance and product price variables. It is due to these significant differences that our thesis will further contribute to the academic research within this subject by especially focusing on the DLT factor for the online retail market.

2.2.2 Delivery charge

Another service factor that we study in this report is the effect of delivery charges on consumer behaviour. In a report conducted by (Lewis, Singh, and Fay, 2006), a wide variety of shipping schedules are gathered from an online retailer's database and used to investigate the impact they have on consumer behaviour. The results from the study show that consumers are highly sensitive to shipping charges and that promotions such as free shipping can significantly increase sales. However, the increased revenues that comes with a reduction of shipping charges are not always large enough to be profitable (Lewis, 2006). What many of the online retailers that offer free shipping do instead, is adding the extra cost on the base price of the product (Yao and Zhang, 2012). Therefore, understanding the connection between consumer behaviour and shipping costs is crucial for the functioning of an online retailer's supply chain.

The profit implications that comes with an unconditional free shipping policy suggest that other, but still consumer friendly, solutions ought to be achieved (Barsh, Crawford, and Grosso, 2000). One marketing promotion concept that is commonly used by online retailers, in order to increase sales, is the value-based free shipping policy. This concept has been one of the most frequently mentioned within the literature research related to this study area. In their study, Huang and Cheng (2015)

examines how consumers evaluate and respond to different forms of threshold free shipping (TFS) policies. Boone and Ganeshan (2013) intend to help online retailers increase total revenues and profits by providing an exploratory model which strives to assist in determining the optimal threshold value. With the intention to accomplish the same goal as the previous mentioned study, Becerril-Arreola, Leng, and Parlar (2013) proposes a two step decision process. The first step consists of the retailer making optimal decisions on the profit margin as well as the free shipping threshold value, and then secondly determine the appropriate inventory level.

Many companies do acknowledge the impact that the delivery charge has on consumer behaviour but are still facing challenges in the setting of an appropriate delivery fee. Recent literature on the topic suggest that most consumers are sensitive to an overpriced delivery charge, which is considered to be a main factor to why online shoppers abandon their shopping cart (Shao, 2017). A study conducted by PostNord (2019a) reveals that, for the Nordic consumers, the delivery option being perceived as too expensive is one of the two primary reasons to an interrupted order purchase. Out of a total of thirteen different options, more than 26 percent of the consumers filled in the answer: *"The delivery options were too expensive"*, as to why they did not complete their order. Consequently, a key marketing decision for online retailers is how to optimally set shipping charges for their delivery services. In order to tackle this complex problem, some of the studies have tried to develop theoretical frameworks with the hope of being able to anticipate consumers response to different shipping fee structures (Schindler, Morrin, and Bechwati, 2005).

It can be concluded that most of the literature related to this topic is fairly weak on actually highlighting the quantified impact that delivery charges has on consumer sensitivity to DLT. The stream of literature is rather general, explaining the consumer behaviour and typically focuses on the different effects between free versus charged shipping policies. Therefore, this particular study is highly relevant in contributing to the researched literature by analysing, and quantify, the consumer sensitivity to DLT when the proportion of delivery charges related to order value varies.

Chapter 3

Method

In this chapter, the methodology of the study is broken down and presented. The chapter starts of with defining the research methodology, describing the general approach used, followed by motivating the choice of strategy and design of the study as well as explaining how the data was managed and analysed using logistic regression.

3.1 Research methodology

The overall choice of methodology is in general based on the objective as well as the characteristics of the research purpose of the study. According to Höst, Regnell, and Runeson, 2006 there are typically four different types of overall research purposes, these are described as the following:

- Descriptive: Aims to portray and assess a phenomenon.
- Exploratory: Same objective as the aforementioned but with a deeper level of understanding and assessment of the phenomenon.
- Explanatory: Objective is to find the relation between different variables and explaining the phenomenon.
- Problem solving: Find the solution to an identified problem.

In this master thesis the purpose is partly to portray and assess a phenomenon but also explaining the relation between different variables, the study is therefore both of descriptive and explanatory character. In the first part we aim to assess the consumer behaviour phenomenon and its related factors within service offerings. In the second part we aim to explain the relationship between DLT and conversion rate of consumer fulfillment, as well as explaining the consumer sensitivity to various service quality factors.

3.2 Research approach

This section presents the overall strategy used to approach the purpose of the thesis. In the two sections that follows, more detailed deceptions of the research strategy and research design will be gone through. The approach used in this study if of both qualitative and quantitative nature. A qualitative approach method gathers observations of non-numerical data and typically focuses on different concepts of human behaviour. It is specially suitable for studies with the objective of answering the questions “Why?” and “How?” and therefore fits well with the first part of our study. A quantitative approach on the other hand is more of numerical character and empirically investigates observable phenomena through mathematical, statistical or computational tools. One

of the objectives of such an approach is to develop mathematical models that can generate results answering the questions “How much” or “How often”. In this particular study, the quantitative research approach is used in the second part of the thesis in order to get the results of consumers DLT sensitivity through statistical regression modeling.

The reasoning approach used for this study is a combination of both deductive and inductive, also called abductive reasoning approach (Thornhill, Saunders, and Lewis, 2009). The process of a deductive reasoning approach starts of with a hypothesis, deducted from theory, and reaches a logical conclusion from the empiric collected solely for the purpose of the study in question (Check and Schutt, 2011). Comparing this to an inductive reasoning approach that more or less follows an inverted deductive process, now starting with empirics that are used to develop a theory based on the collected data (Check and Schutt, 2011). The latter reasoning approach is often used when there is none or very little previous theory on a certain subject (Thornhill, Saunders, and Lewis, 2009). The abductive reasoning approach is, as previously mentioned the combination of the two described approaches and is seen as a continuous process as iterations between theory and data are made throughout the entire study (Van Maanen, Sørensen, and Mitchell, 2007).

The abductive reasoning approach is well suited for this particular study as we combine both deductive and inductive reasoning. The theory on consumer behaviour related to different service quality factors was in general already a well studied area. From that literature we could get some indications of what to expect to see in the data and also help with the segmentation, which can be likened to the deductive approach. At the same time we noticed that previous research literature of quantitative nature that related to consumer sensitivity of DLT was in fact a poor studied subject. Therefore, we used the empirically collected data to develop mathematical models which can be seen as a theory build-up and thus coherent with an inductive approach. The abductive reasoning with the qualitative and quantitative approach can be seen in figure 3.1.

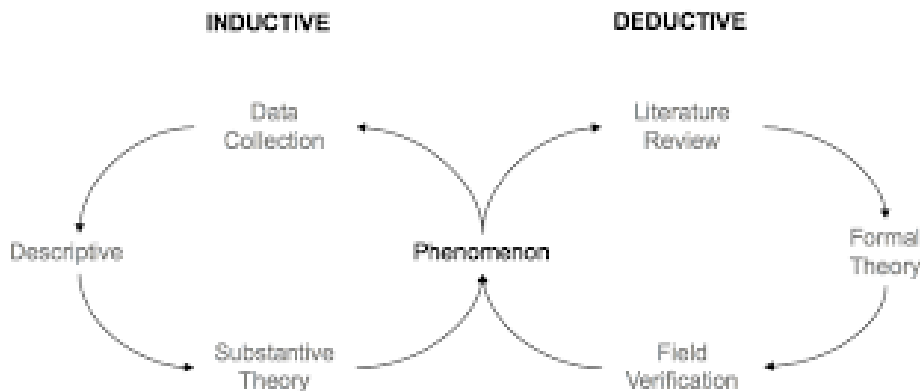


FIGURE 3.1: Abductive research approach, by Woodruff, 2003

3.3 Research strategy

The choice of research strategy is important when conducting a study within a given time-frame. A research strategy that is used by itself in a report is called a *fixed method* and when it is combined with other research strategies it is referred to as a

flexible strategy. According to Yin, 2014, the research strategy is embodied within the following five major research methods: Experiments, surveys, archival analyses, histories and case studies.

Case studies aim to explore a present phenomenon within its real-life context and no control over events is necessary (Yin, 2014). It is particularly appropriate for studies whose objective is to answer research questions "*What*" and "*How*", therefore a case study method is especially suitable for this report. The case study method is considered to be one of the most powerful of all research methods due to its capability of receiving information from several different sources such as interviews, observations and documents (Yin, 2014). Furthermore, other authors also highlight the method's richness of explanation and its potential for testing hypothesis in certain, well described situations as two important advantages (McCutcheon and Meredith, 1993; Eisenhardt, 1989). The main strengths can be summarized with the following three points that Meredith, 1998 presents, originally derived from Benbasat, Goldstein, and Mead, 1987:

1. The phenomenon can be studied in its natural setting and meaningful, relevant theory generated from the understanding gained through observing actual practice.
2. The case method allows the much more meaningful question of why, rather than just what and how, to be answered with a relatively full understanding of the nature and complexity of the complete phenomenon.
3. The case method lends itself to early, exploratory investigations where the variables are still unknown and the phenomenon not at all understood.

This thesis focuses on the phenomenon of consumer behaviour, more precisely the consumer sensitivity to DLT and the impact of various service quality factors. The objective is to answer the research questions: *How* is DLT affecting the probability of a customer fulfilling the order purchase and *What* is the expected change in sales if one is to change the DLT from y to z. According to the first two paragraphs of the section, the case study is a well suited research strategy for studies with a descriptive research purpose and an abductive reasoning approach, just like ours.

3.4 Research design

The research design is a plan that helps guide the researcher throughout the whole report process; from the research questions are set to finally reach the research answers. It helps the researcher with setting a plan of activities that link the data that is being collected and the conclusions to be drawn with the initial research question (Yin, 2014). Although there are no strict rules of how the research design of a case study should look like, there are many guidelines that help authors with the structuring of the report. Yin (2014) proposes that at least these four aspects that follow should be considered: what actual questions are to be studied, what data is relevant to answer the questions, how should the data be collected and how are the results going to be analyzed. It is based on these aspects that we have built our research design on and in chapter 4 it will be more thoroughly presented.

3.5 Logistic Regression

The analysis of the collected customer data will be based on the use of statistical regression analysis. In general, mathematical statistical models are used to investigate the correlation between two or more variables. The most simple form of regression analysis is linear, that is to say when one have a response variable (y) that is linearly dependent on an independent variable (x), and with a hazard deviation variable. In other situations, such as for our case, when the dependent variable (y) is binary, i.e it can only have two possible outcomes for example: yes/no, true/false, purchase/no-purchase and so on, it is appropriate to use another form of statistical regression model, namely the binary logistic regression model. This form of regression model is used to predict the odds of the response variable to occur based on the values of different independent variables. Let us therefore define odds before we continue with explaining the elements of the binary logistic regression model. Odds is defined as the ratio of the probability of an event occurring over the probability of the event not occurring. If we let the probability of the event occurring being p, then the probability of the event not occurring is (1-p). The corresponding odds can then be defined as shown in equation 3.1.

$$Odds[Event] = \frac{p}{p-1} \quad (3.1)$$

With the use of logistic regression we want to relate the probability (p) of the dependent response variable (y) occurring to the explanatory variable (x). Choosing to do this through the equation $p_i = \beta_0 + x_i\beta_1$ is not a good idea since p can only be a number ranging from 0 to 1 ($0 \leq p_i \leq 1$). This problem is solved by using natural logarithm on the odds and we get what is called the logit model seen in equation 3.2.

$$logit[y] = \ln[odds] = \ln\left(\frac{p}{p-1}\right) = \beta_0 + \beta_1 x \quad (3.2)$$

where p is the probability of the event in question occurring and x being the independent explanatory variable, and the parameters of the logistic regression model are β_0 and β_1 . From the logit we can express the probability of an events occurrence as shown in equation 3.3.

$$p = P(Y = 1|X) = \frac{e^{(\beta_0 + \beta_1 x)}}{1 + e^{(\beta_0 + \beta_1 x)}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \quad (3.3)$$

In this case β_1 explains the size of the effect that the independent variable has on the dependent variable and β_0 is the constant for the logit model and represents the baseline probability of an event when the other x variables are equal to 0. The β_i parameter for logistic regression analysis gives a value on the change for the natural logarithm of the odds in order for the dependent variable to be 1. This can be somewhat hard to grasp immediately, but one can make the simplification to think about the change in logarithm as a change in percentage. The generalized logit function graph for symmetry around zero can be seen in figure 3.2 and the corresponding conversion between probability, odds and $\ln(odds)$ can be observed in table 3.1. In this thesis the probability is translated into the predicted probability of a customer fulfilling a purchase or not, or in other words, the predicted conversion rate at a given x.

