FACULTY OF ECONOMICS
AND MANAGEMENT

Price Differentiation in German Online Retailing

- An Empirical Analysis

Master Thesis

Business Economics

Summer Term 2020

Chair of E-Business

Otto-von-Guericke-Universität Magdeburg

Supervisor:	Prof. Dr. Abdolkarim Sadrieh
Submitted by:	Maximilian Piepelow
	Hackstr. 38/1
	70190 Stuttgart
Student id:	223661
E-mail:	Maximilian.piepelow @st.ovgu.de
Handed in:	14.10.2020

Eidesstattliche Erklärung

Ich, Maximilian Piepelow, erkläre hiermit an Eides statt, dass ich die vorliegende Masterarbeit selbständig und ohne unerlaubte Hilfe angefertigt, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt und die den benutzten Quellen wörtlich oder inhaltlich entnommenen Stellen als solche kenntlich gemacht habe.

Die Arbeit wurde bisher in gleicher oder ähnlicher Form keiner anderen Prüfungsbehörde vorgelegt und auch nicht veröffentlicht.

.....

Magdeburg, 14. Oktober 2020

Abstract

Price differentiation is the practice of charging different prices for the same product to different groups of customer. Recent research investigates the topic primarily in the context of online/offline price differentiation. However, recent research by master seminars in cooperation with the Otto-von-Guericke-Universität Magdeburg suggests, that the practice is common on the German e-commerce. Large online retailing groups appear to differentiate prices across different online stores they own.

This thesis investigates the prevalence and height of price differentiation on the German e-commerce market and the possible influence of the factors product category, price height, market price and time of purchase on price differentiation. For this purpose, the thesis examines two kinds of data sets. Firstly, it reexamines the data sets, which were collected by the seminar groups. Secondly, it analyses the data of four retail groups, which was collected with automated data scraping software over a predefined period of time.

The analysis concludes, that price differentiation is very common for retailers and that the factors product category and price height are common determinant for the height of price differentiation. However, it is also shown that the examined retail groups employ various price differentiation strategies in regards to the aforementioned determinants.

Table of content

Figure legend

Table legend

List of Abbreviations

EAN.....*European Article Number*
OvGU.....*Otto-von-Guericke-Universität*
PZN.....*Pharmazentralnummer*
RMD.....*Relative Minimum Distance*

1 Introduction

1.1 Motivation

Price differentiation is the practice of charging different prices for the same product to different customer groups. Even though the concept is relatively simple, it is considered a promising tool for profit maximization(Raza 2015), as it exploits different levels of willingness to pay of different customer groups(Phillips 2005). Recent scientific research mainly focuses on price differentiation in the context of multichannel price differentiation, specifically in the context of online/offline price differentiation. This recent focus has neglected similar opportunities for price differentiation. Specifically, there has been no published research on price differentiation in the context of multiple online stores operated by one retailing group. Many German online retailing groups offer their product range on multiple online stores. Not only do they have the opportunity to maximize profits by employing price differentiation across stores, the ever-rising competiveness of e-commerce gives them a strong incentive to do so.

Several master seminars in cooperation with the chair of e-business of the Otto-von-Guericke-Universität Magdeburg have investigated the aforementioned type of price differentiation. The results suggested, that many German online retailing groups employ price differentiation across their stores. However, the seminar groups were not able to collect sufficiently sizable data sets, to conduct a further investigation into the aspects influencing price differentiation. The solution for this problem lies in data scraping. The term describes a software, which extracts data from the internet in an automated manner. It provides an opportunity to gather large data sets over a prolonged period of time, an thus a solution for the shortcomings of the aforementioned research.

Drawing on both types of data sets, this thesis has the opportunity to provide insight on a previously underreported topic of price differentiation in ecommerce. By analyzing specific aspects such as determinants of price differentiation, the thesis has the opportunity to contribute to the general ongoing discussion on price differentiation.

1.2 Research Approach

This thesis aims to investigate price differentiation in German online retailing. It specifically targets online price differentiation across multiple stores, which belong to the same retail group.

The first step of this scientific research is a review of the recent empirical research on price differentiation to extract existing common themes in the research. The second step is the conception of the analysis and its execution. This thesis relies on two types of quantitative data

sets. The first type of data sets is the data provided by the master seminars. The second type of data sets are data sets collected with the method of data scraping specifically for this thesis. Both types of data sets are analyzed to gain perspective on the prevalence and height of price differentiation among German online retailing groups. The second type of data sets is analyzed to investigate the factors influencing price differentiation. These factors are derived from the prior examination of existing research. The analysis is conducted with standard quantitative methods for the analysis of differentiation between groups, such as ANOVA.

1.3 Structure

Figure 1 provides an overview of the basic structure of the entire thesis. In chapter one, the thesis first provides an overview of the terminology regarding price differentiation. It conceptually embeds the term into the generic term price discrimination in order to form a comprehensive definition. Subsequently, the current state of the empirical research on price differentiation is examined for common themes and factors influencing price definition. This is proceeded by the research questions. Subsequently, the methodology for the investigation of the research questions is described and explained in chapter four. This chapter explores the examined retail groups and data sets. Additionally, the data collection process conducted for this thesis and its transformation for the analysis are described. Chapter five elaborates on the statistical methods chosen for the analysis and subsequently links them to the corresponding data sets and research questions. Chapter six presents the results of the analysis. It does so in an order derived from chapter six. The thesis is concluded by chapter seven, discussion and Outlook. It draws a conclusion, discusses limitation and give an outlook to future research in the topic.

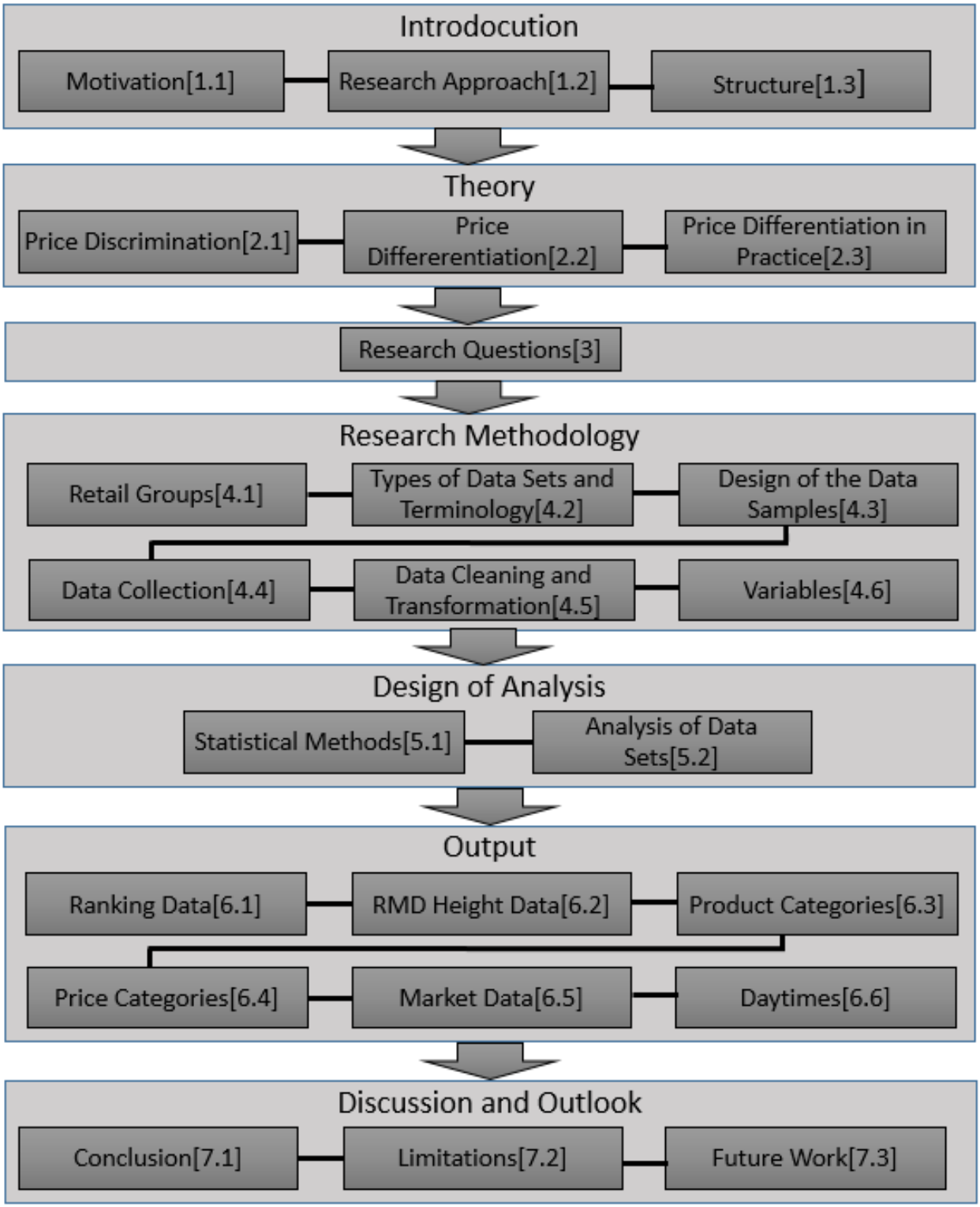


Figure 1: Structure of the thesis

2 Theory

The concepts of price differentiation and price discrimination are closely related. Some researchers even describe the terms as interchangeable(Phillips 2005). In recent research however, the term price differentiation has taken a life of its own. This chapter will first define price discrimination as a generic term and embed price differentiation into this conceptual framework. Subsequently, definitions provided by recent research papers will be examined and accumulated towards a comprehensive definition of price differentiation. Lastly, the chapter examines the findings of empirical research regarding price differentiation.

2.1 Price Discrimination

Pigou(1932, p.279) defines price discrimination as the practice of charging different prices to different customers for the same product or service based on the buyer's willingness to pay. He defined three levels of price discrimination. The first level is perfect price discrimination. In this concept, the seller charges a different price for each unit of a commodity. This shifts all consumer surplus to the seller. The second level is quantity based price discrimination. In this level, the price is differentiated depending on the units sold. The third level is group based price discrimination. In this concept, the prices are differentiated along different groups of customers.

(Faßnacht 1996) accumulated 23 definitions from the past century in order to formulate an overarching definition for price discrimination. In his work, he defines four dimensions, which are relevant for the assessment, whether two units of a product can be regarded as of the same product. These dimensions are the space the product is sold in, the time of the sale, services regarding the product and the quantity of the product. He postulates, that price discrimination occurs, when all dimensions are the same and the product is sold to different customers to different prices. Price discrimination also occurs, if one of the dimensions is altered without creating a new product. However, Faßnacht notes, that the assessment of what constitutes a new product in this case is subjective. Faßnacht further notes, that price discrimination is in practice employed along different segments. He highlights segmentation as an important factor for the implementation of price discrimination. He deems customer to costumer price discrimination as impractical and not economically feasible.

2.2 Price Differentiation

In practice, several authors have defined the term price differentiation. In table 1, these definitions have been accumulated. Firstly, all definitions acknowledge the practice of charging different prices for the same product or slightly altered versions of a product. Most of the authors also agree on the premise, that price differentiation occurs along different customer

segments. There are differing opinions on the conceptual relationship of price discrimination and price differentiation. Phillips(2005) regards the term price differentiation as interchangeable with price discrimination and only choses the former term to avoid the negative connotation of the term “discrimination”. Hupperich et al.(2018) regard price differentiation as differentiation along customer groups and price discrimination as differentiation from customer to customer. All authors in table 1 examine price differentiation along customer groups. Hupperich et al.(2018) investigate online price differentiation across customer segments defined by the customer´s features. Wolk and Ebling(2010) examine differentiation between online and offline channels.

Author	Definition	Empirical Research?
Hupperich et al.(2018)	“Price differentiation is a pricing policy in which providers demand different prices for the same asset, including special offers or discounts.”	Yes
Phillips(2005)	“Price differentiation refers to the practice of a seller charging different prices to different customers, either for exactly the same good or for slightly different versions of the same good.”	No
Raza (2015)	“Price differentiation is among the principal tools of revenue management, in which a firm segments its market demand from one segment to multiple segments. Each market segment is often price differentiated based on the willingness of customers who are attributed by the firm to that particular market segment.”	No
Wolk and Ebling(2010)	“In a market with heterogeneous tastes and different product valuations, companies may increase their profits by segmenting consumers and charging differential prices, which allows for the extraction of additional consumer surplus.” .	Yes

Table 1: Definitions of price discrimination

There is no consensus regarding research discipline of price differentiation. Raza(2015) defines price differentiation as a revenue management tool. Hupperich et al.(2018) describe it as a marketing strategy. Wolk and Ebling(2010) see it in the context of marketing.

For the purpose of this thesis, the author views price differentiation as its own term and chooses to include the following core aspects into the definition. First, the definition of third degree price discrimination by Pigou(1932) is regarded as the basis of the definition. A product

has to be differentiated across customer groups. Additionally, the definition by Faßnacht(1996) of what constitutes the same product is included. Further, no specific kind of customer segmentation practice, such as channel based or time of sale based, is included in the definition. Going forward, all references to price differentiation refer to the aforementioned definition.

2.3 Price Differentiation in Practice

The majority of empirical research on price differentiation has been conducted on online/offline price differentiation. Additionally research has been conducted on offline price differentiation across stores and online price differentiation based on customer location.

Several authors have investigated multichannel price differentiation, which is the differentiation of prices across different sales channels. Wolk and Ebling(2010) analyzed, whether retailers would engage in online/offline channel based price differentiation and what factors influence price differentiation. In two studies they find, that between 29.63%(first study) and 60.66%(second study) of the analyzed retailers were differentiating prices across channels. Those retailers differentiate price for between 12% and 16% of their product range. Both studies show, that in the case of price differentiation, online prices are lower. The found price gaps are 2.54%(study 1) and 5.51%(study 2). Competition also appears to influence the willingness to engage in price differentiation. Homburg et al. (2019) find that approximately 50% of retailers engage in online/offline price differentiation. Overall, they estimate a feasible offline premium of two percent. However, they find heterogeneity regarding of accepted offline price premium depending on product type, height of the products price, consumer segment, and the buying situation being planned or unplanned. Customers accept offline premiums for high priced products and low priced take away products. (Fassnacht and Unterhuber 2016) find a negative attitude towards higher online prices but acceptance for an offline surplus. The acceptance for an offline surplus rises, if customers a provided with a rational for the price difference by the retailer. The height of accepted offline surplus also appears to depend on the product category (such as “look and feel products”).

Cuellar und Brunamonti(2014) investigated the differentiation across different offline retail channels: They note, that differentiation across time, demographic characteristics and space are feasible. They show empirically, that prices can be differentiated across different types of stores depending on the typical clientele of the shop and their spending and shopping habits on the example of wine.

Hupperich et al.(2018) investigated price differentiation for hotel booking and car rental websites. They found, that these websites differentiate prices based on the user’s location.

3 Research Questions

The topic of price differentiation across online stores belonging to the same retail groups has not been present in previous published research. Additionally, there are no published studies, which examine price differentiation on the German e-commerce market. The German ecommerce market exhibits several retail groups, which have the opportunity to engage in price differentiation across their online stores. Thus, this thesis aims to contribute to the scientific discussion by investigating the following research questions.

RQ1: Is there price differentiation on the German e-commerce market?

Several studies have investigated the size of online/offline price differentiation (Homburg et al. 2019; Wolk and Ebling 2010). Therefore, the question arises whether online to online price differentiation is comparable in size.

RQ2: How high is the price differentiation?

The literature provides four possible factors, which influence multichannel price differentiation. These factors are the product category(Fassnacht and Unterhuber 2016; Homburg et al. 2019), the height of the products price(Homburg et al. 2019), market price(Wolk und Ebling 2010) and time of purchase(Cuellar und Brunamonti 2014) These factors are investigated in this thesis.

RQ3: Which factors have an effect on price differentiation?

RQ3.1: Does the product category influence price differentiation?

RQ3.2: Does the height of the product price influence price differentiation?

RQ3.3: Does the market price influence price differentiation?

RQ3.4: Does the time of purchase affect price differentiation?

4 Research Methodology

In this chapter, the three steps of the research process for this thesis are described. First, an overview of the examined retail groups is provided, which includes basic characteristics and information on the group´s presence in the data. Subsequently, the design, collection and general transformation of the analyzed data sets are described.

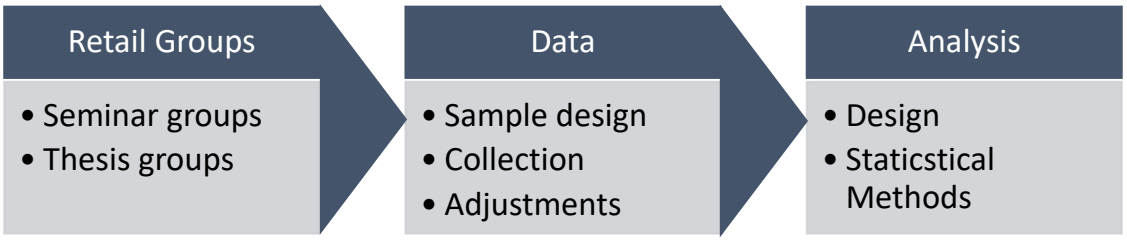


Figure 2: Research methodology

4.1 Retail Groups

For this thesis, price data from 11 retail groups has been analyzed(see table 3). Generally, there are two different types of data sets. The first type are data sets were collected over the course of master seminars in cooperation with the chair of e-business of the Otto-von-Guericke-Universität-Magdeburg(OvGU). The second type of data sets have been collected by the author for this research. With the exception of the retailer Zurrose, all retailing groups are present in both groups of data sets. All retail groups belong to Germany´s top 100 e-commerce retailers(Langer 2020) and consist of at least two stores.

The chair of E-Business has predetermined the retail groups, which were analyzed in the seminars. The author of this thesis has chosen four retail groups for the data collection conducted for this thesis. These groups have been selected based on two metrics. Firstly, the groups had to be a retail group among the top 100 German e-commerce retailers. Secondly, the groups had to be likely to exhibit price differentiation. The groups Mindfactory, Zurrose, Weltbild and Thalia exhibit these traits(Langer 2020). Further, the groups Mindfactory, Weltbild and Thalia exhibited price differentiation in the seminar in the winter term 2019/20, in which the author partook. Zurrose was selected, because it is a retail group specialized on pharmaceutics. Groups, which feature this product range, are not present in the seminar data sets. Thalia and Weltbild have been selected despite their similar product range. The reason for this is the low number of stores of both groups. Table two shows the core characteristics of these retailing groups.

Group	Number of stores	In Data Set	Store category
MediaSaturn	2	Seminar	Consumer electronics
Notebooksbilliger	2	Seminar	Consumer electronics
Otto Group	5	Seminar	Generalist
Hubert Burda Media	2	Seminar	Consumer electronics
Conrad	3	Seminar	Consumer electronics
Mindfactory	6	Seminar, store	Consumer electronics
Hertie Group	2	Seminar	Generalist
Expert	2	Seminar, store	Consumer electronics
Weltbild	3	Seminar, store	Generalist
Thalia	2	Seminar, store	Generalist
Zurrose	6	Store	Pharmaceutics

Table 2: Analyzed reseach groups

4.2 Types of Data Sets and Terminology

As previously mentioned,the basis of this research are two types of data sets. The first group consists of data sets collected in the course of seminars in cooperation with the chair of e-business of the OvGU in the winter term 2019/20 and the summer term 2020. The second group consists of data sets, which were collected specifically for this thesis in the summer term of 2020. The data sets from the seminars are labeled “A”(winter term 2019/20), “B”(summer term 2020(1)) and “C”(summer term 2020(2)). In some parts of the analysis, data from the data sets B and C was combined. This data is labeled as “BC”. The data sets collected by the author are labeled according to the respective retail groups. The labels refer to the data sets used in the analysis(see chapter). The respective labels are, “MF”(Mindfactory), “ZR”(Zurrose), “WB”(Weltbild) and “TH”(Thalia). Data from the price comparison website “guenstiger.de” is labeled as “GU”. For all these groups data has been collected at three different daytimes. The daytimes are labeled as “e”(early), “m”(mid) and “l”(late). Whenever the data of a store is referred without an attached daytime(e.g. “WB”), the term refers to all three daytime data sets at once. If only data from a specific daytime is concerned, the label of the retail group is combined with the daytime label. For example, MFe describes only the data of the group Mindfactory, which was collected in the morning. This terminology is used in all the following chapters.

4.3 Design of the Data Samples

The sample designs for set A,B and C were defined by the chair of e-business. The predefined characteristics were the retail groups present in the data, product categories and the number of products per product category(see table 3). The number of products per category was predefined as 10(data set A, C) and 15. For some products, this number was raised to ensure a sufficient amount of data points in the collection.

Set	Stores	Groups	Product Categories	Products per Category
A	35	8	12	10
B	33	10	11	15
C	33	10	10	10

Table 3: Characteristics of seminar data sets

The author defined the characteristics of the data sets MF, TH, WB, ZR and GU. The core characteristics of these data sets are the number of examined products, the data points to be collected for each product, the collection period and daytimes of collection. No product categories were defined for the groups Mindfactory and Zurrose. For Thalia and Weltbild, the categories were restricted to toys, music and movies. These categories were the shared categories of the shops of the groups besides books. The restriction was necessary, since retailers are prohibited by law from altering the book prices set by the publishers.