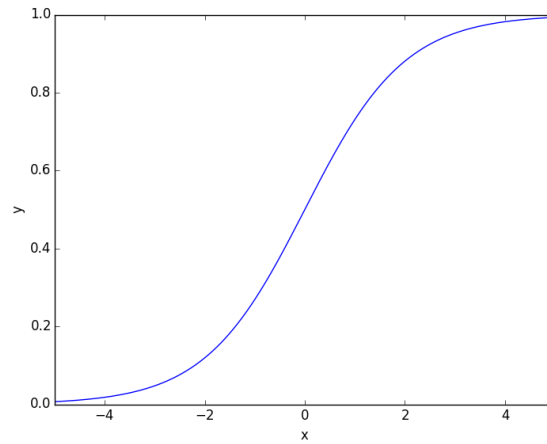


FIGURE 3.2: Logistic regression function

TABLE 3.1: Logistic regression: conversion to odds and $\ln(\text{odds})$ in symmetry around zero

Probability	Odds	Ln(Odds)
0.100	0.111	-2.197
0.200	0.250	-1.386
0.300	0.428	-0.847
0.400	0.667	-0.405
0.500	1.000	0.000
0.600	1.500	0.405
0.700	2.333	0.847
0.800	4.000	1.386
0.900	9.000	2.197

The values that the probability, odds and $\ln(\text{Odds})$ can have and its boundaries are shown in table 3.2.

TABLE 3.2: Logistic regression boundaries

	Min	Middle	Max
p	0	0,5	1
Odds	0	1	∞
ln (Odds)	$-\infty$	0	∞

Furthermore, the simple logistic model can easily be extended to multiple predictors as

$$\text{logit}[y] = \ln[\text{odds}] = \frac{p}{p-1} = \beta_0 + \beta_1 x_1 + \dots \beta_i x_i \quad (3.4)$$

and the probability function as

$$p = P(Y = 1|X) = \frac{e^{(\beta_0 + \beta_1 x_1 + \dots \beta_i x_i)}}{1 + e^{(\beta_0 + \beta_1 x_1 + \dots \beta_i x_i)}} = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \dots \beta_i x_i)}} \quad (3.5)$$

Chapter 4

Case study

In this chapter the case study and data management will be further explained. Starting with a short introduction to the case company and how their current delivery configuration make the issue on DLT relevant. A section is dedicated to explain the underlying empirical data used in this thesis. Explaining how it has been collected, how the authors manage challenges related to validity and reliability as well as the choice of data analysis tools.

4.1 Delivery configuration

The case company for this thesis is a furniture omni-retailer originating from Sweden. The company has been going through a change with a growing focus on the services connected to the purchase of the physical product as well as the online business. In the last years e-commerce has become a major part of the company's revenue and business, and in Sweden it represent roughly fifty percent of sales. The increasing sales generated from the online channel has made the delivery configuration an even more important factor to develop. To enable the reader to further understand the problem setting and background of this case it is of value to give a brief explanation about the current delivery setup adopted by the case company, and how this make this thesis relevant.

Today the company adopt a delivery-setup for their e-commerce that can be divided into two flows:

- **LCD** - Local Customer Delivery, which refer to delivery's made from the physical stores around the country.
- **CCD** - Central Customer Delivery, which refer to delivery's made from the central warehouses known as CDC (Central Distribution Centers). Today there are two CDCs, one in Stockholm that serve the region surrounding the city, and one in Torsvik (outside of Jonkoping) which serve the rest of the country.

The CCD-flow is managed in cooperation with third party logistics providers (3PL) that are responsible for the last mile delivery. So in practice the CDC send the shipments to distribution hubs operated by these 3PLs, which are called Local Service Centers (LSC). The 3PLs then consolidate and distribute the product to the end customer. For the CDC-flow the company adopt different minimum DLT for different parts of the country. Most parts of the country have a minimum DLT of seven days. While Malmö and Gothenburg adopts five days minimum and Stockholm with it's own CDC offer three days DLT. The five days minimum DLT for Malmö and Gothenburg have varied from three to five over the period that data has been collected, but today the setup is five.

The LCD-flow is also managed together with 3PLs that distribute the products from the stores to the customers, however not necessarily the same 3PL used for the CCD-flow. The LCD-flow have much shorter DLT compared to CDC and offers "Express"-delivery which is delivery within 24-hours. However, this require that you are in an area with a physical store close by, that have the item in stock. This mean that the express-delivery is not available to all online customers as you do not necessarily have a store close enough. The scope of this thesis is the CCD-flow, as it has a much longer DLT compared to LCD and hence there is more room for improvement. The case company has requested this focus as they do not see any viable options today to shorten the express-delivery (from 24 hours) further. Before moving on, let us shortly explore how the company manages the CCD-flow operationally in the day-to-day business.

As stated the company work together with 3PLs to distribute the goods. Currently there are two majors 3PLs that are used for the distribution in Sweden, also called *carriers*, excluding the Stockholm area and Haparanda (which also covers a part of northern Finland). Each of these 3PLs have consolidation hubs (LSCs) spread throughout the country, and each of these LSCs cover a pre-determined area determined by the postal codes. Depending on the area and the carrier, the case company have an agreed price set on a forecast of expected number of orders, this can be viewed as the capacity of each LSC. The case company is then in charge of managing the order-flow so that the capacity restraint is respected. In practice the capacity is not truly fixed and can be adjusted if the demand is much higher than expected, but then the distribution price for the company increase and therefore they try to respect the capacity restraint as much as possible. The capacity referred to here is the aggregated capacity of each LSC. In order to manage the capacity restraints the company and the 3PL spread this aggregated capacity into different delivery-templates or weekly plans for which days and time-spans the 3PL should deliver to specific areas depending on the postal code. These time-spans are known as the *delivery-windows* which is the final level of the capacity distribution. Today the capacity allocation is managed manually by increasing delivery-windows that have been saturated. The template for the delivery-windows is then reviewed concurrently together with the 3PLs to examine the need for more/fewer delivery windows for a specific area.

Returning to the problem for the case company. Today there is no standardized or easy way to examine the need to modify the DLT for a specific area, and more so whether or not is it profitable to decrease the DLT by paying the 3PLs to transport more than the capacity-restriction or by permanently adding more delivery windows in that area. To illustrate this issue, in figure 4.1 is a picture of three delivery-windows belonging to the a mock-up-area around Oskarshamn that have different postal codes/areas considered. Some postal codes are included in more than one of the areas, A-C, and some are only included in one. For customers in window A there are deliveries on Mondays, window B on Wednesdays and C on Fridays.

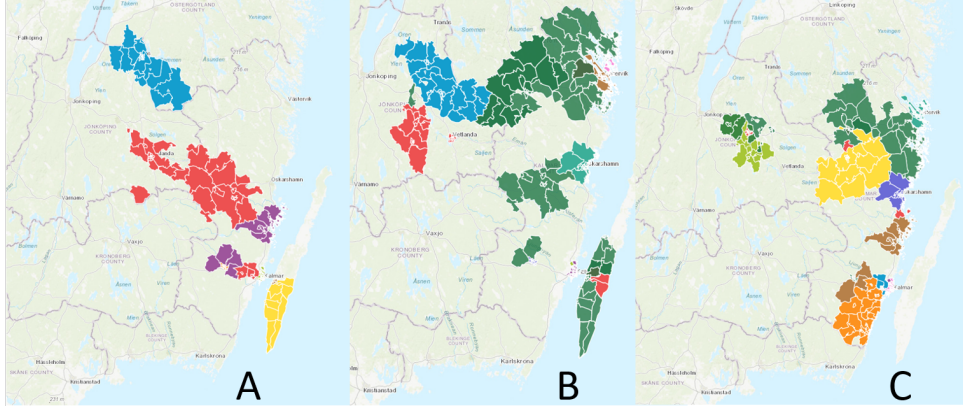


FIGURE 4.1: Illustration of mock-up-area-division for Oskarshamn

Let us consider a scenario in with a customer belonging to an area that is only included in window A, and hence only have deliveries on Mondays. The customer is ordering on a Thursday and the shortest DLT, if capacity is available, would be Monday in two weeks, since the minimum lead-time is seven days. That would mean an offered DLT for this customer of $7 + 4 = 11$ days. However if the capacity of the delivery-window in 11 days is already full/saturated, then the DLT would increase with 7 days to 18 days, as this customer only can get deliveries on Mondays. This in turn might lead to this customer not completing the purchase and hence loss of sales. The dilemma for the case company is whether or not it is profitable to increase the capacity of the delivery-window, or add a permanent extra delivery window. Is the loss of orders large enough to add this window?. In other words, how much more can the company expect to sell if they decrease the DLT? This thesis focus on the relationship between conversion rate and DLT which could be translated into changes in sales measured as number of orders, or in monetary value by for example considering the average customer spending in a specific area. However, this translation is not considered in this thesis as the company mainly focus on the loss of orders at this point.

4.2 Empirical data

The input data for this thesis is the online demand data collected by the case company over a time period of 24 months. It was done by digitally tracking a customer at the checkout in the online-store, both the ones completing a purchase and the ones not fulfilling it. However, the data only contain customers that actually proceeds to the checkout page where one enters the postal code and receive a the suggested delivery price as well as a delivery date. In other words, the customers just browsing the website putting things in the cart and not putting their postal code in, are not tracked. This is an important aspect as it affect the overall conversion rate. The data is the basis for the quantitative analysis in this thesis. The company collected information regarding the value of the customers cart, the suggested delivery-cost, the offered DLT which in the data is recognized as *EarliestDateDifference*, along with information about which postal-code the customer has entered and various other characteristics. The data has been tracked through an in-house built tracking software which is still under development, this will be discussed more later in this chapter.

In this thesis some terms and abbreviations are used that can be defined in different ways. The following list aim to clarify how we define some of the most important terms used throughout the thesis.

- **Conversion rate** is defined as the rate of customers that fulfill an order. Which in the input data is defined as the customer having reached the checkout-page, moved on to the payment-page and payed for the goods. The rest of the customers is considered to not having fulfilled their purchase.
- **Delivery lead time (DLT)** is measured as the earliest date difference between the order date and the first possible delivery date. This is a good definition as the case company currently (and during the data collection period) adopts a system where the customers are given the first possible delivery date and not given the ability to select a delivery date later than the first available.
- **Cart value** is defined as the total value of the products in the online shopping cart. This is used as proxy for customer commitment as well as a denominator in the relative delivery cost ratio measure.
- **Delivery cost** (or **delivery charge**) is defined as the price the customer is offered for the delivery in SEK which is related to the weight, volume and location of their order.
- **Delivery cost ratio** (or **delivery charge ratio**), is used as a determinant for the delivery cost. The authors view the relative cost in relation to the value of the purchase as a better indicator than the absolute monetary value of the delivery charge. The argument is that a customer purchasing a cart with a value of SEK1000 with a delivery charge of SEK100 (0.1 ratio) is considering the delivery charge less than a customer purchasing a cart of SEK200 with a delivery charge of SEK100 (0.5 ratio). It is computed as $\text{delivery cost ratio} = \frac{\text{Delivery-cost}[SEK]}{\text{Cart-value}[SEK]}$.

As mentioned in chapter 1.3 the case company had selected some LSCs that were of particular interest for them. Due to confidentiality these areas will be identified as "city 1", "city 2" and so on. However, to get an understanding for the size of these, see table 4.1 where the population of each city is displayed. The population number is retrieved from Statistics Bureau of Sweden for each municipality. Further the distance to the closest physical store (of the case company) is displayed, this is retrieved via Google Maps and measured as the distance by car from the central station in each city. City number four is the only city out of the five that have a brick-and-mortar store in the municipality and hence the smallest distance to store.

TABLE 4.1: Population of selected regions

City	Population (entire municipality)	Distance to store
1	142 818	44 km
2	102 457	74 km
3	56 584	88 km
4	155 356	11 km
5	56 128	160 km

4.2.1 Validity

Validity is asking the question if one is measuring the correct data, meaning are you measuring data that will help answer your question (Heale and Twycross, 2015). In our case the data is well in line with the research questions and purpose of the thesis, to examine online customers sensitivity of DLT in a specific industry. It does track customers actual behaviour in the checkout phase online, which imply that it

is not subject to the perception of the customer, rather just the action of it. One could for example study the sensitivity through a survey, but then the respondents would answer based on their previous experience and perception of DLT, which not necessarily is in line with their actual behaviour. However, the data collected does not consider the possibility of customers going to the online store to browse, check the delivery charge and then deciding to go to the brick-and-mortar store of the case company to purchase the products.

4.2.2 Reliability

Reliability is asking the question if the data is correct, or if the data measured in a trustful way, which usually is referred to as consistency (Heale and Twycross, 2015). This section focus on explaining how the data was managed and the considerations made when cleaning the data.

The data was first managed with Microsoft Excel in order to filter out the data relevant for this study. First by removing unnecessary columns and data, add relevant information and finally conduct a preliminary analysis. An example of data removed are orders that are parcel or pickup orders, as the relevant data was home delivery, by CDC. Thereafter each order row was connected to the corresponding LSC as this is used as segmentation. This was done by matching the postal code from the order data with LSC data from a delivery matrix provided by the company. The orders missing a matching postal number in the delivery matrix resulted in N/A-value and were removed. The share of orders with this issue represented 2.5% of the overall data. Further, the delivery cost ratio was computed for each order line. When the data was sorted, preliminary analysis was made through the use of pivot-tables and graphs where different data characteristics were examined. In this analysis it was noted that data collected after May 2018 changed character completely. After some investigation it was determined that this data could not be used as there were several strange occurrences in the order data, for example where the same customer is registered multiple times, both as a non-conversion and as a conversion resulting in a faulty conversion rate. In the data after May 2018 the share of the data with this fault was roughly 14 percent while for the pre May 2018 data had only 1 percent had this fault. Note, that this was not the only fault observed in the data after 2018, but we found no viable solution to clean this data and the partner company were okay with us only considering the data prior to May 2018. The analysis in this thesis is hence based on the data collected between September 2017 and May 2018. This translate to a total data-set reduction from 360 737 data points to 125 578 data points. An explanation to the change in the underlying data could be operational and technological changes in the company that occurred during 2018, but this is something the case company will have to investigate further. In addition to this data cleaning the decision was made to include 99 percent of the total order data as it contained several outliers in terms of DLT, for example an offered DLT of 60 days which only occurred once in the 125 578 orders. This cut-off is done for fraction data-set as well, that is for each segment of order data. For example a cut-off at 99 percent for all data result in the highest DLT considered is 26, while when only considering data for the three largest cities, the highest DLT considered is 25. The removal of the data was in other words done to to increase the reliability of the data-set used for analysis.

4.2.3 Data analysis

After the preliminary analysis was done as described above, the segmentation was decided. First the data for all areas are analyzed. Then segmentation is made between the three larger cities, adopting the shorter minimum DLT, and the rest of the country adopting the seven day minimum DLT. Further, the segment for the selected areas/LSCs are studied both as a group and individually. Then, segmentation of delivery charge ratio and cart value is made. This is done by dividing the data into one *LOW* and one *HIGH* segment, determined by the mean value of the variable-interval. This was done solely on the value and not considering the frequency of each variable, which resulted in a significantly larger data-set for the *LOW* segment in both cases. Another comment on the segmentation is the correlation between the two segmentation's, that is the high segment of cart value is correlated with the low segment of the delivery charge ratio. This follow from the way the delivery charge ratio is computed, using cart value in the denominator. The effect of this is discussed further in the chapters covering the analysis and discussion of the thesis. After the segmentation the logistic regression was computed using a statistical software called SPSS.

Chapter 5

Results

In this chapter, the result of the conducted study is presented along with comments on the output from the logistic regression models. Corresponding graphs are presented along with the model outputs as well as a frequency chart displaying the offered DLT in the underlying data.

5.1 Preliminary assessment

In order to get a first understanding of the general data configuration the data was first managed in Microsoft Excel as described in chapter 4.2.2 and some basic charts were computed. This was made as a first assessment to have a better idea of what to expect moving on with the logistic regression analysis, and to understand if any major changes needed to be considered for the chosen method. Figure 5.1 show the overall average conversion rate in the underlying data for all LSCs in the span of $3 \leq DLT \leq 26$ days. The graph indicate that there is a negative relationship between the DLT and the conversion rate. However, this is just a graphical analysis where a linear regression line is fitted to the line-dotted conversion rate data, and not a strict mathematical analysis. As shown in the following chapter, the frequency of DLT, delivery cost and cart value is, as one could expect, not symmetrical. Which makes the use of linear regression inappropriate. All graphs have had the values removed due to requests from the case company. However, all regression charts uses the same scale on the y-axis which make it possible to see the differences in level when comparing.

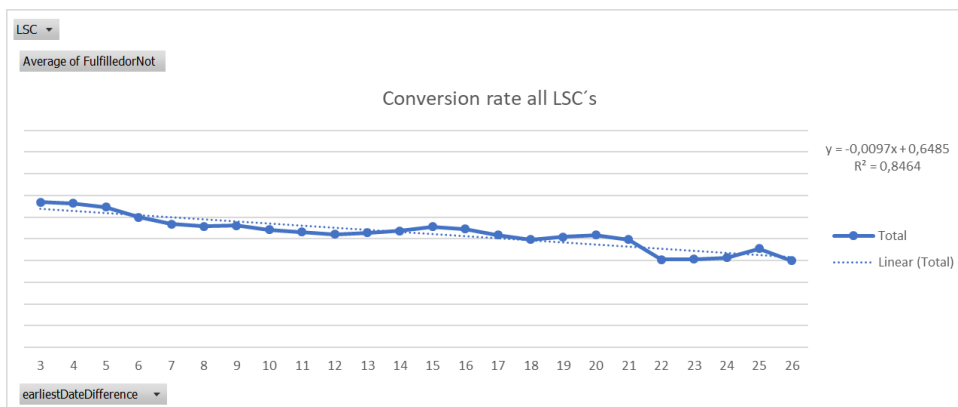


FIGURE 5.1: Preliminary assessment All LSC, 3-26 days DLT

This preliminary result showed that the approach and ideas discussed earlier in this thesis seem feasible and that one could proceed to the regression analysis.

5.2 Regression analysis

In this chapter the result from the regression analysis conducted in SPSS (a statistical analysis software from IBM) is presented along with comments on the different cases they represent. Table 5.1 present a summary of the logistic regression variables for each case studied relative to DLT. There are some general aspects we would like to notify the reader on before presenting the regression graphs. The predicted probability graphs show, as stated, the predicted probability of conversion at a specific x-value (DLT) as computed by the logistic regression model, this can be translated into the predicted conversion rate. It does not display the actual conversion rate in the underlying data at a given DLT. Hence the graphs look linear compared to the excel graph in chapter 5.1 where one observe the variations in the underlying data. It is important to understand that the graphs of the underlying conversion rate (as shown in appendix A as well) does not consider the frequency of how many orders that have been offered each DLT, it simply computes the average conversion of customers at each given DLT. In the following chapters predicted conversion rate and predicted probability of conversion is used synonymous as it translate to the same practical implication. That is for a specific x-value the logistic regression model predicts the probability that a customer characterized by that x-value will complete a purchase, which further translate into conversion rate. The difference in DLT-span for the different cases are due to the management of outliers with a cutoff-ratio of 99 percent as discussed in chapter 4.2.2.

Table 5.1 below display each case along with the parameters from the logistic regression model. The N column display the number of observations (orders) for the specific case, *coefficient/constant* denote which parameter in the β_i column is considered. Then the β_i column display the value for either the constant β_0 or the independent variable β_1 , $S.E$ represent the standard-error for each parameter and $Sig.$ display whether the DLT is found to be statistically significant, and if so, with at which level. Finally a lower and upper bound is presented for a confidence interval of 95 %. This means that the true mean of the parameters β_0 and β_1 lies with 95 % certainty within the given range of values.

TABLE 5.1: Logistic regression results DLT

Case	N	Coefficient/Constant	β_i	Sig. ^a	S.E	CI95 - Min	CI95 - Max
All LSCs, DLT: 3 - 26 days	124 206	DLT	-0.040	***	0.001	-0.042	-0.038
		Constant	0.653	***	0.014	0.626	0.680
Large cities, DLT: 3 - 25 days	65 717	DLT	-0.075	***	0.002	-0.079	-0.071
		Constant	0.898	***	0.019	0.861	0.935
All LSC ex. large cities, DLT: 7-27 days	57 252	DLT	-0.015	***	0.002	-0.019	-0.011
		Constant	0.392	***	0.027	0.339	0.445
Selected LSCs, DLT: 7 - 24 days	11 701	DLT	-0.035	***	0.005	-0.045	-0.025
		Constant	0.643	***	0.064	0.518	0.768
LSC city 1, DLT: 7 - 24 days	1 984	DLT	-0.010	N/S	0.017	-0.043	0.023
		Constant	0.408	*	0.172	0.071	0.745
LSC city 2, DLT: 7 - 24 days	3 085	DLT	-0.043	***	0.012	-0.067	-0.019
		Constant	0.715	***	0.136	0.448	0.981
LSC city 3, DLT: 7 - 24 days	1 283	DLT	-0.054	**	0.017	-0.087	-0.021
		Constant	0.986	***	0.206	0.582	1.390
LSC city 4, DLT: 7 - 24 days	2 336	DLT	-0.023	N/S	0.012	-0.047	0.0005
		Constant	0.261	N/S	0.146	-0.025	0.547
LSC city 5, DLT: 7 - 24 days	3 013	DLT	-0.050	***	0.009	-0.068	-0.032
		Constant	0.999	***	0.128	0.748	1.250

^a Significance: * < 5 % ; ** < 1 % ; *** < 0.1 % ; N/S - not significant

5.2.1 All LSCs throughout Sweden

The first case studied covers all LSCs in Sweden over the span $3 \leq DLT \leq 26$ days. This implies that both areas that have three days minimum DLT and those that have seven days DLT are included. The frequency graph display the number of orders that

have proceeded to the checkout at different offered DLT, and how many of these have fulfilled their purchase, denoted with a "1"-label in the graphs.

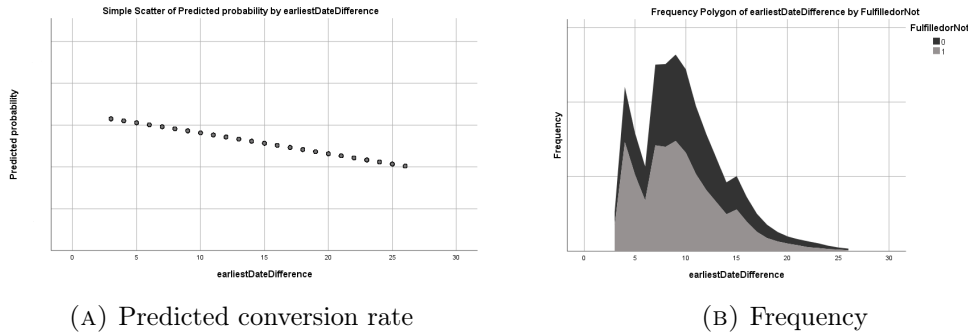


FIGURE 5.2: 3-26 DLT for all LSC

5.2.2 Large cities: Stockholm, Gothenburg and Malmo

This case focuses on the area served by the LSCs in the three large cities that adopt a three or four days minimum DLT (during the data period) over the span $3 \leq DLT \leq 25$ days.

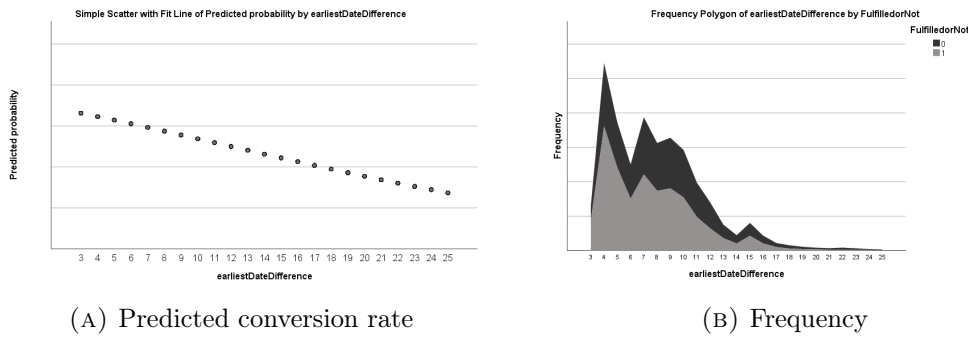


FIGURE 5.3: 3 - 25 DLT for Stockholm, Gothenburg and Malmo

5.2.3 All areas excluding Stockholm, Gothenburg and Malmo

This case focuses on the areas that adopt a seven days minimum DLT over the span $7 \leq DLT \leq 27$ days. This translate to all LSCs excluding Stockholm, Gothenburg and Malmo.

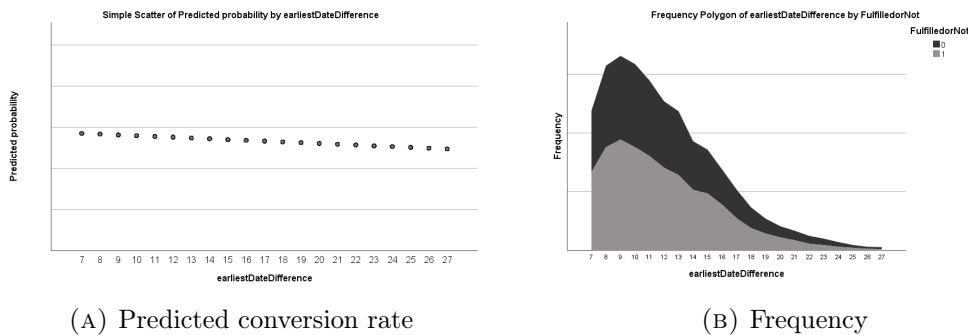


FIGURE 5.4: 7-27 DLT for all areas excluding Stockholm, Gothenburg and Malmo

5.2.4 Selected areas

In the following graphs the result for each of the selected areas/cities/LSCs are displayed as well as the pooled analysis of these. All areas has had the analysis made on the span $7 \leq DLT \leq 24$ which represent the 99 percent cutoff-value for the pool of these areas. Each respective city is denoted in the figure-text belonging to each graph.