The size of the data sets was set at 1000 products. This number was adjusted based on the expected loss of data during the collection period. The sizes of the data sets were adjusted to 1050 products(MF, WB, TH) and 1100 products(ZR). The data sets for GU were collected for each group and thus adjusted based on the group´s sample sizes. For each group a list of product ids was designed. This list contained identification numbers for each product. For TH, WB and MF, the European Article Number(EAN) was chosen as a mean identification. The EAN is an internationally valid trade number to identify a specific product. The “Pharmazentralnummer”(PZN) is a German identification number pharmaceutics. The EAN and the PZN were employed for guenstiger.de according to the adjacent data sets. The purpose of the ids was the accurate identification of the products on different websites. For each product, the price was the data point chosen to be collected in each iteration of the data collection process. For the price comparison website guenstiger.de, each price found on the website for the respective id of a product was chosen as data points for the collection. Additionally, the start and end time of the collection of each website was chosen to be collected. The period of collection was slated to be May 18th 2020 until July 19th 2020. The scheduled start times of the data collection were 9:00 am, 3:00 pm and 9:00 pm.

A data scraping script was designed to collect the ids of products available in all stores of a group. It was written in the programming language python. The script relies mainly on the python library BeautifulSoup[1], which is designed for the purpose of simple HTML data scraping. The script selects as many products as possible from one store out of a group and subsequently collects the id of each product. Subsequently, the id is used as a search term in the adjacent online stores of a group to check, whether the product is available. This process produces a list with all product ids of one store and additional data points indicating, which products are available in the adjacent stores of a group. All products, that are not available in all other stores, are excluded from this list. Such a reduced list was generated for each retail group. Subsequently, the predefined number of products for the data sample is chosen at random from the reduced list for each group to create the sample id list. This sample id list was used as the basis for the data collection for the data sets MF, ZR, WB and TH.

4.4 Data Collection

This chapter elaborates on the details of the data collection process regarding all data sets analyzed for this thesis.

The data for the data sets A,B and C was collected in the course of seminars in cooperation with the chair of E-Business of OVGU. All price data was collected by hand and copied into an excel spreadsheet. Set A was collected in the winter term 2019(12th of December 2019 until 2nd of February 2020). Set B and C were collected in the summer term 2020. The data for set B was collected in the period 27th of May until 10th of June. The data for Set C was collected between May and June of 2020.

For the purpose of the collection of the data sets for Mindfactory, Zurrose, Weltbild, Thalia and Guenstiger.de, 20 individual python scripts were designed. For each store of a group a script was designed. For each group a script for guenstiger.de was designed. The scripts are based on the python library Selenium[2]. Selenium enables automated web browser interaction with python. It employs a chrome browser specifically designed for the library. This browser does not allow any extensions and thus does allow cookies on the websites. Each script selects the ids from the predefined id list of a group and uses the search function of a store´s website to collect the price of the product(see figure 3). Missing prices are coded as “-9”. For each iteration of the script, the collected prices are stored in a separate CSV file.

[1] https://www.crummy.com/software/BeautifulSoup/
[2] https://www.selenium.dev/

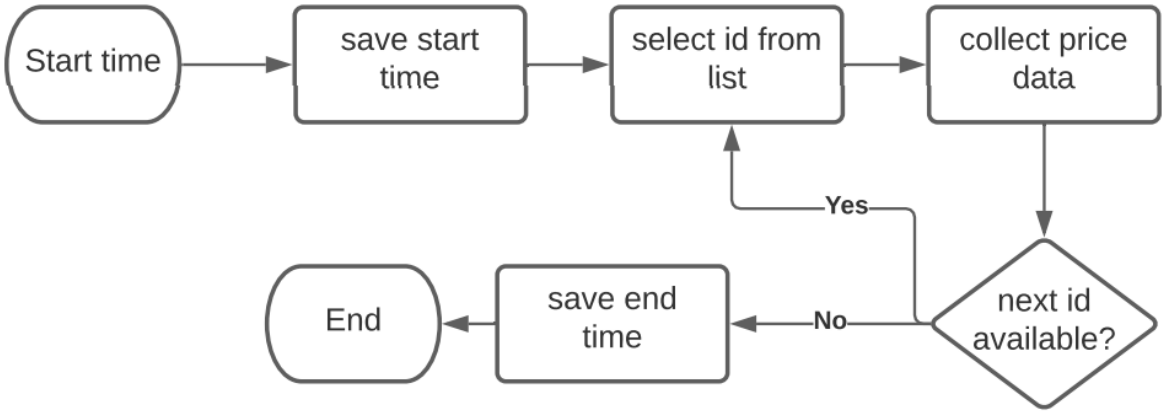


Figure 3: Data scraping process

Running all scripts in parallel was not feasible due to technical limitations. Thus, the scripts were started in groups. The parallel execution was handled by a python script relying on the python library multiprocessing. Multiprocessing is a standard library is python[3]. This script enabled the execution of all data scraping scripts with one general script. Figure 3 depicts, which store specific data collection scripts have been run in parallel.

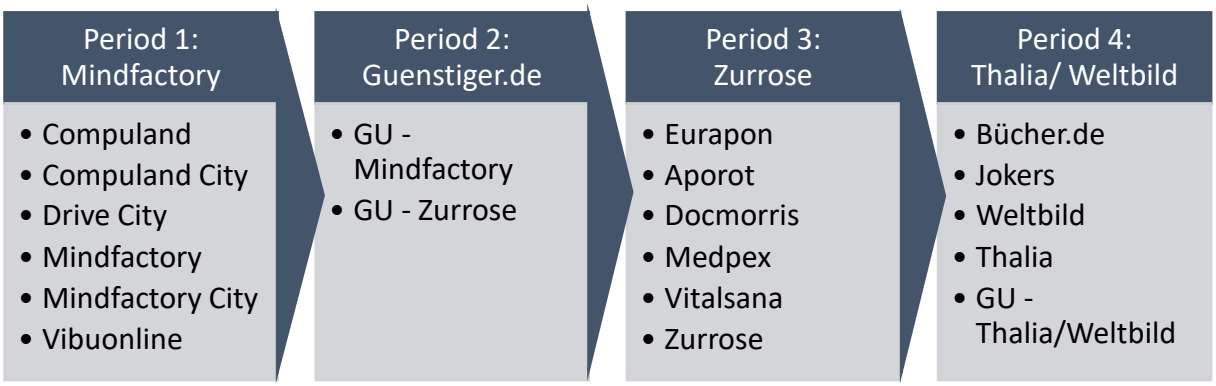


Figure 4: Data scraping running order

The start times for the general script were 9:00 am, 3:00 pm and 9:00 pm CET. The script was started manually from May 18th until until June 18th. In this time frame, the scripts from period two(figure 3) were run in period 1 and 3. From June 19th until July 23rd, the script was started automatically by the windows task manager. From June 19th onwards, parts of the functionality of the collection scripts for Mindfactory were altered. This was necessary due to Mindfactory disabling the search function for some of their stores. This change in the scripts delayed the start of each scraping process by on average 15 to 20 minutes. Generally, for some dates the start times have been delayed by technical problems, such as internet outtakes or changes in

[3] https://docs.python.org/3/library/multiprocessing.html

some of the stores websites. The windows task manager limited the possible number of parallel scripts to six. Thus, the order of figure 3 was instituted. Due to technical problems in the beginning of the collection period, valid data was collected from the May 25th until July 23rd.

4.5 Data Cleaning and Transformation

This chapter elaborates on the data cleaning, transformation and the variables constructed in the process of transformation. The data sets MF, ZR, WB, TH and GU are the result of the data transformation process. The variables contained in these data sets are vital for the analysis. Thus, the construction is described in detail in this chapter.

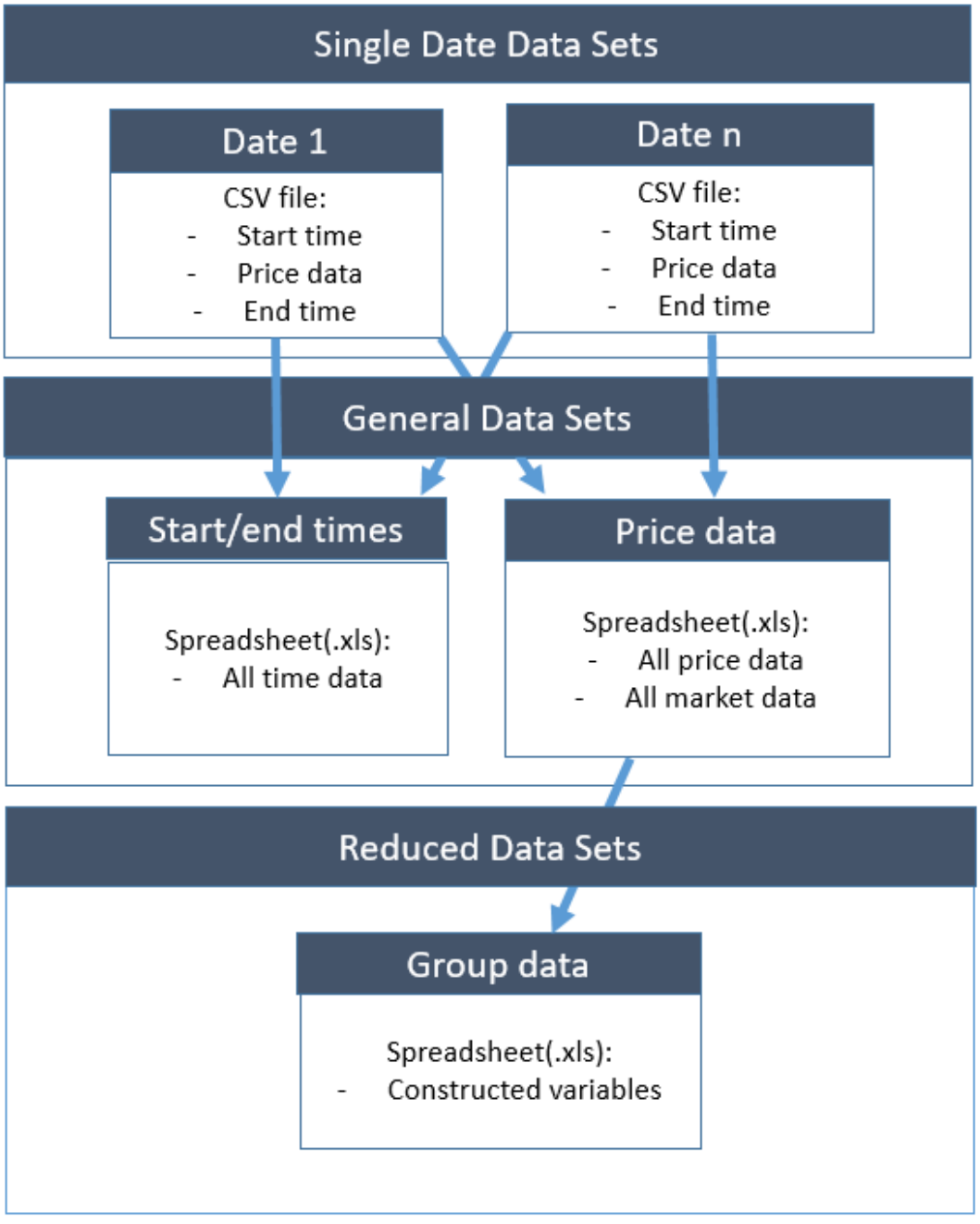


Figure 5: Data transformation

After the collection process ended, the collected data was retrieved from the date specific CSV files with a python script and stored in two large excel spreadsheet for each group and daytime. For each group, three price data spreadsheets and three start/end time data spreadsheets were created according to the daytimes of the collection. The time data files contain all the start and end times of the data scraping process for each website sorted by collection dates. The price data sheets contain all price data for one daytime of one retail group and the adjacent data from günstiger.de. The associated data from guenstiger.de was added to the price data spreadsheets. For each date, the number of collected prices, the minimum price, the maximum price, the mean price and the 0.2/0.4/0.6/0.8 quantiles were generated and stored in the price data spread sheets.