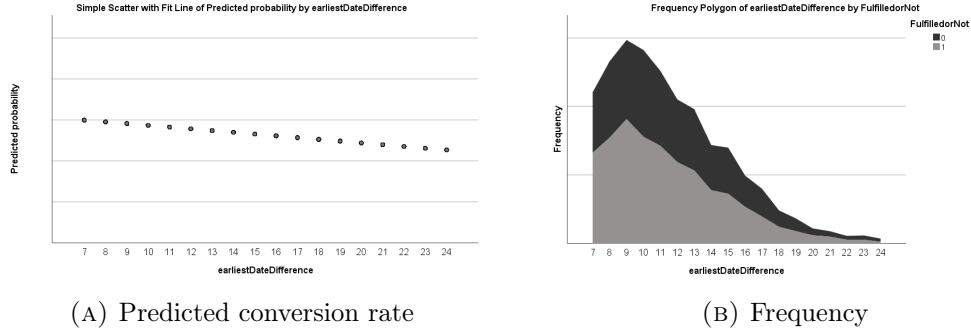


FIGURE 5.5: 7-24 DLT for selected LSCs

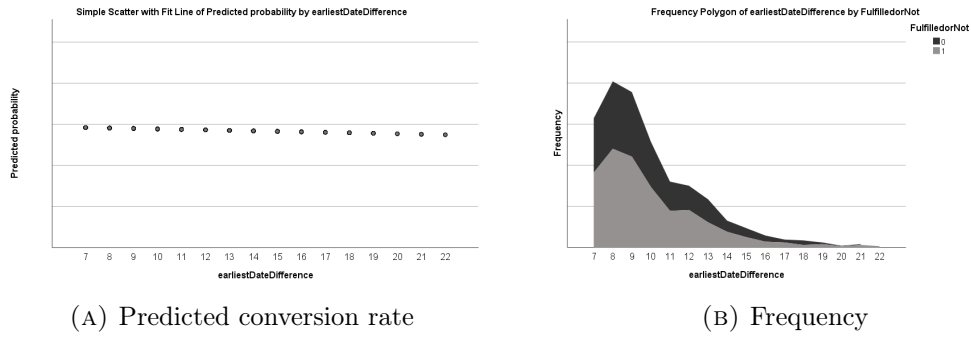


FIGURE 5.6: 7-24 DLT for LSC city 1

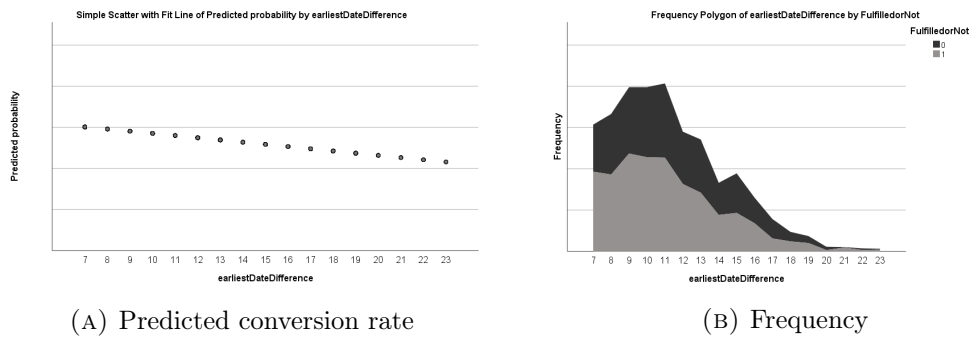


FIGURE 5.7: 7-24 DLT for LSC city 2

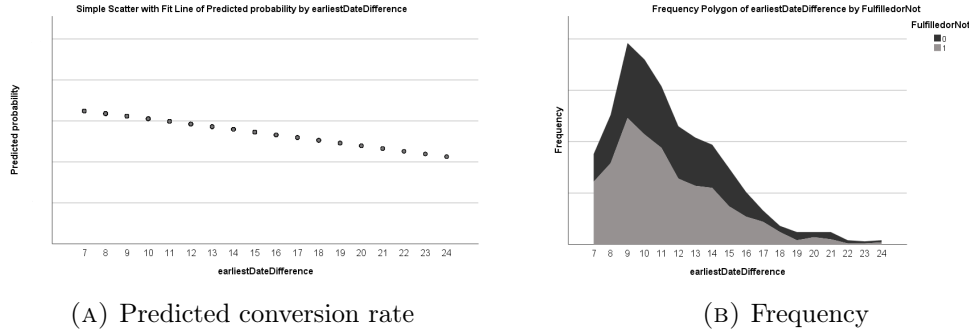


FIGURE 5.8: 7-24 DLT for LSC city 3

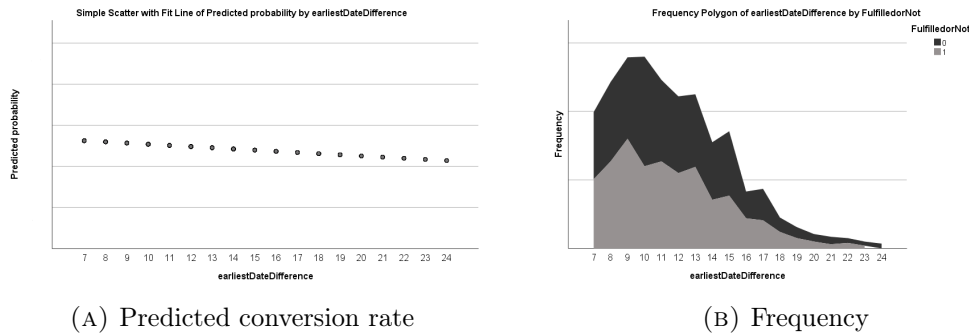


FIGURE 5.9: 7-24 DLT for LSC city 4

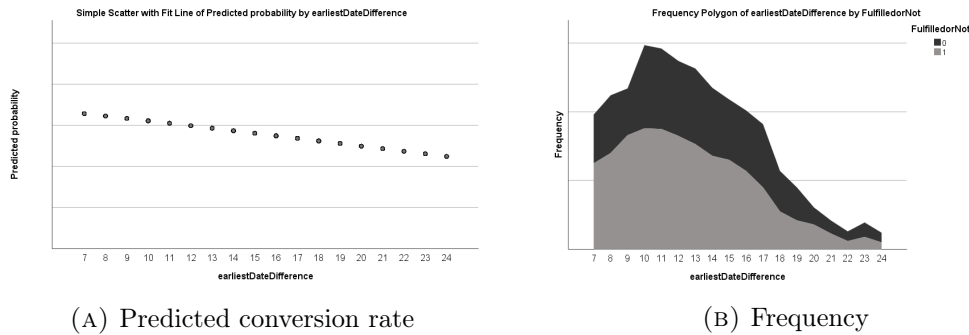


FIGURE 5.10: 7-24 DLT for LSC city 5

5.2.5 Delivery charge ratio impact on conversion rate

In this section the impact of delivery-charge-ratio on conversion rate is displayed. First the delivery-charge-ratio is studied as the independent variable with conversion rate as the dependent. Then the impact of a high or low delivery-charge-ratio is displayed with the DLT as the independent variable. The *LOW* segment is determined as a delivery-charge-ratio in the span of 0-0.25 while the *HIGH* segment is represented by orders in the 0.25 - 0.50 span. As discussed previously the segmentation is made on the mean value-wise, and not considering the weight or frequency. This result in the large difference in observations between the low and high segments, with 110 109 for the low segment and 11 871 for the high.

TABLE 5.2: Logistic regression results delivery cost ratio

Case	N	Coefficient/Constant	β_i	Sig. ^a	S.E	CI95 - Min	CI95 - Max
All LSCs, DLT: 3 - 26 days	121 980	Deliverycost	-3.485	***	0.073	-3.628	-3.342
Deliverycost: 0 - 0.5		Constant	0.754	***	0.011	0.732	0.776
All LSCs, DLT: 3 - 26 days	110 109	DLT	-0.041	***	0.001	-0.043	-0.039
Deliverycost: LOW		Constant	0.771	***	0.015	0.741	0.800
All LSCs, DLT: 3 - 26 days	11 871	DLT	-0.053	***	0.005	-0.063	-0.043
Deliverycost: HIGH		Constant	0.051	N/S	0.047	-0.041	0.143

^a Significance: * < 5 % ; ** < 1 % ; *** < 0.1 % ; N/S - not significant

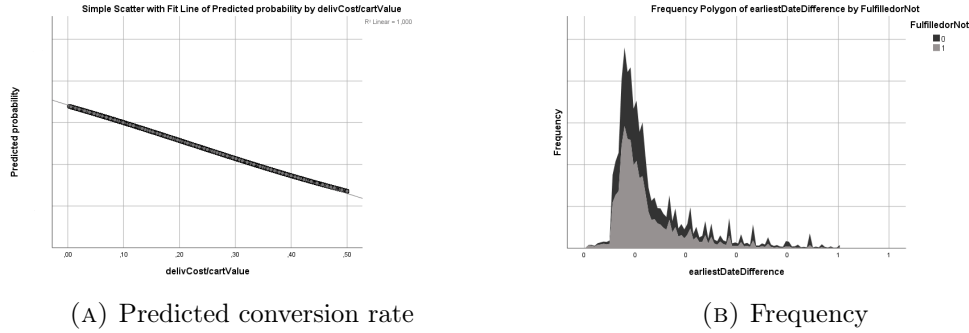


FIGURE 5.11: Deliverycost vs conversion rate

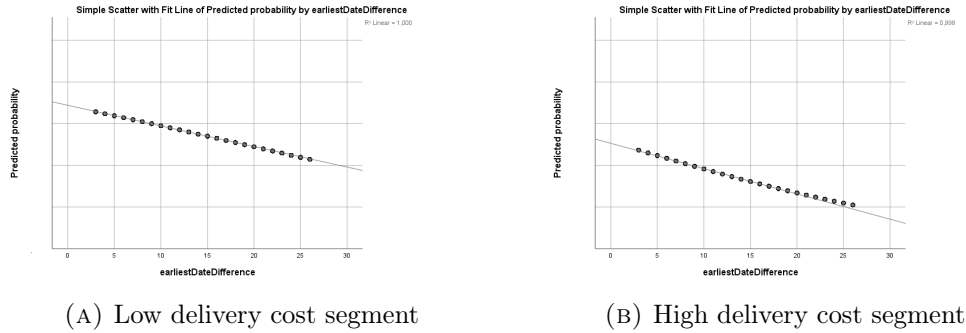


FIGURE 5.12: Delivery-cost and DLT sensitivity

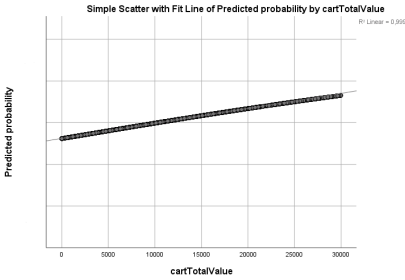
5.2.6 Consumer commitment impact on conversion rate

In this section the impact of consumer commitment (determined by the cart value) on conversion rate is displayed. Similar to the previous chapter first the impact of cart value as the independent variable is displayed, followed by the impact of low and high segments on DLT sensitivity. The *LOW* segment is categorized as a cart value below or equal to 15 000 SEK, while the *HIGH* segment is represented by orders with a cart value between 15 001 to 30 000 SEK.

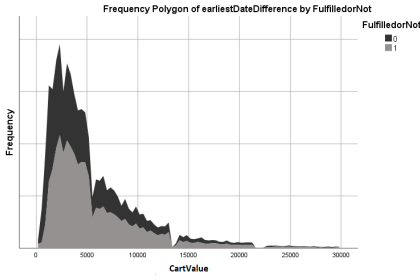
TABLE 5.3: Logistic regression results cart value

Case	N	Coefficient/Constant	β_i	Sig. ^a	S.E	CI95 - Min	CI95 - Max
All LSCs, DLT: 3 - 26 days	122 546	Cart Value	0.000030	***	0.000001	0.000028	0.000032
Cart value: 0 - 30 000 SEK		Constant	0.094294	***	0.009043	0.076570	0.112018
All LSCs, DLT: 3 - 26 days	115 922	DLT	-0.041	***	0.001	-0.043	-0.039
Cart value: LOW		Constant	0.659	***	0.015	0.630	0.688
All LSCs, DLT: 3 - 26 days	6 624	DLT	-0.030	***	0.006	-0.042	-0.018
Cart value: HIGH		Constant	0.677	***	0.064	0.552	0.802

^a Significance: * < 5 % ; ** < 1 % ; *** < 0.1 % ; N/S - not significant

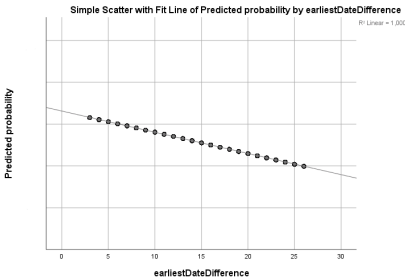


(A) Predicted conversion rate

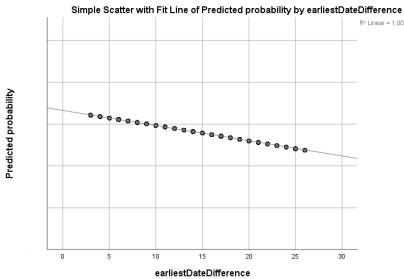


(B) Frequency

FIGURE 5.13: Cartvalue vs conversion rate



(A) Low cart value segment



(B) High cart value segment

FIGURE 5.14: Cart value and DLT sensitivity

Chapter 6

Analysis

In this chapter the results for the different cases and factors will be analysed and compared to the theoretical framework. Further this chapter will discuss potential reasons for these differences.

6.1 DLT's impact on conversion rate

6.1.1 All LSCs

First thing we notice from the preliminary assessment is that there is a negative relation between the independent variable DLT offered to customers and the dependent variable conversion rate. In other words, this means that the more the offered DLT to customers increases, the lower the probability of the customer fulfilling the order becomes. This does not come as a big surprise as it is what more or less all literature suggest. The studies from theory are implying that customers have preferences for shorter waiting time (Bitner, 1990; Clemmer and Schneider, 1996), and that the higher the waiting time the lower the probability for a customer fulfilling the purchase becomes (Marino and Montagna, 2018; Berman, 2019). For this thesis, it is rather more interesting to have this relation quantified. The case of all LSCs, containing 124 206 orders as data input, we receive the parameters $\beta_1 = -0.040$, $\beta_0 = \text{Constant} = 0.653$ and statistical significance over 99.9 percent. These parameters are defined in chapter 3.5, and we can use these to compare them to previous research studies. The interpretation of our β_1 value put in words would be that if the independent variable DLT increases with 1, the natural logarithm of the odds for a customer fulfilling the order decreases with 0.040. Converting this odds ratio value into percentage using by equation 3.2, we get that for an increase of the DLT with 1 corresponds to a relative decrease in the odds of 3.92 %. Furthermore, looking at the p-value, the predicted probability that a customer fulfills the order for a given DLT, changes from 0.630 to 0.404 when going from 3 days to 26 days. Meaning that the relative decrease in percentage is 46,29 %. For a shorter time-span, going from three days to ten days, the predicted probability decrease from 0.630 to 0.563, which is a relative decrease of 10.67 %. This confirms the theory suggesting that consumers are strongly sensitive to DLT (Berman, 2019) and that improvements in delivery lead-time can be used to gain competitive advantage over competitors (Brynjolfsson, Hu, and Rahman, 2009; Mak, 2018). We also note from the frequency chart that almost 90 % of the customers received a DLT ranging between 3-15 days.

Our received values are interesting to compare with the previous and similar research study conducted by Marino and Montagna, 2018 for the Italian offline market. A reason as to why it is particularly interesting to compare our results with their study is that it is more or less the only study of similar quantitative nature within the subject area. Although we are investigating the same type of phenomenon we

note from the theory chapter that there are some differences between their study and this thesis. The main thing we wish to compare is the consumer sensitivity to DLT, therefore we especially look at the received probability values for varying DLT and β values. The Italian study performed analysis on a six month period year 2014, a study sample containing 19.000 units sold, product prices varying between 150 - 1200 euro and an offered DLT to customers ranging between 2-31 days. Apart from DLT the report also included the previously mentioned explanatory factors such as: product display in store, competitor distance and product price. The product price variable can in some sense be seen as similar to the cart value factor of our thesis, and the DLT is defined the same for both studies. In order to reduce the effect of the difference in covariates and control variables, included in the Italian study, we are comparing our results for when these other factors are fix and only the DLT factor vary. The results for the study by Marino and Montagna (2018), when keeping the additional factors constant to values representing an average selling case, are the following: When going from a promised DLT from two to seven days the probability of selling the product decreases from 0.110 to 0.069, meaning a 37.5 % relative reduction. For a larger time-span, when promised DLT changes from 2 to 31 days, the same probability decreases from 0.110 to 0.0062, representing a relative reduction of 94.4 %. Their received β_1 value was equal to - 0.103. Looking instead on the a different more extreme scenario, when all the other variables for the Italian study are set to a top selling case: The probability values of selling a product instead went from 0.960 to 0.935 when going from two to seven DLT days, representing a relative decrease of 2.6 %, and when increasing the DLT to 31 days it reached a value of 0.548, meaning that the relative decrease becomes 42.9 %. This implies that the other factors also play a very big role in customers purchasing decisions and affect their DLT sensitivity. Comparing these results to our thesis we can confirm that the conversion rate for this study is in general much higher than the Italian study for the average selling case scenario. An explanation to this is that they are looking at the the probability of a specific product being sold, while we study the probability of any group of products being sold. Further, in this thesis we study the consumers that have already selected their desired items, continued to the checkout and entered their postal code. Whereas in the Italian study they look at all potential consumers for different products. One could summarize the findings of comparing the two studies in the way that, DLT is an important factor for converting a customer to purchase, but other factors, such as price, also play a major role.

6.1.2 Three largest cities compared to the rest

According to the results presented in table 5.1 it is evident that consumers in the large cities have a higher sensitivity to changes in DLT compared to the rest of the country. The β_1 coefficient is -0.075 for the larger cities, and -0.015 for the rest. This would translate to a decrease in conversion rate of 0.13 (from 0.662 to 0.592) or 18.91%, if increasing the DLT from three to ten days for the large cities. For the case of the rest of the country, it would translate to a decrease in conversation rate of 0.026 (from 0.571 to 0.545) or 4.53%, if increasing the DLT from seven to fourteen days, the increase in DLT for both cases are seven days. As one notice, the difference is big, however the large cities have a higher conversion rate at the start for a DLT of three days, than the rest have at DLT of seven days. This can also be observed in graph 5.3a and figure 5.4a, where the incline is much steeper for the larger cities, but at the same time starting from a higher value. The difference could be explained

perhaps due to different consumer expectations and behaviours, where those living in the larger cities are used to a short DLT, and hence are more sensitive to a change. Or it could be due to minimum offered DLT. As observed in the frequency graphs 5.3b and 5.4b the majority of consumers in the larger cities are offered less than 10 days DLT (80 percent), whilst for the rest a majority are offered less than 15 days DLT considering the same percentage of 80. In other words, the difference could be due to differences in the average service offering towards consumers in large cities versus the rest. However, one must also consider the difference in delivery setup and offered DLT. I might be that if the same three days minimum DLT would be offered to the rest of the country, they would have an increased sensitivity.

Another explanation could be that all of the larger cities have a brick-and-mortar store from the company in connection to the city, for Stockholm there is even two physical stores. This could potentially explain why consumers in this case disregard purchasing online if the DLT is too long or the delivery charge is too high, and rather go to the store to purchase it there instead. A counterargument to this would be the fact that they most likely have the possibility to select the more expensive option of express-delivery described in short in section 4.1. However then one must consider the increase in delivery charge. Another factor one could consider is the consumer commitment. The average cart value between the two groups are rather similar, though with the larger cities having a five percent higher cart value on average. The impact of consumer commitment is discussed later in this chapter, but it is determined that higher commitment (cart value) is related to less sensitivity for DLT, so this factor is, if anything, counteracting the observed difference between larger cities and the rest.

To summarize the analysis on these two cases, the change in DLT have a larger impact on conversion rate for larger cities as compared to the rest, however it is not evident if this is due to difference in preference among consumers of the different categories, or due to the difference in delivery setup.

6.1.3 Selected areas/LSCs

Moving into the analysis of the selected areas requested from the case company, the first thing to notice is that the sensitivity for change in DLT in terms of β_1 is between that of the larger cities and the rest, considering the selected LSCs as a group. In other words, the selected areas are more sensitive than other areas in general, excluding the three largest cities. The selected group of cities show similar parameters as the first case considering all LSCs (all of Sweden). An increase in the DLT from seven to fourteen days would, according to the model, result in a decrease in the conversion rate of 0.06 or 10.04%.

Looking at the distribution of offered DLT to customers in figure 5.5b it follows the same distribution as that of areas excluding large cities displayed in figure 5.4b. All the LSCs in the selected group display a negative correlation of increased DLT and conversion rate, however as observed in table 5.1 only three out of the five have a logistic regression model that is significant at the 99.9%-level. Before moving further into the analysis of each individual city we would like to remind the reader that, as described in chapter 4.2, the only city which have a physical store in the county is city number four.

It is established that city two, three and five have a greater sensitivity to DLT than the group of selected LSCs. These cities also have a greater sensitivity than the rest of the country in general excluding large cities which imply that the case company should have a greater focus on keeping the DLT short for these selected cities, compared to the others.

City 1

City one is one of the larger cities in the selected group. However as seen in table 5.1 the number of orders during the data collection period is the second lowest one, which could be one factor explaining why the regression did not yield a significant outcome. The lack of significance is perhaps the combination of a low number of observations and a rather flat underlying conversion rate as can be seen in appendix A. Due to the outcome being non significant there is not so much to discuss regarding the result for city one.

City 2

Next selected LSC represented by city two is in the middle, in terms of population out of the five. The logistic regression model for city two is significant and the β_1 value of -0.043 imply that the consumers of city two are more sensitive then the selected cities as a group which had a β_1 of -0.035. The β_1 of -0.043 for city two translate to a decrease in conversion rate of 0.12 or 23.84%, if increasing the DLT from seven to fourteen days.

City 3 and 5

These two cites are the smaller ones in the group with about 56 000 people in population. The results of city three and five are very similar both in terms of significance and model parameters, hence these two cities are analyzed together. City three had a β_1 of -0.054 and city five -0.050, which translate to a decrease in conversion rate of 0.14 or 25.48%, respective, 0.13 or 24.72%, if increasing the DLT from seven to fourteen days. Both of these cities are just as city two, more sensitive to changes in the DLT than the group of the selected cities, and than the case excluding large cities. Another factor common for city three and five is the distance to a physical store. City five has the furthest and city three the second furthest, this could influence the overall average conversion rate which is higher for these cities as observed by the constant β_0 which is higher for these two compared to the other cities. However, the incline or coefficient of change β_1 is greater for these cities implying that the consumers are more sensitive to change.

City 4

The logistic regression model for city four does not provide an outcome that is significant at the 99.9%-level, but it would be considered as significant at the 90%-level. Looking at the parameters, they indicate that city four is less sensitive to changes in DLT than the group of cities. With a β_1 of -0.023, which at an increase from seven to fourteen days translate to a decrease in conversion rate of 0.08 or 20.48%. This while starting from an already lower conversion rate (at DLT 7), observed through the β_0 of 0.261, compared to 0.643 for the group. It is tricky to analyze why city four would have a lower sensitivity to changes in DLT, but one factor unique for city four is the presence of a physical store in connection to the city. In the section regarding larger cities compared to the rest, the argument was made that this factor could influence the sensitivity in the other way, that the presence of an offline store in connection to the city would make consumers more sensitive to change in DLT for the online store. The result for city four is inconsistent with that theory or argument, however as this is a much smaller sample, and it did not provide the same level of significance, one should maybe not draw much conclusions from it.

6.2 Purchasing factors impact on DLT sensitivity

The delivery charge ratio and consumer commitment are the two factors studied in relation to DLT in order to investigate their impact on the conversion rate. For these two factors it is however important to note the relationship between them. As mentioned in the subsection 4.2.3 the segmentation on delivery charge ratio and consumer commitment is made in a way that make the two segments co-variate. That is, the orders belonging to the *HIGH* segment of consumer commitment is likely to be in the *LOW* segment of delivery charge ratio, as it is in the denominator of the latter. The same goes for the *LOW* segment of consumer commitment being related to the *HIGH* segment of delivery charge ratio. The implications of this is discussed in the analysis of the delivery charge ratio and consumer commitment below. We would however like to stress that it is not necessarily the case that all consumers belonging to the low segment of cart value is present in the high segment of delivery charge ratio and vice versa. It is however likely that there is a correlation among these segments.

6.2.1 Delivery charge

This section of the analysis aims to first investigate the direct impact that the delivery charge ratio has on consumers predicted probability of fulfilling an order, and second to assess the difference in consumer sensitivity to DLT for the two different segments. The β_i values are to be interpreted in the same manner as previously explained, but with the exception of the scenario when the dependent variable is set as the delivery cost ratio instead of DLT. Looking at the predicted conversion rate figure, 5.11a, we see that the predicted conversion rate decreases significantly as the delivery charge ratio increases. When going from a delivery charge ratio of 0.025 to 0.500, the predicted conversion rate decreases from 0.661 to 0.271, which can be translated to a relative decrease of 58.96 %. These numbers confirm the theory and previous literature suggesting that the delivery charge influences the consumers behaviour (Lewis, Singh, and Fay, 2006) and that the probability of abandoning the shopping cart increases with the increase of delivery charge ratio (Shao, 2017; PostNord, 2019a). As the delivery charge ratio has a significant effect on consumers purchasing decision, it also means that the setting of an appropriate delivery charge becomes important for the overall profitability of a company, as earlier concluded from theory. However, the decision of how the delivery charge setting should be structured is beyond the scope of this thesis which instead focuses on highlighting that the relation between conversion rate and delivery charge ratio actually exists.