For the purpose of the data cleaning and transformation of the collected data, a python script was written by the author. This script was designed for the purpose of transforming the price data into a suitable form for the analysis. The script constructs the variables, which are the foundation for the data sets MF, ZR, WB and TH. Additionally, the script excluded data not suitable for the analysis. The constructed variables are explained in detail in the following chapter.

4.6 Variables

This chapter elaborates on the construction and general purpose of the variables, which were constructed in the data cleaning and transformation process. The constructed variables are mean price, mean price variance, mean ranks, price categories, relative minimum distance(RMD), product category, mean price quantile values and daytime. Additionally, the construction of ranking data and RMD for the data sets A,B and C is discussed.

4.6.1 Mean Prices and Variances

If a product in the scraped data sets examined more than 20 price data points, the mean and the variance of the price data were calculated by the script. These values were calculated for each product for every store of a group. Additionally, the mean value of all means of a retail group was calculated for each product. If the criteria for construction was not met, the value was coded as missing(“-9”). If a product exhibited a missing value for a store mean, product was excluded from further analysis. Additionally, the relative variance(R_s) was generated for each store mean.

$$R_s = \frac{V_s}{M_s} \qquad (1)$$

V_s depicts the variance of a product for a store(“s”). M_s depicts the mean value of a product for a store(“s”). In the case of TH, WB and ZR, an inspection of the price data revealed numerous products, which exhibited unusually large fluctuations in the price data. Some products exhibited different package sizes, which were presented at random when accessing the website. The relative variance was used to identify these products and exclude them from further analysis. For the scraped data sets, products exhibiting a relative variance above 0.2 were excluded from further analysis.

4.6.2 Ranking Data

In the case of data set A,B and C, the data of each group was analyzed separately. For each product, the prices of the stores were examined. If all stores exhibited price data for a product, a ranking was constructed for this product. Products with incomplete price pairings were excluded. The prices of each price pairing were ranked from lowest(“1”) to highest(highest possible ranking). Subsequently, the differentiation rate of a group was constructed.

$$D_g = \frac{P_D}{P_G} \qquad (2)$$

The differentiation rate of a group(Dg) is equal to the number of price pairings with differentiated prices(P_D) divided by the number of total price pairings(P_G). If a group exhibited a total number of valid pairings equal to or greater than 30 and a differentiation rate above 0.6, the ranking data was analyzed further. Ranking data was constructed for the combined data of the data sets B and C, if either one of the data sets exhibited below 30 and above 10 data points, or if both exhibited less than 30 data points and exceeded 30 data points when combined.

In the case of the data sets MF, ZR, TH and WB, the ranking data was constructed with the data transformation script. For the construction of ranking data, the prices of all stores were ranked for each day of the data collection from lowest(“1”) to highest(highest possible ranking). If a price pairing did not exhibit price data for all stores for one specific date of the collection, this data was excluded from the analysis. From the accumulated rankings of each store per product, the mean ranking was calculated. Additionally, for each product, the differentiation rate was constructed for each product with the same principle as previously described. Products that exhibited less than 20 valid price pairings were excluded from further analysis.

4.6.3 Price Categories

The price categories are binominal variables, which indicate, whether a product is low-, mid- or high-priced. The variable was generated for the data sets MF, ZR, TH and WB. The

categorization is measured with the group mean of a product(M_G), which is the mean of the respective store prices($P_1, \dots, P_N$).

$$M_G = \frac{P_1 + P_2 + P_N}{N} \quad (3)$$

The price categories are modeled along the definitions for low-, mid- and high-priced products by Homburg et al. (2019). Homburgs categorizes products below 30€ as low-priced, between 30€ and 100€ as mid-priced and above 100€ as high-priced. For the purpose of this thesis, the low priced products were additionally divided into products below 10€ and above 10€. This is due to the fact, that the majority of products in the datasets are low priced products. The binary price categories were additionally combined into one ordinal price category variable.

4.6.4 Relative Minimum Distance

The relative minimum distance(RMD) was generated for the purpose of measuring the height of the price differentiation of a group and its stores.

$$RMD = (\frac{P_S}{Min_G}) - 1 \quad (4)$$

The relative minimum distance is a product´s price(P) for a specific store(S) in a price pairing divided by the minimum price in the examined price pairing(Min_G) minus one. In the case of the data sets A,B and C, RMD was constructed in excel. It was constructed for every group, which examined more than 30 complete price pairings. In the case of MF, ZR, WB and TH, RMD was constructed as described above by the transformation script. The values were constructed for the mean values of the product prices.

4.6.5 Mean Price Market Quantiles

The mean price market quantile values(Q, Qo) were constructed for the data sets MF, ZR, WB and TH. The transformation script constructed mean values for the number of prices, the minimum price, the maximum price, the mean price and the 0.2/0.4/0.6/0.8 quantiles of the market data from Guenstiger.de for each product. Market data, that exhibited less than 20 data points was excluded and coded with “-9”. Subsequently, the mean prices(group mean and store means) of a product were compared to the mean quantile values of the market data. Each product´s mean prices were assigned a value based on that comparison(see table 4). Q and Qo indicate between which quantile values the product mean prices are positioned. Q is measured as the mean of the two quantile values. Q is an ordinal measure of the position.

	Quantile position						
Variable	**<min**	**<= 0.2**	**0.2<x<=0.4**	**0.4<x<=0.6**	**0.6<x<=0.8**	**0.6<x<=1**	**>1**
Q	0	0.1	0.3	0.5	0.7	0.9	1
Qo	0	1	2	3	4	5	6

Table 4: Mean price market quantile values

4.6.6 Product Categories

The product categories were collected with a python script based on the data scraping script for the price data. For each group, one script was designed: It collected the categories for each product, for one of the group´s stores. The lists containing the categories were copied to the respective data sets MF, ZR, WB and TH. The categories were coded with numbers. Products, which did not exhibit a category or a category containing less than 30 products, were coded with “1”. The other groups were coded with ascending numbers.

4.6.7 Daytime

The daytime variable was constructed for the scraped data sets. In order to construct the variable daytime, all complete mean price pairings of the different daytime data sets were copied to a separate excel sheet. The price data was labeled numerically according to the daytimes of collection. The variable was constructed for the data sets MF, ZR, WB and TH.

5 Analysis

This chapter elaborates on the methodology employed to investigate the research questions. Firstly, the employed statistical methods for the purpose of the analysis of the quantitative data are described. Subsequently, it is described, which variables and data sets have been analyzed with these statistical methods.

5.1 Statistical Methods

For the purpose of investigating the research questions, the influence of categorical data on parametric and non-parametric data was tested. As a non-parametric test, the Kruskall-Wallis and the Mann-Whitney test were employed. As parametric tests, the t-test and ANOVA were employed. The Kruskall-Wallis test and ANOVA were employed for the data sets MF, ZR, WB and TH. The t-test and Mann-Whitney test were employed for TH in the cases of store to store comparison, due to the group Thalia consisting of two stores.

The ANOVA was employed in combination with Levene´s test and two post hoc tests. Levene´s test was employed to determine the correct post hoc test based on its assessment of the homogeneity of variances of the compared groups. The employed post hoc test were the Games-Howell-test and the Ryan-Einot-Gabriel-Welch Q test. Their purpose was to test the individual differences of the compared groups. All analyses were carried out in SPSS and stored as .spv files.

5.2 Analysis of Data Sets

In order to investigate the individual research questions, different variables and data sets were chosen. Table 6 shows the dependent and independent variables and data sets, which were chosen, to investigate the research questions.

Research question	Independent variable	Dependent variable	Data sets	Results in Chapter
RQ1	Store	Rank/ Mean Rank	A, B, C, BC, MF, ZR, TH, WB	6.1
RQ2	Store	RMD	A, B, C, BC, MF, ZR, TH, WB	6.2
RQ3.1	Product Category	RMD	MF, ZR, TH, WB	6.3
RQ3.2	Price Category	RMD	MF, ZR, TH, WB	6.4
RQ3.3	Q(mean price market quantile)	RMD	MF, ZR, TH, WB	6.5
RQ3.4	Daytime	RMD	MF, ZR, TH, WB	6.6

Table 5: Methodology of analysis

The analysis of the ranking data was conducted for all available data sets. For the data sets A, B, C and BC, the complete ranked price pairs(see chapter 4.6.2) were analyzed. All groups,

which exhibited a differentiation rate above 0.6 and more than 30 complete price pairs, were analyzed. The Kruskall-Wallis test was employed for the groups Conrad, Mindfactory and Weltbild. The Mann-Whitney test was employed for the analysis of the groups Notebooksbilliger, Hubert Burda Media, Expert and Thalia. For the data sets MF, ZR, WB and TH, the analysis was conducted for all complete pairings of mean rank values. In the case of ZR, WB and TH, all products, which exhibited a relative variance above 0.2, were additionally excluded from the analysis. For the analysis of the data sets MF, ZR and WB, ANOVA was used. For the data set TH, the t-test was employed.