Furthermore, comparing the customer sensitivity of DLT sensitivity for the *LOW*- and *HIGH* delivery charge ratio segments it is evident that the low segment is less sensitive. From table 5.2 we can observe that the low segment, which we define as the ratio ranging from 0 - 0,25, the value of β_1 is equal to -0.041. Meanwhile for the high segment, with a delivery charge-cart value ratio ranging from 0.25-0.50, the β_1 value is equal to -0.053. This means that consumers with a higher delivery charge ratio are more sensitive to an increase of DLT. When going from a DLT of seven days to fourteen days the probability of a consumer fulfilling the purchase decreases from 0.619 to 0.549 and 0.441 to 0.372 for the low- and high segment respectively. Meaning that the relative decrease is 11.3 % for the low segment and 15.6 % for the high segment. The reason for this difference is likely the combination of experiencing that one pay for an expensive service (delivery) which is of poor performance (long DLT). Here it is however important to highlight the above discussed relation between the segments of delivery charge ratio and cart value. As will be discussed in the analysis

of consumer commitment, cart value has a positive correlation on the conversion rate and an increase in cart value is related to less sensitivity for DLT change. These results are in line with the result of the corresponding segments of delivery charge ratio, low cart value/high delivery charge ratio and vice versa. Hence, there is the possibility that the results for delivery charge ratio is not as significant as the presented result, in measuring consumers behavior in relation to delivery charge in general.

It is hard to draw any major conclusions regarding the business implications for the case company following the presented analysis of delivery charge ratio. The difference in DLT sensitivity between the two segments is most likely hard to translate into a strategy targeting the high segment rather than the low segment or vice versa. However, one thing to consider is how the delivery fee is computed in the system, as of now it is based on weight and volume and not considering cart value. One way to take cart value into consideration would perhaps be to set a maximum delivery charge ratio so no customer is offered a delivery charge ratio over 0.25. As observed in 5.2 the number of observations in the low segment, under 0.25 ratio, represent more than 90 per cent of the consumers, implying that the mentioned action only affect a small portion of the customers.

6.2.2 Consumer commitment

The consumer commitment or involvement, is in this thesis measured as the cart value of an order, as mentioned earlier. The idea is that consumers making a purchasing decision will have different behaviours depending on their experienced importance of the decision, and one way to emphasize this importance is the economical impact for the individual. Looking at the results presented in table 5.3 it is clear that the cart value have a positive impact on the conversion rate. This would imply that consumers are more likely to fulfill a purchase that is more expensive, which goes well in line with theory regarding consumer commitment. This could perhaps be explained by the information search theory related to consumer behaviour, which imply that a purchase decision that is considered more important, is related to a larger information search effort from the consumer. That would then result in the consumer having decided about their action to purchase or not, before entering the check-out in the online store. To put some numbers on things, comparing a customer purchasing for SEK5000 and a customer purchasing for SEK20 000, the predicted conversion rate increase with 0.106 or 20.27% relative. An important factor to note is that the latter customer is contributing with four times more sales than the first along with the higher conversion rate.

However, in this thesis the main purpose was not to look at consumer commitment as an independent variable affecting conversion rate as the dependent, the purpose was to examine the sensitivity for changes in DLT. Observing the results in table 5.3 one notice that the customers in the *LOW* segment is more sensitive to changes in DLT than those in the *HIGH* segment. This imply that an increase in the degree of commitment make the consumer less sensitive to waiting time or increase in DLT, which in turn could be explained by the same reasoning as above. That is consumers who have a higher commitment, make a more extensive information search before the purchase decision, which in turn make it less sensitive to other factors affecting the purchasing decision in the finalizing moment. An example related to the case company of this thesis could be a customer purchasing a simple plain set of pillows for a couple of hundred SEK, will be more sensitive to a higher than expected DLT, than a customer buying a new bed with mattress and accessories for several thousands SEK. As the latter have most likely done more research before deciding to make the

purchase and hence is not as sensitive to a higher than expected DLT, they wanted that specific bed. However, looking at the underlying data the significance of cart value seem to be of greater importance in the lower span from SEK0 to SEK5 000. This is not so big of a surprise as the relative increase in cart value is much larger, going from SEK100 to SEK1 000 is an increase of ten times, whilst going from SEK5 000 to SEK15 000 is an increase of three times. As seen in table 5.3 the *LOW* segment have 115 922 observations whilst the *HIGH* segment only have 6 624, this is due to the segmentation being done on the parameter value and not considering the weight or frequency of it. This is also evident in the frequency graph 5.13b, with a mean cart value of SEK5 602 and roughly 85 percent of the orders have a cart value below SEK10 000. However, as the regression yielded in a significant outcome for both segments it could be argued that the effect of cart value on DLT sensitivity is established. A counterargument to this could be that the effect might be related to the delivery charge ratio, which as mentioned previously is correlated to the cart value.

Chapter 7

Discussion

In this chapter of the thesis the aim is to have a discussion regarding the results of the thesis, reflect on the conducted study and what could be improved. As well as suggest further research areas and topics, both specific for the case company and general research topics to be studied a more academic perspective.

7.1 Discussion and Reflection

Through the analysis it is evident that DLT have a major role in consumer behaviour and in the decision making process of an online purchase. There are several discussion topics regarding the analysis and the results presented in this thesis, one of which is the difference in delivery setup that is adopted by the case company. This is a factor that most likely have a major effect on the outcome, especially when comparing the larger cities with the rest. The fact that all areas apart from the larger cities start at seven days minimum DLT make it hard to draw major conclusions regarding the large difference between that group and the three larger cities, employing the much lower three days minimum DLT. The reason being that it is hard to determine whether the difference is due to sensitivity of DLT, or that the same consumers now offered the seven days minimum DLT, would have the same degree of sensitiveness if they were offered a three days minimum DLT instead. In other words, is it the fact that the relative increase of seven days from three to ten days is much larger (3.33x) than the seven days increase from seven to fourteen days (2x) and hence the consumers are more sensitive. However, as the difference among the selected cities differed, one can assume that there are other factors than the minimum DLT affecting the sensitivity of different areas in Sweden. One such factor considered in the thesis was the distance to the closest physical store. Considering the results presented in this thesis it, seem like a good idea for the case company to try and establish shorter minimum DLT for the rest of the country as well, however it is not clear how much higher conversion rate one should expect from this action.

The data for this thesis was discussed in short earlier, but one can elaborate a little bit more on this issue, as it play a large role for the output. As described in section 4.2 the original data set covered the time span of September 2017 to August 2019, but the data collected after May 2018 was considered to unreliable to be used. This is of course something that the case company need to investigate further and establish a solution to. This would enable the company to make more extensive analysis and get better models. Another factor relating to the data affecting the result, is the fact that consumers might choose to browse the website, check the delivery charge and DLT at the checkout, and then decide to go to the physical store of the retailer to purchase the products. This has been highlighted earlier as something that is out of scope of this thesis. However, it is an important aspect to consider as it might make the potential loss of sale, expressed as a decreased conversion rate, seem more significant than it

really is. Since the customer not fulfilling their orders online, but purchasing it offline is not considered in the data which make it look like a loss of sale, when it really is not. For the retailer an offline purchase is just as good as an online purchase, in terms of sales revenue.

Another major important fact to highlight is that the study in this thesis focus on the offered DLT, and not the actual delivered DLT. In the study we do not consider whether or not the customers actually received their order on the offered date. In other terms we do not consider the delivery precision, only the offered delivery time. Delivery precision is something that has been discussed in several studies related to DLT. It would be interesting both from a research point of view to further study the importance of delivery precision in relation to offered DLT. It would also benefit the case company to better understand which of these are the more important service quality factor, and maybe not just delivery precision but also service factors related to the delivery in general. Such as the option to choose the delivery date instead of having to accept the earliest offered date or maybe the option to select a more sustainable delivery option but with extended DLT. These are factors that could potentially be more important than the actual DLT, and these factors are discussed as very important in the study by PostNord (2019b). Especially sustainability is likely to be something that continues to increase in importance for the consumers which is highlighted in the PostNord (2019b) report. Also, sustainability is getting an increased attention in several forums of society globally so a study focusing on this would be very relevant.

Another major reflection to be commented is the segmentation of delivery charge ratio and consumer commitment, and how these were correlated in this study. When performing the analysis of the output results it became clear that this correlation in the segmentation was not considered when initially setting up the logistic regression models. This is something that could have been performed in several other ways to better separate the result and impacts of these factors. An example would be to make the segmentation of HIGH/LOW cart value first and then define the delivery charge ratio within these segments. This is a lesson learned and something the authors will be sure to make use of in future occasions when faced with a similar decisions.

7.2 Future research proposals

As mentioned in the beginning of this thesis, there are many things that are not considered in this thesis. There are several interesting questions and topics both related to the specific case company as well as the research topic in general. In this section we try to highlight some suggestions for both the case company to further investigate, as well as topics that are more of an academic character. First of all, it would be interesting for the case company to study the combination of both the CDC-flow and LDC-flow, examining whether customers who think the CDC option offer to long DLT and select the LCD-delivery option instead. This would enable the case company to further understand the behaviour of their customers online and potentially identify thresholds for when customers switch from one option to another. Another interesting study would be one that capture the customers going to the physical store after checking the delivery option in the online store. This could be defined as a omni-channel study where one examine the dynamics of online and offline consumer behaviour in combination. However, it is hard to imagine the design for a study that would be able to capture that behaviour in a reliable way, but it is still a very interesting topic.

As discussed in the previous section, the delivery precision and its relation to DLT would be a very interesting topic to explore further. This, along with other service factors related to deliveries out of which maybe foremost the importance of sustainability for consumer preferences and behaviour. Are customers willing to wait longer or pay more if the delivery option is sustainable? Further, it would be interesting to see if the same results obtained in this study of the furniture and home decor industry is in line with other sectors such as groceries, home electronics and so on. From the PostNord (2019a) it was clear that customers say they expect different DLT for different product categories, but a study on whether or not they do actually behave different in these categories would be of great interest.

In direct relation to the case study performed in this thesis, the following list suggest some potential developments that could perhaps be the basis for other thesis's or projects at the case company.

1. A study focusing on more recent data to understand if the behaviour among the customers have changed over time.
2. Extended analysis of the different cases considering the effect of delivery cost and consumer commitment for each sub-case, such as large cities, selected LSCs and so on.
3. If one can extract reliable data for the entire data-collection period (24 months) it increase the possibility of creating a more sophisticated model for each LSC and create a model that predict the expected increases of sales due to a reduction in DLT. Further, it would be possible to build models based on another method than logistic regression.

Chapter 8

Summary and Conclusion

This chapter aim to summarize the major findings and conclusions of the thesis as well as make a short comment on the implications of them.

8.1 Conclusion

The purpose of this thesis was to investigate the relation between DLT and conversion rate and to quantify this relationship, as well as study the impact of delivery charge and consumer commitment. It is made clear that DLT has a major impact on the conversion rate for online customers within the furniture industry. Over the entire sample the model presented in the thesis suggest that an increase from three to ten days DLT result in a decrease of the conversion rate of 0.0673 (from 0.630 to 0.563) or a relative decrease of 10.67 %. This might not sound that severe, but relating this to the total number of orders for the specific case company it would translate to a loss of 8 360 orders over a period of nine months. With an average cart value of SEK6 100 it would translate to a potential loss of sales of 51 million SEK, extrapolating this figure it amount to 68 million SEK a year.

Further more, the delivery charge ratio was proven to have a significant negative effect on the conversion rate, as expected from theory. A high delivery charge ratio implied an increase of sensitivity for longer DLT, and vice versa. The conclusion of this being that he case company should perhaps put a maximum delivery charge ratio in the system so it never offers customers a ratio above a specific value. Last, the factor of consumer commitment was found to have a counteracting effect on the DLT sensitivity, that is a higher degree of commitment was related to a decreased sensitivity of changes in DLT. Also, an increase in consumer commitment in itself was related to an increase in the expected conversion rate, or put in other terms, consumers spending more, are more likely to fulfill their purchase.

The major contribution of the research in this thesis is the quantified relationship of DLT and how consumer behavior is affected by changes in the offered DLT. The major difference with this research being that it is based on actual sales data, rather than surveys or interviews. It studies the actual decision of the consumers and not their opinion in the matter of DLT.

8.2 Summary

The conclusions and result of the thesis is summarized in the list below.

- Delivery lead time is negatively correlated with conversion rate and on average for the entire data set an increase from three to ten days is according to the logistic regression model corresponding to a relative decrease of 10.67% in conversion rate.