The analysis of the differences of RMD across the stores of a group was conducted for all data sets. For the data sets A, B, C and BC, the complete price pairs(see chapters 4.6.1 and 4.6.4) were analyzed. All groups, which exhibited a differentiation rate above 0.6 and more than 30 complete price pairs, were analyzed. The ANOVA was employed for the groups Conrad, Mindfactory and Weltbild. The t-test was employed for the analysis of the groups Notebooksbilliger, Hubert Burda Media, Expert and Thalia. In case of the data sets MF, ZR, WB and TH, only complete mean price pairings were considered for the analysis. Additionally, products exhibiting a relative variance above 0.2 were excluded from the analysis. ANOVA was performed for MF, ZR and WB. The t-test was performed for TH.

The influence of the variables product category(chapter 6.4.6), price category(chapter 4.6.3) and mean price market quantile(chapter 4.6.5) on price differentiation was tested in the data sets MF, ZR, WB and TH. The influences were measured for all stores in the groups and the groups overall. In case of the data sets MF, ZR, WB and TH, only complete price pairings were considered for the analysis. Additionally, products exhibiting a relative variance above 0.2 were excluded from the analysis for the data sets ZR, WB and TH. For the analysis of the mean price market quantile values, only complete price pairing were analyzed, which exhibited a mean number of prices of equal to or greater than five. ANOVA was employed for the analysis of all data sets.

The influence of daytime of data collection on price differentiation was tested on the combined daytime data sets(see chapter 4.6.7). For all examined data sets, an ANOVA was carried out.

6 Output

In this chapter, the output of all analyses is displayed. The order of the subchapters corresponds to the order of the research questions. The terminology of the data sets MF, ZR, WB, TH and the corresponding daytimes(e, m ,l), as described in chapter 4.2, is applied throughout this chapter. Additionally, the stores of the groups are assigned specific terms for this chapter. The stores of the group Mindfactory are denoted as “CL”(Compuland), “CLC”(Compuland City), “DC”(Drivecity), “MF”(Mindfactory), “MFC”(Mindfactory City) and “VO”(Vibuonline). The stores of the group Zurrose are denoted as “EP”(Eurapon), “AP”(Aporot), “DC”(Docmorris), “MP”(Medpex), “VS”(Vitalsana) and “ZR”(Zurrose). The stores of the group Weltbild are denoted as “BU”(Bücher.de), “JO”(Jokers) and “WB”(Weltbild), The stores of the group Thalia are denoted as “BO”(Bol) and “TH”(Thalia). Additionally, if values are displayed, which depict a mean value of a group, they are denoted as “ALL”.

6.1 Ranking Data

In the case of the data sets A, B and C, two groups did not meet the criteria for further analysis. MediaSaturn exhibited a sufficient number pairings and a differentiation rate below 0.6 in all the aforementioned data sets. Otto did exhibit an insufficient number of complete price pairs in data set A, B and C. In the case of the combined data set BC, the amount of valid pairs was sufficient. In this case, the differentiation rate was below 0.6. All other groups exhibited a sufficient amount of complete price pairings and a differentiation rate above 0.6 in at least one of the data sets A, B, C or BC.

The group Conrad was analyzed in the data sets A, C and BC. In all cases the rankings exhibit statistically significant results in the Kruskall-Wallis test(p=0.00). The mean rank values(table 6) show, that Conrad exhibits the highest mean rank, Voelkner exhibits the middle mean rank and Digitalo exhibits the lowest rank in all Sets.

Store	Ranking A	Ranking C	Ranking BC
Conrad	58.10	88.27	130.56
Voelkner	50.65	65.35	100.74
Digitalo	32.26	41.38	67.20

Table 6: Mean ranks Conrad

The group Mindfactory was analyzed in the data sets A, C and BC. For all these data sets, The Kruskall-Wallis test exhibits a p-value of p=0.00. The rankings of the stores is consistent for all the data sets. In ascending order from lowest mean rank to highest, the order is Mindfactory, Compuland, Vibuonline, Drive City and Compuland City(see table 7).

Store	Mean Rank A	Mean Rank C	Mean Rank BC
Mindfactory	18.97	20.53	30.06
Vibuonline	86.06	82.36	119.3
Drive City	117.97	102.05	143.02
Compuland	51.00	53.06	72.61
Compuland City	153.50	144.50	200.01

Table 7: Mean ranks Mindfactory

The group Weltbild was examined in the data sets A and BC. In the case of data set A, the test results are statistically significant(p=0.00). In the case of data set BC, the result is not statistically significant.

Store	Mean rank A	Mean rank BC
Weltbild	54.98	50.08
Bücher.de	77.44	49.00
Jokers	53.59	46.42

Figure 8: Mean ranks Weltbild

The group Notebooksbilliger was analyzed in data set BC. The p-value of the test is p=0.00. The store Notebooksbilliger exhibits a mean rank of 66.50 and the store Nullprozentshop exhibits a mean rank of 30.50.

The store Hubert Burda Media was analyzed for the data sets A, B and C. In the case of the data sets A and C, the test exhibits not statistically significant results. In the case of data set B the p-value is p=0.04. The mean ranks are 35.50 for the store Cyberport and 27.50 for the store Computeruniverse.

The group Expert was analyzed in the data sets A and C. Both analyses exhibit a p-value of p=0.00. In both cases, the mean rank values show a consistent ranking over time. In the case of data set A, the mean rank of the store Expert is 46.00 and the mean rank of the store Expert Technomarkt is 73.00. For data set C, the mean ranks are 34.50(Expert) and 52.50(Expert Technomarkt).

The group Thalia was analyzed in the data sets A and BC. The analysis of data set A exhibits a p-value of p=0.00. The store Thalia exhibits a mean rank of 44.00. The store Bol.de exhibits a mean rank of 71.00. The analysis of data set BC exhibited not statistically significant results.

In the case of the data sets MF, ZR, TH and WB, the analysis of all data sets exhibit statistically significant results(p=0.000). The data sets for Mindfactory exhibit the sample sizes N=943(MFe), N=951(MFm) and N=948(MFl). In the case of ZR, the sample sizes are N=498(ZRe), N=517(ZRm) and N=359(ZRl). The sample sizes of Thalia are N=662(THe),

N=675(THm) and N=658(THl). The sample sizes of Weltbild are N=291(WBe), N=326(WBm) and N=337(WBl).

The mean rank values of the statistical analyses are displayed in table 9. The ranking of the groups Mindfactory, Zurrose and Weltbild are consistent across the different daytime data sets. For MF, the ranking from lowest to highest mean rank is Mindfactory, Compuland, Vibuonline, Drive City, Mindfactory City, Compuland City. In the case of ZR, the ranking from lowest to highest mean rank is Aporot, DocMorris, Eurapon, Medpex, Vitalsana, Zurrose. For Weltbild, the order of mean ranks is Bücher, Jokers, Weltbild. In the data set TH, the store Thalia is the lower ranked store for all three daytimes.

Group	**Store**	**Mean rank**		
		Early	Mid	Late
Mindfactory	Compuland	1474.65	1495.54	1501.21
	Compuland City	4619.97	4653.62	4637.86
	Drivecity	3385.88	3413.44	3398.71
	Mindfactory	500.76	516.29	522.72
	Mindfactory City	4596.59	4617.84	4601.67
	Vibuonline	2399.15	2424.27	2404.84
Zurrose	Eurapon	1309.72	1380.54	1008.10
	Aporot	1059.07	1074.35	750.77
	Docmorris	1278.40	1323.04	929.17
	Medpex	1551.83	1604.76	1135.27
	Vitalsana	1814.13	1897.04	1279.29
	Zurrose	1953.85	2029.28	1362.40
Weltbild	Bücher.de	314.45	347.87	374.50
	Jokers	454.53	516.94	519.10
	Weltbild	542.02	603.69	624.40
Thalia	Thalia	814.05	823.95	802.33
	Bol	510.95	527.05	514.67

Table 9: Mean ranks MF, ZR, WB, TH

6.2 RMD Height Data

In the data sets A, B, C and BC, the analysis was conducted for all stores, which were previously analyzed in the ranking analysis. In data set A, the groups Conrad, Expert, Hubert Burda Media, Mindfactory, Thalia and Weltbild were examined. In data set B, Hubert Burda Media was analyzed. In data set C, Hubert Burda Media, Conrad, Mindfactory and Expert were analyzed. In data set BC, Weltbild, Thalia, Notebooksbilliger, Conrad and Mindfactory were analyzed.

Hubert Burda exhibits statistically insignificant results in data set A, B and C.

The ANOVA yields statistically not significant results for the group Conrad in data set A. The results are statistically significant in data set C and BC. The numbers of analyzed price pairings are N=43(C) and N=66(BC). In both cases, the p-value is p=0.000. The ranking of the stores in terms of height of RMD is consistent in both data sets. The RMD mean values for data set C are 0.084(Conrad), 0.021(Voelkner) and 0.01(Digitalo). For data set BC, the RMD mean values are 0.066(Conrad), 0.017(Voelkner) and 0.01(Digitalo). In both data sets, the individual differences between the stores validated with statistically significant results of the post hoc tests.

The group Expert exhibits statistically significant results of the t-test in the data sets A and C. The sample sizes are N=59(A) and N=43(C). In both cases, the store Expert Technomarkt shows the higher RMD mean values(A:0.081, C:0.099). The store Expert exhibits RMD mean values of 0.005(A) and 0.015(C).

The group Mindfactory shows statistically significant results in the ANOVA in data set A,C and BC. The sizes of the data sets are N=34(A), N=32(C) and N=45(BC). In all cases the p-value is p=0.000. For the store Mindfactory, the RMD mean values are 0.000(A,B) and 0.003(C). For the store Vibuonline, the RMD mean values are 0.023(A), 0.009(C) and 0.019(BC). For the store Drive City, the RMD mean values are 0.023(A), 0.011(C) and 0.018(BC). In case of the store Compuland, the RMD mean values are 0.023(A), 0.011(C) and 0.018(BC). For the store Compuland City, the RMD mean values are 0.154(A) and 0.165(C and BC). In all data sets, the post hoc tests show statistically significant differences between the store Compuland City and all other stores.

Thalia exhibits N=57(A) and N=41(BC) complete price pairings, which were analyzed. The t-test yields statistically significant results(p=0.000) in both cases. In both data sets, the store Thalia exhibits the lower RMD mean values(A:0.026, BC:0.012). The store bol.de exhibits the mean RMD values 0.094(A) and 0.083(BC).

The group Notebooksbilliger was analyzed in data set C. It shows a sample size of N=48 and a p-value of p=0.000 in the t-test. The RMD mean values for the stores are 0.063(Notebooksbilliger) and 0.008(Nullprozentshop).

In data set A and BC, the ANOVA shows no statistically significant results for the group Weltbild.

In the case of data sets MF, the sizes of the examined data sets are 696(early), 651(mid) and 972(late). For all data sets, the ANOVA showed statistically significant results(p=0.000). The individual RMD mean values exhibit the same ranking for all three daytimes. The ranking of the stores from lowest to highest value is Mindfactory, Compuland, Vibuonline, Drive City, Mindfactory City, Compuland City. The post hoc test suggest a grouping of the RMD values of the stores into low(Mindfactory), mid(Compuland, Vibuonline, Drivecity) and high(Mindfactory City, Compuland City) The post hoc tests exhibit statistically significant differences between these groupings in all three daytime data sets. The groupings are marked with the colors red(high), yellow(mid) and green(low) in table 10. Additionally, the RMD values, for which the post hoc tests exhibit statistically significant results are marked(“*”).

Group	Store	RMD			RMD rank
		Early	Mid	Late	
Mindfactory	Mindfactory	0.003*	0.003*	0.003*	Low
	Compuland	0.061*	0.064*	0.061*	Mid
	Vibuonline	0.067*	0.083*	0.071*	Mid
	Drivecity	0.077*	0.074*	0.072*	Mid
	Compuland City	0.851*	0.854*	0.847*	High
	Mindfactory City	0.859*	0.911*	0.845*	High
Zurrose	Aporot	0.105*	0.109*	0.111*	Low
	DocMorris	0.116*	0.119*	0.120*	Low
	Medpex	0.149*	0.151	0.153	Mid
	Eurapon	0.152*	0.160*	0.166*	Mid
	Zurrose	0.307*	0.316*	0.301*	High
	Vitalsana	0.308*	0.335*	0.318*	High
Thalia	Thalia	0.020*	0.0205*	0.020*	Low
	Bol.de	0.060*	0.061*	0.061*	High
Weltbild	Bücher.de	0.050*	0.050*	0.059*	Low
	Jokers	0.202*	0.207*	0.205*	High
	Weltbild	0.223*	0.227*	0.214*	High

Table 8: Mean RMD values of the stores

In the case of ZR, the sizes of the data sets are N=543(early), N=554(mid) and N=515(late). For all these data sets, the ANOVA exhibits statistically significant results(p=0.000). The mean values of RMD are showing a coherent ranking for all three daytimes. This ranking, from lowest to highest, is Aporot, Docmorris, Medpex, Eurapon, Zurrose, Vitalsana. The outcomes of the post hoc test suggest, that the stores´ RMD values can be grouped into the three categories “low”(Aporot, Docmorris), “mid”(Medpex, Eurapon) and “high”(Zurrose, Vitalsana).

The sizes of the data sets for the group Weltbild are N=374(early), N=410(mid) and N=443(late). All ANOVAs exhibit statistically significant results(p=0.000). The post hoc tests suggest a grouping of the RMD values of the stores into “low”(Bücher.de) and “high”(Jokers,

Weltbild). For all daytimes, these groupings are validated by statistically significant differences between these groupings in the post hoc tests.

For the group Thalia, the sample sizes are N=808(early), N=815(mid) and N=792(late). The t-test exhibit statistically significant results(p=0.000). For all daytimes, the store Thalia exhibits the lower mean RMD values.

6.3 Product Categories

The analyzed categories for MF are “Other”, “Hardware”, “Heim und Garten”(=home and garden), “Kommunikation”(=communication) and “Notebook/PC”. Table 11 depicts the mean prices and the number of products in the categories for each daytime.

Category	**Early**		**Mid**		**Late**	
	N	Mean price	N	Mean price	N	Mean price
Other	74	36.02€	54	36.12€	55	35.84€
Hardware	261	170.63€	254	170.42€	260	168.99€
Heim und Garten	497	13.80€	490	13.69€	500	13.71€
Kommunikation	108	81.85€	109	81.95€	109	81.91€
Notebook/PC	48	272.32€	44	292.08€	48	272.26€

Table 9: Mindfactory, categories

Table 12 shows the mean RMD values of the categories of the group Mindfactory(“ALL”) and its stores, if they exhibit statistically significant results in the ANOVA and if they are validated in the respective post hoc tests. Values are marked as not significant(“n.s.”), if they cannot be validated by the post hoc test by statistically significant differences to at least one other store. The ANOVAS exhibit significant results for ALL, Compuland, Compuland City and Mindfactory City for all daytimes. For ALL, Compuland and Compuland CIty, the p-values are p=0.000 for all daytime data sets. Compuland exhibits the p-values p=0.046(early), p=0.034(mid) and 0.037(late). The RMD mean values of the categories show a consistent ranking for all data sets. The ranking from lowest to highest RMD value is “Kommunikation”, “Hardware”, “Notebook/PC”, “Other”, “Heim und Garten”. The ranking is not validated by the respective post hoc tests.

		RMD				
Dataset	Daytimes	Other	Hardware	Heim und Garten	Kommunikation	Notebook/PC
ALL	Early	0.277	0.166	0.454	0.135	0.196
	Mid	0.280	0.171	0.473	0.139	0.227
	Late	0.274	0.167	0.449	0.135	0.200
CL	Early	0.037	n.s.	0.086	0.017	0.028
	Mid	0.037	n.s.	0.093	0.017	0.026
	Late	n.s.	n.s.	0.086	0.017	0.025
CLC	Early	0.775	0.427	1.219	0.360	0.544
	Mid	0.780	0.435	1.124	0.358	0.577
	Late	0.766	0.427	1.209	0.450	0.556
MFC	Early	0.774	0.424	1.217	0.357	0.543
	Mid	0.877	0.431	1.60	0.461	n.s.
	late	0.762	0.428	1.205	0.356	0.554

Table 10: Mindfactory, RMD values of categories

The analyzed categories for the group Zurrose are “Other”, “Erkältung und Grippe”(=cold and flu), “Hauterkrankungen und Hautverletzungen”(=skin disease and skin injury), „Kosmetik”(=cosmetics), „Schmerzen“(pain) and „Zähne und Mund“(=teeth and mouth). The category “Schmerzen” was analyzed in the data set ZRm only. It does not exhibit a sufficient amount of data points in the other data sets. The number of products per category and the mean price values of the categories are displayed in table 13.

Category	Early		Mid		Late	
	N	Mean	N	Mean	N	Mean
Other	301	15.84	280	17.21	281	15.71
Erkältung Und Grippe	76	9.29	75	9.55	74	9.35
Hauterkrankungen Hautverletzungen	44	12.49	43	12.20	40	12.44
Kosmetik	84	17.06	84	17.06	83	17.10
Schmerzen	-	-	34	11.03		
Zähne	38	8.06	38	7.79	37	7.85

Table 11: Zurrose, categories

Table 14 shows the mean RMD value of the product categories. The displayed values are validated by the respective post hoc tests by at least one statistically significant difference to another store. The majority of stores exhibits statistically significant results for the ANOVA. For ZRe, ALL, Eurapon and Vitalsana show a p-value of p=0.000. Aporot exhibits a p-value of p=0.013. Docmorris exhibits a p-value of p=0.002. Zurrose exhibits a p-value of p=0.001. Medpex shows a statistically insignificant result. In the data set ZRm, the exhibited p-values are p=0.000(ALL), p=0.001(Eurapon), p=0.002(Vitalsana) and p=0.003(Zurrose). Aporot, Docmorris and Medpex show statistically insignificant results. In the case of ZRl, the p-values are p=0.000(ALL, Eurapon, Vitalsana) and p=0.001(Zurrose). Aporot, Docmorris and Medpex exhibit statistically insignificant results. No consistent ranking for the RMD values of the categories can be found in the post hoc tests for the data sets.

		RMD					
Store	**Daytime**	**Other**	**Earkältung**	**Haut**	**Kosmetik**	**Schmerzen**	**Zähne**
ALL	Early	0.206	0.278	0.166	0.091	-	0.138
	Mid	0.228	0.268	n.s	0.091	0.209	0.123
	Late	0.228	0.283	0.154	0.091	-	0.126
EP	Early	0.144	0.306	0.127	0.059	-	0.147
	Mid	0.161	0.292	0.131	0.058	0.161	0.146
	Late	0.165	0.315	0.131	0.060	-	0.153
AP	Early	0.115	0.144	0.076	0.068	-	0.058
	mid	0.128	0.140	n.s.	0.069	n.s.	0.058
	Late	n.s.	n.s.	n.s.	n.s.	-	
DM	Early	0.123	0.169	0.077	0.086	-	0.060
	Mid	0.135	0.162	0.076	0.086	0.093	0.060
	Late	n.s.	n.s.	n.s.	n.s.	-	
VS	Early	0.351	0.414	n.s.	0.136	-	0.162
	Mid	0.404	0.389	n.s.	0.137	0.423	0.123
	late	0.380	0.420	n.s.	0.137	-	0.124
ZR	Early	0.357	0.328	0.302	0.138	-	n.s.
	Mid	0.378	0.333	0.303	0.139	0.338	0.204
	Late	0.357	0.336	0.266	0.137	-	0.210

Table 12: Zurrose, mean values of categories

The analyzed groups for the group Weltbild are “Other”, “Filme”(=movies), “Musik”(=music), and “Spielwaren”(toys). Table 15 displays the mean price values of the categories and the number of products for each category sorted by daytimes.

Category	Early		Mid		Late	
	N	Mean	N	Mean	N	Mean
Other	60	25.78€	63	23.43€	58	25.33€
Filme	109	15.71€	124	16.10€	132	15.46€
Musik	31	19.51€	30	20.27€	36	18.81€
Spielwaren	174	22.12€	194	22.83€	189	23.70€

Table 13: Weltbild, categories

Table 16 displays the RMD mean values of the categories for the different data sets. The displayed values have been validated by the ANOVAs and the respective post hoc tests. All p-values for the respective ANOVAs are p=0.000. There are two consistent rankings of the RMD values of the categories across the stores. Since the only possible categories for a product are “Filme”, “Musik” and “Spielwaren”(see chapter), the category “other” is not included in the ranking of the categories. The store Bücher.de exhibits low RMD values for the categories “Spielwaren” and “Musik” and high RMD values for “Musik”. The stores Jokers and Weltbild exhibit lower RMD mean values for “Filme” and “Musik” and high RMD mean values in the category “Spielwaren”. These grouping are validated by the respective post hoc tests through statistically significant differences of the RMD values between the groupings. The groupings have been color coded as “low”(green) and “high”(red).

		RMD			
Store	**Daytime**	**Other**	**Filme**	**Musik**	**Spielwaren**
All	Early	0.142	0.087	0.120	0.216
	Mid	0.137	0.084	0.125	0.224
	Late	0.151	0.096	0.117	0.215
BU	Early	0.048	0.106	0.050	0.016
	Mid	0.047	0.105	0.047	0.017
	Late	0.055	0.117	0.064	0.014
JO	Early	0.177	0.054	0.154	0.313
	mid	0.173	0.050	0.163	0.325
	Late	0.186	0.081	0.138	0.312
WB	Early	0.200	0.101	0.156	0.320
	Mid	0.193	0.098	0.163	0.330
	Late	0.212	0.091	0.150	0.317

Table 14: Weltbild, mean values of categories

For the group Thalia, table 17 displays the number of products in each category and the mean prices for each of the daytimes. The analyzed categories are “Other”, “Filme”(=movies), “Musik”(=music) and “Spielwaren”(=toys).