- Larger cities are more sensitive to changes in DLT, compared to the rest of the country. An increase of seven days, from three to ten, translate to a relative decrease in conversion rate of 18.91% for the larger cities while a seven day increase, from seven to fourteen, translate into a decrease of 4.53% for the rest.
- For the selected cities or areas of interest, three out of five resulted in models of statically significance, which all were more sensitive then the sample of the rest of the country, excluding large cities. The group of the selected LSCs also yielded a model more sensitive then the rest of the country excluding large cities, in which a seven days increase, from seven to fourteen, in DLT result in a 10.04% relative decrease in conversion rate. Implicating that the case company should put focus on keeping a lower DLT for these cities/areas.
- A high delivery charge ratio is determined to increase the sensitivity for changes in DLT, which could be related to the experience of paying for an expensive service (delivery) that is of poor performance (long DLT).
- Consumer commitment was established as an important factor to consider in consumer behaviour and in this study the cart value has been used as a proxy for this. It is made evident that a higher cart value is correlated with a decreased sensitivity for longer DLT.

Appendix A

Underlying conversion rate

A.1 Underlying conversion rate in demand data

Note, the graphs consider the average conversion of orders at the given DLT and does not consider the number of orders offered each DLT. Please refer to the frequency graphs in chapter 5.2 to observe the underlying distribution of DLT offered.

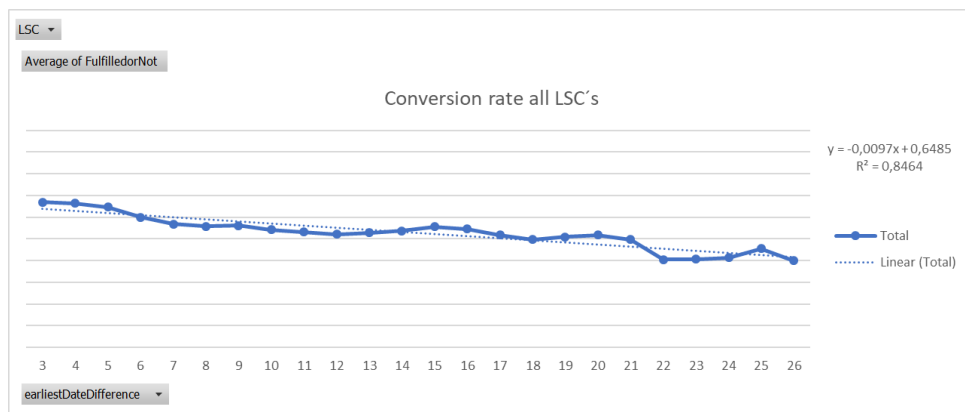


FIGURE A.1: Underlying conversion rate all LSCs, 3-26 days DLT

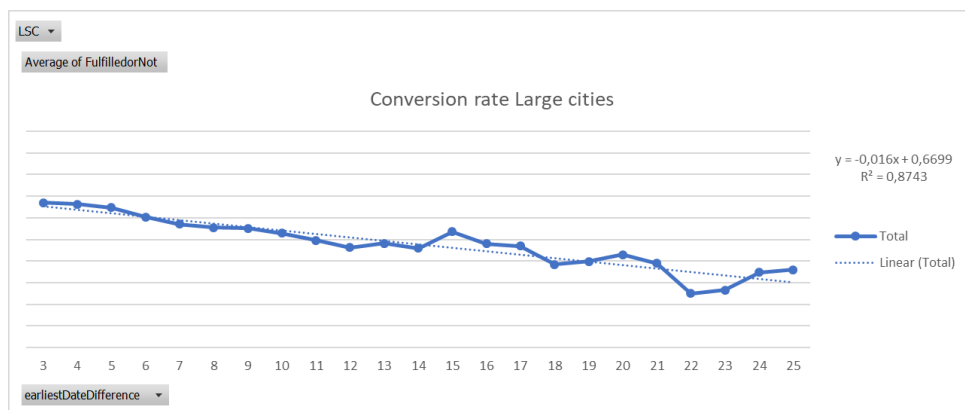


FIGURE A.2: Underlying conversion rate large cities, 3-25 days DLT

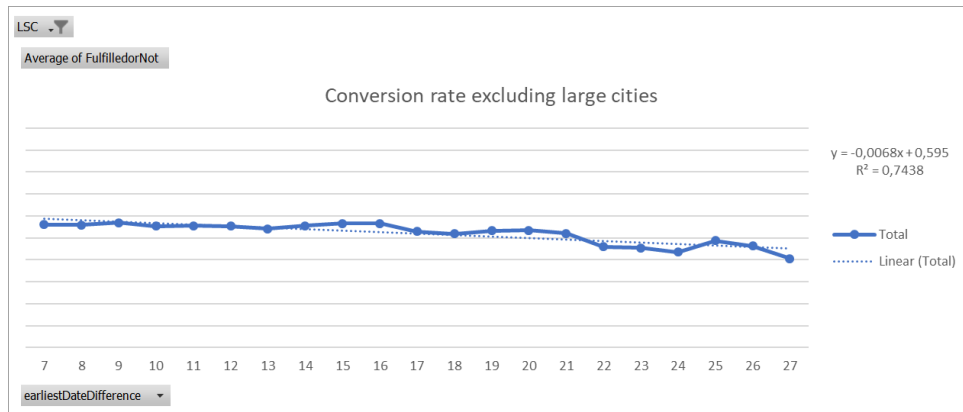


FIGURE A.3: Underlying conversion rate excluding large cities, 7-27 days DLT

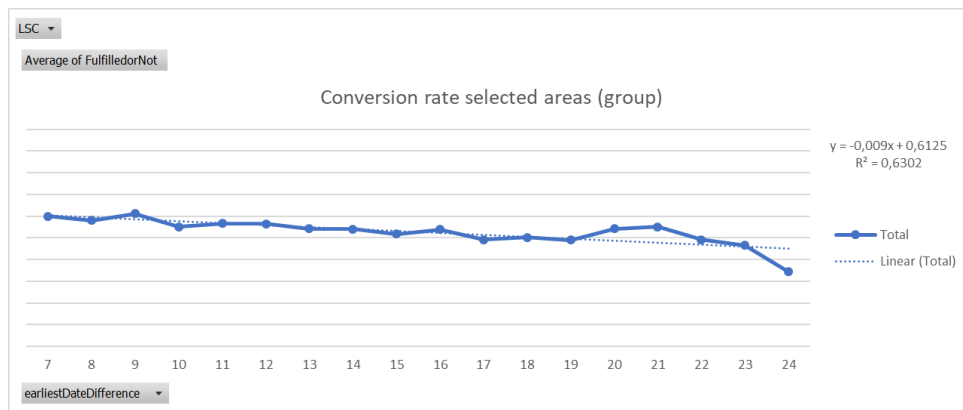


FIGURE A.4: Underlying conversion rate selected group of cities/LSCs, 7-24 days DLT