Category	**Early**		**Mid**		**Late**	
	N	Mean	N	Mean	N	Mean
Other	153	16.71€	154	16.83€	147	16.76€
Filme	166	14.97€	172	15.17€	166	14.75€
Musik	271	16.07€	271	16.07€	267	16.10€
Spielwaren	218	18.06€	219	18.35€	211	18.28€

Table 15: Thalia, categories

The RMD mean values of the data sets have been analyzed for the group Thalia(“ALL”), the store Thalia(“TH”) and Bol(“BO”). The ANOVAs yields statistically significant results for ALL and TH for all daytimes. Table 18 displays the RMD mean values, which are validated by the respective post hoc tests. For the store Thalia, a consistent ranking is present for all day times. The ranking is, from lowest to highest RMD mean value, “Musik”, “Filme”, “Spielwaren”. This ranking is validated by statistically significant differences between the categories in the respective post hoc tests.

		RMD			
Store	**Daytime**	**Other**	**Filme**	**Musik**	**Spielwaren**
ALL	Early	0.045	n.s.	0.028	0.054
	Mid	0.045	n.s.	0.028	0.054
	Late	0.046	0.039	0.028	0.054
TH	Early	0.018	0.013	0.001	0.051
	Mid	0.018	0.013	0.001	0.050
	Late	0.019	0.013	0.001	0.050

Table 16: Thalia, mean values of categories

6.4 Price Categories

For the group Mindfactory, the price categories were examined for the group and all stores. Table 19 displays the numbers of products(N) for the different price categories for all daytimes. The analyzed categories are under 10€("<10"), greater than 10€ and under 30€("<30"), greater than 30€ and under 100€(<100) and over 100€(>100).

	N		
Category(€)	Early	Mid	Late
<10	382	378	386
<30	309	303	309
<100	155	151	155
>100	123	119	122

Table 17: Mindfactory, price categories

Table 20 shows the mean RMD values of the price categories for the different stores. The ANOVAs exhibit significant results(p=0.000) for the group and all stores except Mindfactory. There are consistencies regarding the ranking of the RMD mean values of the categories. In the case of the stores Compuland, Drivecity and Vibuonline, the products below 10€ exhibit high RMD values. The other three categories exhibit lower RMD mean values. This grouping is validated in the post hoc tests by statistically significant differences between these groupings. In the case of Compuland City and Mindfactory City, the post hoc tests show a negative correlation of the height of the price and the RMD mean values. The ranking is, from lowest to highest RMD mean values per category, ">100", "<100", "<30", and below "<10". The values are validated for both stores in the post hoc tests by statistically significant differences

between all categories for all day times. The statistically significant RMD rankings have been color coded from lowest(green) to highest(red) in table 20.

		RMD			
Store	Daytime	<10	<30	<100	>100
ALL	Early	0.652	0.140	0.064	0.057
	Mid	0.666	0.153	0.068	0.058
	Late	0.648	0.132	0.063	0.056
CL	Early	0.130	0.017	0.008	0.021
	Mid	0.137	0.018	0.009	0.023
	Late	0.129	0.017	0.008	0.021
CLC	Early	1.733	0.382	0.178	0.135
	Mid	1.731	0.377	0.180	0.137
	Late	1.723	0.370	0.177	0.134
DC	Early	0.167	0.020	0.009	0.030
	Mid	0.157	0.020	0.009	0.030
	Late	0.153	0.020	0.008	0.027
MFC	Early	1.723	0.381	0.178	0.135
	Mid	1.795	0.473	0.192	0.133
	Late	1.719	0.368	0.177	0.133
VO	Early	0.144	0.019	0.008	0.023
	Mid	0.170	0.032	0.013	0.023
	Late	0.155	0.018	0.006	0.022

Table 18: Mindfactory, mean RMD values of price categories

For Zurrose, the categories “<10”, between “<30” and “<100” have been analyzed for the group and the stores. The category “>100” has been removed due to an insufficient number of products in the category. The number of products in the remaining categories are displayed in table 21.

	N		
Category(€)	Early	Mid	Late
<10	246	249	234
<30	264	265	251
<100	31	40	30

Table 19: Zurrose, price categories

The mean RMD values for the different price categories are displayed in table 22 for the group and the stores. The ANOVAs for ZRe exhibit statistically significant results for the stores Eurapon, Aporot, Docmorris and Medpex. In case of ZRm, all ANOVAs exhibit statistically significant values. The values for all tests are p=0.000, except in the case of Medpex(p=0.009). For ZRl, all ANOVAs exhibit statistically significant results. The tests for ALL, Eurapon, Aporot and Docmorris exhibit a p-value of p=0.000. The remaining values are p=0.001(Medpex), p=0.016(Vitalsana) and p=0.030(Zurrose).

		RMD	
Store	Daytime	<10	<30
ALL	Early	n.s.	n.s.
	Mid	0.208	0.164
	Late	0.210	0.165
EP	Early	0.242	0.078
	Mid	0.240	0.075
	Late	0.247	0.079
AP	Early	0.081	0.122
	Mid	0.080	0.113
	Late	0.083	0.114
DM	Early	0.088	0.137
	Mid	0.086	0.127
	Late	0.090	0.126
MP	Early	0.171	0.132
	Mid	0.170	0.124
	Late	0.171	0.123
VS	Early	n.s.	n.s.
	Mid	0.289	0.320
	Late	0.283	0.318
ZR	Early	n.s.	n.s.
	Mid	0.313	0.271
	Late	0.310	0.271

Table 20: Zurrose, mean RMD values of price categories

For all stores and daytimes, the post hoc tests exhibited no significant results for the category “<100”. The relationships of the RMD mean values of the remaining groups exhibit two different patterns, which are validated in the post hoc test of the respective ANOVAs. In the case of ZRe, Eurapon and Medpex exhibit higher RMD mean values for the group “<10”. For Aporot and Docmorris, “<30” exhibit higher RMD mean values. This pattern is consistently statistically

significant in the post hoc test for ZRm and ZRl. In those data sets, Vitalsana exhibts higher values for “<30” and Zurrose in “<10”. The statistically significant patterns have been color coded as described above.

The group Weltbild exhibits no products in the category “<100” and “>100”. The numbers of products in the remaining categories are displayed in table 23.

	N		
Category(€)	Early	Mid	Late
<10	37	38	51
<30	294	317	330
<100	43	55	62

Table 21: Weltbild, price categories

The mean RMD values of the categories for the group and the stores are displayed in table 26. All ANOVAs show statistically significant p-values(p=0.000). The stores show two consistent patterns in terms of the relationship of the mean RMD values and the height of the price for all daytimes. The store Bücher.de shows a positive correlation. The ascending ranking of the RMD values of the categories is “<10”, “<30” and “<100”. This relationship is reversed for the stores Jokers and Weltbild. For these stores, the ranking from lowest to highest RMD mean value is “<100”, “<30” and “<10”. Both patterns are validated by statistically significant differences between all stores in the post hoc tests.

		RMD		
Store	Daytime	<10	<30	<100
ALL	Early	0.131	0.148	0.259
	Mid	0.133	0.149	0.251
	Late	0.135	0.150	0.229
BU	Early	0.280	0.029	0.000
	Mid	0.293	0.030	0.000
	Late	0.296	0.034	0.000
JO	Early	0.051	0.195	0.386
	Mid	0.046	0.197	0.375
	Late	0.047	0.204	0.341
WB	Early	0.062	0.219	0.391
	Mid	0.060	0.220	0.380
	Late	0.062	0.213	0.347

Table 22: Weltbild: mean RMD values of price categories

For the group Thalia, the category “>100” has not been analyzed due to an insufficient amount of products in the categories. The remaining categories are present as previously described. The numbers of products in the categories are displayed in table 25.

	N		
Category(€)	Early	Mid	Late
<10	182	184	181
<30	578	580	562
<100	48	51	49

Table 23: Thalia: Price Categories

All ANOVAs show statistically significant results. For all daytimes, the group overall and the store Bol exhibit a p value of p=0.000. Thalia exhibits p-values of p=0.008(THe), p=0.010(THm) and p=0.016(THl). In the case of the store Thalia, the category “<10” exhibits no significant results in the post hoc tests. For the remaining categories, the data shows a positive correlation of the mean RMD values and the height of the price category. This relationship is validated in all post hoc tests by statistical significant differences between the two categories. For the store Bol, the mean RMD values and the height of the price exhibit a negative correlation. The ranking of the RMD values from lowest to highest is “<100”, “<30” and “<10”. All the differences between the categories are statistically significant in the prost hoc tests.

		RMD		
Store	Day time	<10	<30	<100
ALL	Early	0.057	0.036	0.027
	Mid	0.057	0.036	0.025
	Late	0.057	0.036	0.028
TH	Early	n.s.	0.016	0.039
	Mid	n.s.	0.016	0.038
	Late	n.s.	0.016	0.040
BO	Early	0.085	0.056	0.015
	Mid	0.087	0.056	0.012
	Late	0.088	0.056	0.016

Table 24: Thalia, mean RMD values of price categories

6.5 Market Data

The numbers of products, for which a mean quantile value could be constructed, are N=204(early), N=202(mid) and N=201(late) for Mindfactory. The quantile values are displayed in table 27.

For all daytimes, the ANOVA shows statistically significant results(p=0.000). The post hoc tests show, that there are two store groupings, between which the differences are statistically significant for all daytimes. The first grouping consist of the stores Mindfactory City and Compuland City, which exhibit high quantile values(above 8.0). The second grouping consists of the stores Compuland, Drive City, Vibuonline and Mindfactory, which exhibit values between 0.2 and 0.4.

	Quantile		
Store	Early	Mid	Late
Compuland	0.318	0.322	0.321
Vibuonline	0.324	0.340	0.330
Drive City	0.326	0.337	0.329
Mindfactory	0.249	0.246	0.249
Mindfactory City	0.842	0.843	0.839
Compuland City	0.841	0.845	0.839

Table 25: Mindfactory. Mean quantile values

In case of the group Zurrose, the numbers of mean quantile values are 540(early), 550(mid) and 513(late). For each daytime, the ANOVA exhibits statistically significant results(p=0.000). The stores can be grouped into three groupings. The first grouping, Eurapon, Aporot and Docmorris, show mean quantile values between 0.6 and 0.7. Secondly, Medpex and Vitalsana show mean quantile values between 0.7 and 0.8. Lastly, Zurrose exhibits a mean quantile value above 0.8. These groupings are validated in the post hoc tests by statistically significant differences between these groups for all three daytimes.

	Quantile		
Store	Early	Mid	Late
Eurapon	0.638	0.638	0.650
Aporot	0.615	0.615	0.619
Docmorris	0.649	0.649	0.650
Medpex	0.734	0.734	0.738
Vitalsana	0.759	0.759	0.755
Zurrose	0.808	0.808	0.803

Table 26: Zurrose, Mean quantile values

The group Weltbild exhibits the data set sizes of N=30(early), N=41(mid) and N=38(late). In the case of WBe, the ANOVA exhibits a p-value of p=0.042. The post hoc tests yield no significant differences between the stores. For WBm, the quantile mean values of the stores are 0.810(Bücher.de), 0.963(Jokers) and 0.966(Weltbild). For WBl, the quantile mean values are 0.829(Bücher.de), 0.966(Jokers) and 0.936(Weltbild). In the case of both daytimes, the ANOVA exhibits a statistically significant result(p=0.000). The post hoc tests suggest, that the stores Jokers and Weltbild are grouped together. Both stores exhibit statistically significant differences towards the store Bücher.de but not amongst each other. This is also the case for WBm and WBl.

The group Thalia exhibits the sample sizes N=40 for all daytimes. The t-tests show statistically not significant results for all daytimes.

6.6 Daytimes

In the case of Mindfactory, the size of the analyzed data set is N=2892, consisting of 969(early), 951(mid) and 972(late) products. The group and all stores have been analyzed. The exhibited RMD mean values of ALL are 0.318(early), 0.332(mid) and 0.316(late). The ANOVA does not exhibit statistically significant results for both the group and the stores.

For the group Zurrose, the size of the data set is N=1612, consisting of 543(early), 554(mid) and 515(late) products. The exhibited RMD mean values of ALL are 0.190(early), 0.200(mid) and 0.197(late). The ANOVA does not exhibit statistically significant results for the group and the stores.

For the group Weltbild, the size of the data set is N=1227, consisting of 374(early), 410(mid) and 443(late) products. The exhibited RMD mean values of ALL are 0.159(early), 0.161(mid) and 0.160(late). The ANOVA does not exhibit statistically significant results for the group and the stores.

In the case of Thalia, the size of the exhibited data set is N=2415, consisting of 808(early), 815(mid) and 792(late) products. The exhibited RMD mean values of ALL are 0.040(early), 0.040(mid) and 0.041(late). The ANOVA does not exhibit statistically significant results for the group and the stores.

7 Discussion and Outlook

7.1 Conclusion

This thesis aimed at investigating price differentiation on the German e-commerce market. In order to do so, three research questions were pursued in the research. Two types of data sets were analyzed to answer the research questions. The first type of data sets was collected in the course of master seminars in the winter term of 2019 and the summer term of 2020. The second type of data sets was collected with data scraping software in the summer term 2020. Both types of data sets were analyzed with quantitative methods.

The first research question is related to the existence and of price differentiation at the German e-commerce market. Both types of data sets were analyzed to answer this question. Overall, out of 10 groups, eight were proven to employ price differentiation across their stores. These groups exhibited a consistent ranking across their stores. Six of these stores did employ this ranking in data sets in both examined time periods. It can be concluded, that price differentiation does exist prevalently on the German e-commerce market.

The second research question aimed at an investigation of the height of price differentiation. The related part of the analysis was conducted in all data sets. Overall, the rankings of the stores established in the ranking analysis holds true. However, when operating a bigger number of stores, the examined retailing groups institute groupings of stores and employ a ranking across these groupings and not for the individual stores. Additionally, there are sizeable differences between the levels of price differentiation exhibited by the different retailing groups. The measures for price differentiation found in the seminar data sets mostly show price differentiation between 1% and 3% on the low end and between 6% and 17% on the high end of the spectrum. These numbers confirm the range of price differentiation found in prior research. However, the data sets collected with data scraping, conflict prior findings. While one group(Thalia) confirms previous research, the three remaining groups greatly exceed the previously mentioned levels of price differentiation. They exhibit levels of price differentiation up to 23%(Weltbild), 34%(Zurrose) and 91%(Mindfactory) across their respective stores. Overall, the height of the price differentiation appears to be oriented on the levels of recent research, if retailing groups operate two stores. Yet, retail groups operating a larger number of stores employ significantly larger price differentiation rates for some stores.

The third question aimed at the influence of product categories, price height, market prices and time of purchase on price differentiation. This was analyzed in the scraped data sets. The influence of the product categories on price differentiation could be proven two groups(Thalia and Weltbild) of the four examined groups. The retailing group Weltbild exhibited different

differentiation strategies for the categories across stores, as it changed the rankings of the categories across stores. Overall, it appears, that the product category is a factor that influences price differentiation.

The product price was proven to have an influence on the height of price differentiation for all groups of the scraping data sets. Weltbild, Thalia and Zurrose operated stores, which exhibit a negative correlation of price differentiation and the product price as well as stores, which exhibit a positive correlation of the product price and price differentiation. Mindfactory exhibited a negative correlation of the product price and price differentiation and additionally employed by far the largest difference between the price categories. It exhibited price differentiation values up to 179.5% in the lowest price category, where as the highest price differentiation value for any price category in another group was 32%(Zurrose). Overall, price differentiation appears to be an important determinant for price differentiation.

The analysis of the market price as a determinant of price differentiation provided limited insight. The groups with a more than two stores(Mindfactory, Zurrose and Weltbild) exhibited groupings of the stores in terms of the mean market quantile values. All three groups did exhibit different strategies in terms of the mean quantile values of the stores. However, the analysis could not show a specific influence of the market price on price differentiation.

The daytime of the price data collection does not have an influence in price differentiation. Throughout the entire analysis, there are no significant deviations across the daytimes. Additionally, when directly compared, the price differentiation values of the daytimes show no differences.

It can be concluded, that price differentiation is a commonly employed practice on the German e-commerce market. Additionally, the product categories and the height of the product price are common determinants of price differentiation. However, retailing groups diverge in their approach to price differentiation.

7.2 Limitations

The process of data scraping did provide the opportunity to automate the data collection process and collect large data sets. It has also proven itself to be difficult to execute at scale, as each website presented individual problems to attend to. The resulting technical shortcomings of the data collection have been described in the thesis. With a more fine-tuned technical approach, more precise research and conclusions might have been possible. A more focused approach to single aspects or groups would have allowed for a more precise analysis and outcome. Additionally, more technical expertise and knowledge by author in terms of data

scraping and programming could have caused a more technically proficient data collection process, and thus bigger and more comprehensive data sets.

The insight of this research is also limited by some aspects of the research methodology. In the analysis, data sets with predetermined categories of product exhibited more coherent results. It is plausible, that a more focused approach on a limited number of product categories with controlled features, such as the mean price of the categories and the number of products per category, would have yielded better results. A different approach to the analysis of the market data could have yielded more satisfactory results. The analysis of quantiles positions did not provide more than a superficial insight on the relation of the market price and price differentiation. Additionally, a different price comparison website could have provided more data points. This was prevented by anti data scraping measures of other price differentiation sites.

7.3 Future Work

This thesis showed, that further research on price differentiation should yield interesting results. One promising direction of further research is tied to a technically more advanced data collection process. A more sophisticated approach to data scraping could provide a much more comprehensive and detailed analysis of price differentiation across online stores. Future analyses could also test for more advanced techniques of segmentation. As Hupperich et al.(2018) pointed out, segmentation based on a customer´s location is already employed. A more detailed look at differentiation based on customer features, such as technical details of the customers hardware, appear to be a promising field of research.

A more focused data collection process and analysis appears to be promising. As this thesis pointed out, there are common determinants to price differentiation. Specifically, the height of the price and the category of products are shown to be common determinants. First, research on the strategies employed by different retailers regarding these two determinants and their interaction appears to be promising. Further studies should investigate retail groups, which are in direct competition to gain more perspective on the impact on price differentiation.

Literaturverzeichnis

Cuellar, Steven S.; Brunamonti, Marco (2014): Retail channel price discrimination. In: *Journal of Retailingand Consumer Services* (21), S. 339–346.

Faßnacht, Martin (1996): Preisdifferenzierung bei Dienstleistungen : Implementationsformen und Determinanten. 1. Aufl. Wiesbaden: Gabler (Neue betriebswirtschaftliche Forschung 188, 188).

Fassnacht, Martin; Unterhuber, Sebastian (2016): Consumer responsetoonline/offline pricedifferentiation. In: *Journal ofRetailingandConsumerServices* (28), S. 137–148.

Homburg, Christian; Lauer, Karin; Vomberg, Arnd (2019): The multichannel pricing dilemma: Do consumers accept higher offline than online prices? In: *International Journal of Research in Marketing*.

Hupperich, Thomas; Tatang, Dennis; Wilkop, Nicolai; Holz, Thorsten (2018): An Emprircal Study on Online Price Differentiation. In: *Conference Papepr*.

Langer, Nina (2020): Top 100 umsatzstärkste Onlineshops in Deutschland. EHI Retail Institute. Available online at https://www.ehi.org/de/top-100-umsatzstaerkste-onlineshops-in-deutschland/.

Phillips, Robert L. (2005): Pricing and Revenue Optimization. 1. Aufl. Stanford: Stanford University Press.

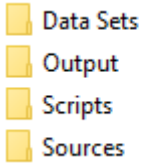
Pigou, A. C. (1932): The Economics of Wellfare. 1. Aufl. London: Macmillan.

Raza, Syed Asif (2015): An integrated approach to price differentiation and inventory decisions with demand leakage. In: *International Journal of Production Economics* (164), S. 105–117.

Wolk, Agnieszka; Ebling, Christian (2010): Multi-channel price differentiation: An empirical investigation of existence and causes. In: *Intern. J. of Research in Marketing* (27), S. 142–150.

Appendix

The appendix provides an overview of the structure of the digital appendix of this thesis.



The digital appendix is divided into the folders the “Data Sets”, “Output”, “Scripts” and “Literature”. The folder Data Sets includes all data, which was analyzed in this thesis. It is divided into the seminar data sets and the scraped data sets. The scraped data sets include the general data sets(price data sets and start/end time data sets) and the transformed data sets(see chapter 4). The seminar data sets include the data sets A, B, C and BC.

The folder output includes all SPSS output of the analysis. It is divided into scraped data and seminar data. All output files are labeled with according to the analyzed data sets and the part of the analysis.

The folder scripts contains all data scraping scripts and the transformation scripts for the different groups.

The folder “Sources” contains all sources, which were available to download.