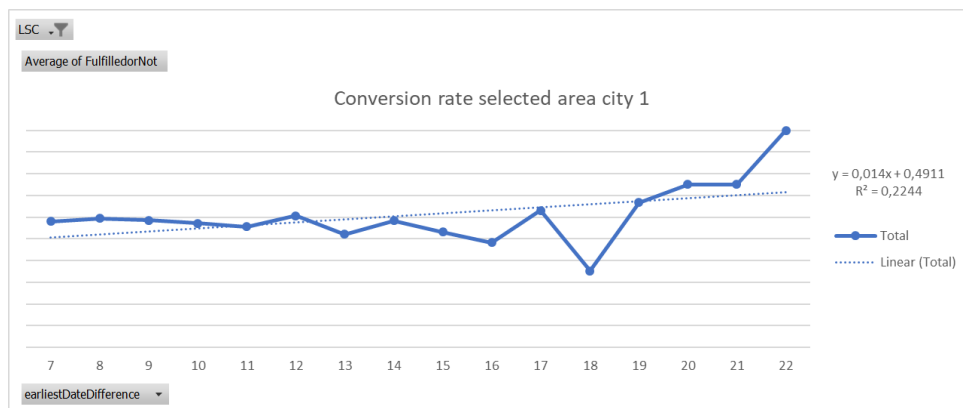


FIGURE A.5: Underlying conversion rate city 1, 7-24 days DLT

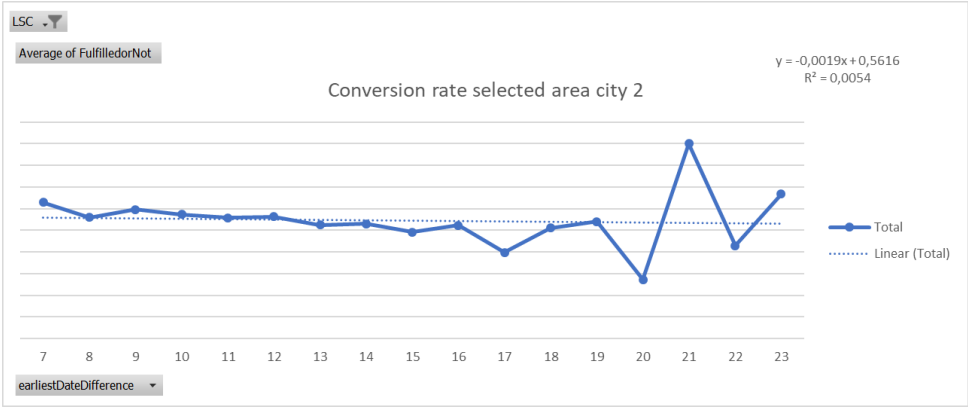


FIGURE A.6: Underlying conversion rate city 2, 7-24 days DLT

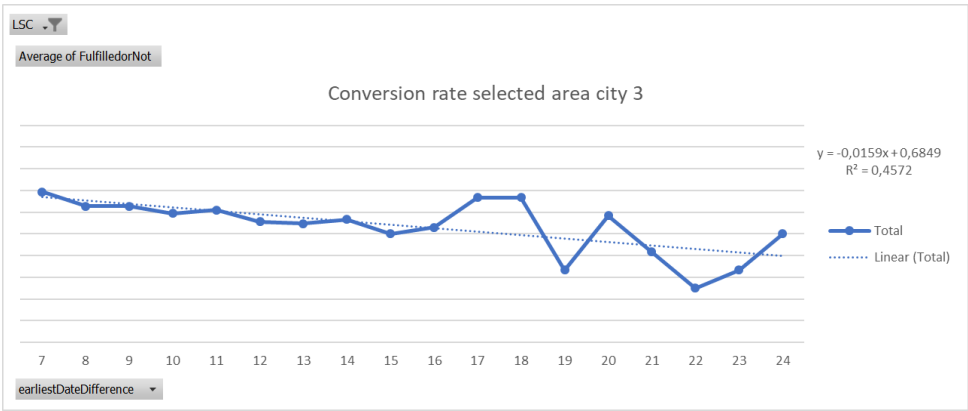


FIGURE A.7: Underlying conversion rate city 3, 7-24 days DLT

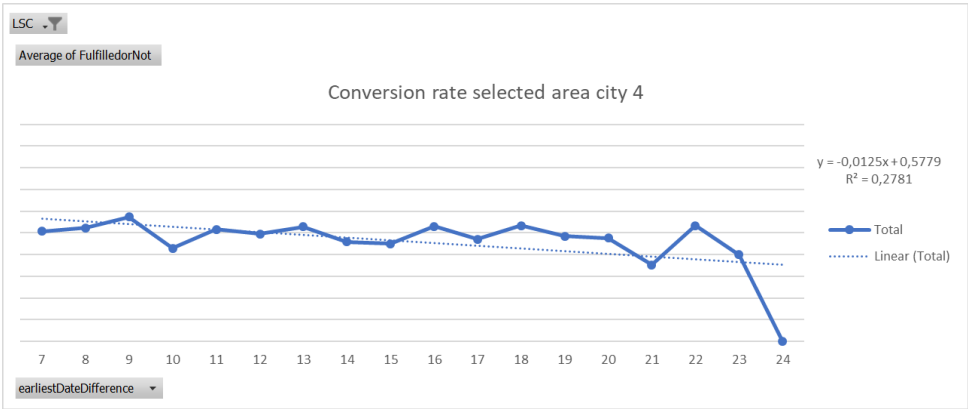


FIGURE A.8: Underlying conversion rate city 4, 7-24 days DLT

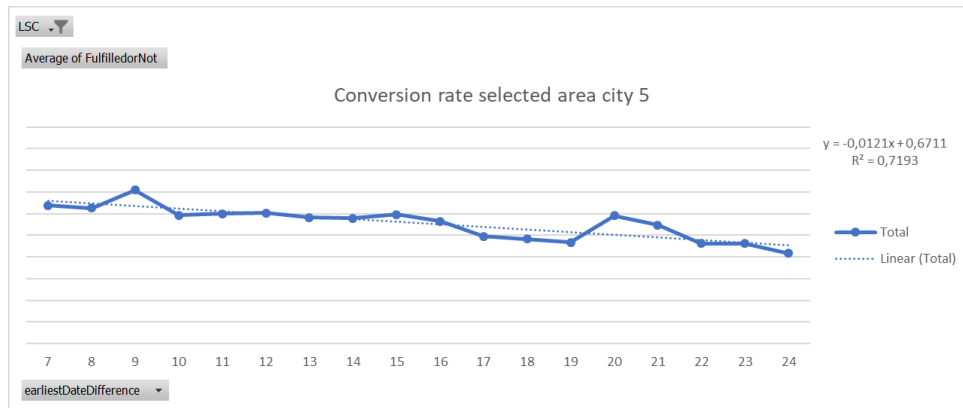


FIGURE A.9: Underlying conversion rate city 5, 7-24 days DLT

Bibliography

- Ames, B. (2015). *Pursuing the promise of omnichannel retailing*. Ed. by Supply Chain Quarterly. URL: [at:www.supplychainquarterly.com/topics/Strategy/20151228-pursuing-the-promise-of-omnichannel-retailing/](http://www.supplychainquarterly.com/topics/Strategy/20151228-pursuing-the-promise-of-omnichannel-retailing/) (visited on 11/07/2019).
- Barsh, Joanna, Blair Crawford, and Chris Grosso (2000). "How e-tailing can rise from the ashes". In: *The McKinsey Quarterly*, pp. 98–98.
- Becerril-Arreola, Rafael, Mingming Leng, and Mahmut Parlar (2013). "Online retailers' promotional pricing, free-shipping threshold, and inventory decisions: A simulation-based analysis". In: *European Journal of Operational Research* 230.2, pp. 272–283.
- Benbasat, Izak, David K Goldstein, and Melissa Mead (1987). "The case research strategy in studies of information systems". In: *MIS quarterly*, pp. 369–386.
- Berman, Jeff (2019). *Convey survey takes a long look at shoppers' holiday shipping expectations SC*. URL: https://www.logisticsmgmt.com/article/convey_survey_takes_a_long_look_at_shoppers_holiday_shipping_expectations (visited on 11/20/2019).
- Bitner, Mary Jo (1990). "Evaluating service encounters: the effects of physical surroundings and employee responses". In: *Journal of marketing* 54.2, pp. 69–82.
- Boon-Itt, Sakun and Chee Yew Wong (2011). "The moderating effects of technological and demand uncertainties on the relationship between supply chain integration and customer delivery performance". In: *International Journal of Physical Distribution & Logistics Management* 41.3, pp. 253–276.
- Boone, Tonya and Ram Ganeshan (2013). "Exploratory analysis of free shipping policies of online retailers". In: *International Journal of Production Economics* 143.2, pp. 627–632.
- Brynjolfsson, Erik, Yu (Jeffery) Hu, and Mohammad S. Rahman (2009). "Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition". In: *Management Science* 55, pp. 1755–1765. DOI: 10.1287/mnsc.1090.1062.
- Check, Joseph and Russell K Schutt (2011). *Research methods in education*. Sage Publications.
- Clemmer, Elizabeth C and Benjamin Schneider (1996). *Managing customer dissatisfaction with waiting: Applying social-psychological theory in a service setting, in advance in service marketing and management, 2, Greenwich*.
- DemandSolutions (2019). *Definitions SC*. URL: <https://www.demandsolutions.com/resource-center/supply-chain-glossary/supply-chain-glossary-d/delivery-lead-time.html> (visited on 11/20/2019).
- Eisenhardt, Kathleen M (1989). "Building theories from case study research". In: *Academy of management review* 14.4, pp. 532–550.
- Esper, Terry L, Thomas D Jensen, Fernanda L Turnipseed, and Scot Burton (2003). "The last mile: an examination of effects of online retail delivery strategies on consumers". In: *Journal of Business logistics* 24.2, pp. 177–203.

- Fisher, Marshall L, Santiago Gallino, and Joseph Jiaqi Xu (2019). "The Value of Rapid Delivery in Omnichannel Retailing". In: *Journal of Marketing Research* 56.5, pp. 732–748.
- Goebel, Philipp, Sabine Moeller, and Richard Pibernik (2012). "Paying for convenience: Attractiveness and revenue potential of time-based delivery services". In: *International Journal of Physical Distribution & Logistics Management* 42.6, pp. 584–606.
- Gronroos, Christian (1990). "Relationship approach to marketing in service contexts: The marketing and organizational behavior interface". In: *Journal of business research* 20.1, pp. 3–11.
- Heale, Roberta and Alison Twycross (2015). "Validity and reliability in quantitative studies". In: *Evidence-based nursing* 18.3, pp. 66–67.
- Höst, Martin, Björn Regnell, and Per Runeson (2006). *Att genomföra examensarbete*. Studentlitteratur AB.
- Huang, Wen-Hsien and Yi-Ching Cheng (2015). "Threshold free shipping policies for internet shoppers". In: *Transportation Research Part A: Policy and Practice* 82, pp. 193–203.
- ICSC (2019). *Customer Service: A Key Part of the Retail Renaissance*. Ed. by International Council of Shopping Centers Industry Insights. URL: [at:https://www.icsc.com/uploads/t07-subpage/Customer_Service_Consumer_Series.pdf](https://www.icsc.com/uploads/t07-subpage/Customer_Service_Consumer_Series.pdf) (visited on 11/25/2019).
- Immonen, Mika, Sanna Sintonen, and Jouni Koivuniemi (2018). "The value of human interaction in service channels." In: *Computers in Human Behavior* 78, pp. 316–325. ISSN: 0747-5632.
- Ishfaq, Rafay, Cliff Defee, Brian Gibson, and Uzma Raja (2016). "Realignment of the Physical Distribution Process in Omnichannel Fulfillment". In: *International Journal of Physical Distribution Logistics Management* 46, pp. 543–561. DOI: 10.1108/IJPDLM-02-2015-0032.
- Katona, George (1968). "Consumer Behavior: Theory and Findings on Expectations and Aspirations." In: *The American Economic Review* 58.2, p. 19. ISSN: 00028282.
- Leclerc, France, Bernd Schmitt, and Laurette Dubé (1995). "Waiting Time and Decision Making: Is Time Like Money?" In: *Journal of Consumer Research* 22, pp. 110–119. DOI: 10.1086/209439.
- Lewis, Michael (2006). "The effect of shipping fees on customer acquisition, customer retention, and purchase quantities". In: *Journal of Retailing* 82.1, pp. 13–23.
- Lewis, Michael, Vishal Singh, and Scott Fay (2006). "An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions". In: *Marketing Science* 25.1, pp. 51–64.
- Loewenstein, George (1987). "Anticipation and the valuation of delayed consumption". In: *The Economic Journal* 97.387, pp. 666–684.
- Mak, Robyn (2018). *Breakingviews - Alibaba rival's switch in logistics stacks up*. Ed. by Reuters. URL: [at:https://www.reuters.com/article/us-jd-com-logistics-fundraising-breaking/breakingviews-alibaba-rivals-switch-in-logistics-stacks-up-idUSKBN1F50T9](https://www.reuters.com/article/us-jd-com-logistics-fundraising-breaking/breakingviews-alibaba-rivals-switch-in-logistics-stacks-up-idUSKBN1F50T9) (visited on 12/12/2019).
- Marino G., Zotteri G. and F. Montagna (2018). "Consumer sensitivity to delivery lead time: a furniture retail case". In: *International Journal of Physical Distribution Logistics Management* 48, pp. 610–629. DOI: <https://doi.org/10.1108/IJPDLM-01-2017-0030>.
- MC (2018). *Consumers Are Getting More Impatient About Delivery Times*. Ed. by Marketing. URL: [at:ConsumersAreGettingMoreImpatientAboutDeliveryTimes](https://www.marketing.com/consumers-are-getting-more-impatient-about-delivery-times) (visited on 12/12/2019).

- McCutcheon, David M and Jack R Meredith (1993). "Conducting case study research in operations management". In: *Journal of Operations Management* 11.3, pp. 239–256.
- Meredith, Jack (1998). "Building operations management theory through case and field research". In: *Journal of operations management* 16.4, pp. 441–454.
- MH&L (2016). *Delivery time top priority for online shoppers*. URL: www.mhlnews.com/transportation-distribution/delivery-time-toppriority-online-shoppers (visited on 10/02/2019).
- Murfield, Monique, Christopher Boone, Paige Rutner, and Rodney Thomas (2017). "Investigating logistics service quality in omni-channel retailing". In: *International Journal of Physical Distribution Logistics Management* 47. DOI: 10.1108/IJPDLM-06-2016-0161.
- Nobelprize (2017). *The Prize in Economic Sciences 2017 - Press Release*. URL: https://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2017/press.html (visited on 04/09/2018).
- Palaka, Kondalarao, Steven Erlebacher, and Dean H Kropp (1998). "Lead-time setting, capacity utilization, and pricing decisions under lead-time dependent demand". In: *IIE transactions* 30.2, pp. 151–163.
- Parry, Tim (2016). *Delivery Time Influences 87 % of Online Shoppers' Purchase Decisions SC*. URL: <https://multichannelmerchant.com/must-reads/delivery-time-influences-87-online-shoppers-purchase-decisions/> (visited on 11/20/2019).
- Patwardhan, Padmini and Jyotika Ramaprasad (2005). "Rational Integrative Model of Online Consumer Decision Making". In: *Journal of Interactive Advertising* 6.1, pp. 2–13. DOI: 10.1080/15252019.2005.10722103.
- Peter, J Paul, Jerry C Olson, and Klaus G Grunert (1999). *Consumer behaviour and marketing strategy*. McGraw-Hill London.
- Ponder, Nicole (2013). "Consumer attitudes and buying behavior for home furniture". In: *Report prepared for the Furniture Outreach Program at Franklin Furniture Institute, Starkville, Mississippi, USA*.
- PostNord (2019a). *E-commerce in the Nordics Six-month report 2019*. URL: https://www.postnord.com/contentassets/9e5ef8a408834cb982f30f145a6b2208/en_e-handeln-i-norden_halvar_2019_highres.pdf (visited on 11/04/2019).
- PostNord, Svensk Digital Handel HUI Research (2019b). *E-barometern Q2 2019*. URL: https://dhandel.se/wp-content/uploads/2019/09/e-barometern_q2_2019.pdf (visited on 10/02/2019).
- Richter, F (2019). *Online Furniture Sales Are Booming [Picture]*. URL: <https://www.statista.com/chart/14771/e-commerce-sales-of-furniture/> (visited on 10/02/2019).
- Robertson, Thomas S. (1976). "Low-Commitment Consumer Behavior." In: *Journal of Advertising Research* 16.2, p. 19. ISSN: 00218499.
- Schindler, Robert M, Maureen Morrin, and Nada Nasr Bechwati (2005). "Shipping charges and shipping-charge skepticism: Implications for direct marketers' pricing formats". In: *Journal of Interactive Marketing* 19.1, pp. 41–53.
- Schmidt, Jeffrey B. and Richard A. Spreng (1996). "A proposed model of external consumer information search". In: *Journal of the Academy of Marketing Science* 24.3, pp. 246–256. ISSN: 1552-7824. DOI: 10.1177/0092070396243005. URL: <https://doi.org/10.1177/0092070396243005>.
- Shao, Xiao-Feng (2017). "Free or calculated shipping: Impact of delivery cost on supply chains moving to online retailing". In: *International Journal of Production Economics* 191, pp. 267–277.

- Smith, J. Brock and Julia M. Bristor (1994). "Uncertainty Orientation: Explaining Differences in Purchase Involvement and External Search." In: *Psychology Marketing* 11.6, pp. 587–607. ISSN: 07426046.
- Solomon, Michael R (2010). *Consumer behaviour: A European perspective*. Pearson education.
- Tersine, Richard J and Edward A Hummingbird (1995). "Lead-time reduction: the search for competitive advantage". In: *International Journal of Operations & Production Management* 15.2, pp. 8–18.
- Thaler, Richard H and LJ Ganser (2015). *Misbehaving: The making of behavioral economics*. WW Norton New York.
- Thornhill, Adrian, Mark Saunders, and P Lewis (2009). *Research methods for business students*. Prentice Hall: London.
- Tom, Gail and Scott Lucey (1995). "Waiting time delays and customer satisfaction in supermarkets". In: *Journal of Services Marketing* 9.5, pp. 20–29.
- Van Maanen, John, Jesper B Sørensen, and Terence R Mitchell (2007). "The interplay between theory and method". In: *Academy of management review* 32.4, pp. 1145–1154.
- Woodruff, R (2003). "Alternative paths to marketing knowledge". In: *Qualitative Methods Doctoral Seminar, University of Tennessee*.
- Yao, Yuliang and Jie Zhang (2012). "Pricing for shipping services of online retailers: Analytical and empirical approaches". In: *Decision Support Systems* 53.2, pp. 368–380.
- Yin, Robert K. (2014). *Case Study Research and Applications*. 5th ed. SAGE Publications Inc.