

Oskar Larsen

Determinants of Attendance at Sport Events

- *What affected attendance at Tappara home games during the 2014-2018 Liiga regular seasons?*

Master's Thesis in Information Systems
Supervisor: Anssi Öörni

Faculty of Social Sciences, Business and
Economics
Åbo Akademi University
Åbo 2018

ABSTRACT

ÅBO AKADEMI – Faculty of Social Sciences, Business and Economics	
Subject: Information Systems	
Author: Oskar Larsen	
Title: Determinants of Attendance at Sports Events – <i>What affected attendance at Tappara home games during the 2014-2018 Liiga regular seasons.</i>	
Supervisor: Prof. Anssi Öörni	
<p>Abstract: Decades ago the airline and hotel industries pioneered methods for changing prices in real time. This type of approach was developed in order to keep pace with the fluctuating nature of customers and changing levels of consumer demand. This demand-based approach was named revenue management. Contrary to the early adopters, the sports industry has been slow to move away from their traditional cost-based pricing approach. The growth of operating costs in combination with the emergence of vibrant secondary ticket markets has forced sports organizations to reconsider their pricing strategies. The adaptation of dynamic pricing has seen success, especially in the North American sports market. Still, utilization of dynamic pricing is sparse in the Finnish market.</p> <p>Research within dynamic pricing and its potential benefits is still limited. This is especially true in the context of Finnish sports and ice hockey. This thesis utilizes previous research on attendance and price determinants in the North American market with the purpose of studying the potential of dynamic pricing and determinants of attendance in the Finnish ice hockey market.</p>	
Key words: Dynamic pricing, attendance determinants	
Date: 15.10.2018	Pages: 83
The abstract is approved as a maturity test:	

TABLE OF CONTENTS

ABSTRACT	1
LIST OF FIGURES	6
LIST OF APPENDICES	7
SUMMARY	8
1 INTRODUCTION	9
1.1 BACKGROUND.....	9
1.2 PURPOSE	13
1.3 RESEARCH QUESTIONS	13
1.4 CONTEXT	14
1.5 LIMITATIONS	14
1.6 THESIS STRUCTURE	15
2 PRICING – FROM STATIC TO DYNAMIC	16
2.1 FIXED VS DYNAMIC PRICING STRATEGIES.....	16
2.1.1 <i>Advantages of fixed pricing</i>	16
2.1.2 <i>Disadvantages of fixed pricing</i>	16
2.1.3 <i>Advantages of dynamic pricing</i>	17
2.1.4 <i>Disadvantages of dynamic pricing</i>	17
2.2 DYNAMIC PRICING	17
2.3 PIONEERS OF DYNAMIC PRICING	20
2.3.1 <i>Travel and hospitality industry</i>	21
2.3.2 <i>Retail Industry</i>	21

2.4	ANALYTICS AND DYNAMIC PRICING	23
2.4.1	<i>When Does Dynamic Pricing Work?</i>	23
3	SPORTS TICKETING	25
3.1	FIXED TICKET PRICING	26
3.2	VARIABLE TICKET PRICING (VTP).....	27
3.3	DTP AND SPORTS.....	28
3.3.1	<i>Sports tickets and dynamic pricing – a good fit?</i>	29
3.4	MANAGERIAL CONSIDERATIONS.....	32
3.4.1	<i>Data Management And Pricing Decision</i>	32
3.4.2	<i>Revenue Maximization Vs Attendance Maximization</i>	33
3.4.3	<i>Secondary Market Sponsorships</i>	34
3.4.4	<i>Time</i>	35
3.4.5	<i>Season Ticket Holders</i>	36
3.4.6	<i>Price Ceilings And Price Floors</i>	37
3.4.7	<i>Price Transparency</i>	38
3.4.8	<i>Face Value</i>	39
4	REVIEW OF LITERATURE	41
4.1	VTP AND DTP IN SPORTS.....	41
4.2	ATTENDANCE DETERMINANTS	42
4.2.1	<i>Venue Quality And Location</i>	43
4.2.2	<i>Effect Of Promotions</i>	44
4.2.3	<i>Game-Related Factors</i>	45
4.2.4	<i>Other Factors</i>	45

4.3	PRICE DETERMINANTS	46
5	METHOD	50
5.1	RESEARCH DESIGN	50
5.2	DATA COLLECTION	51
5.3	DEPENDENT VARIABLE	51
5.4	INDEPENDENT VARIABLES	51
5.4.1	<i>Time-Related Variables</i>	51
5.4.2	<i>Game-Related Variables</i>	52
5.4.3	<i>Environmental</i>	52
5.4.4	<i>Team Performance Variables</i>	53
5.5	DATA ANALYSIS	53
6	RESULTS	54
6.1	MULTIPLE LINEAR REGRESSION	54
6.1.1	<i>Fit of the model</i>	56
6.2	STEPWISE REGRESSION	59
6.2.1	<i>Fit of the model</i>	60
7	CONCLUSIONS	63
7.1	THEORETICAL CONCLUSIONS	63
7.2	MANAGERIAL CONCLUSIONS	63
7.2.1	<i>Opposition</i>	64
7.2.2	<i>Weekday versus weekends</i>	65
7.2.3	<i>Team performance</i>	65
7.2.4	<i>Other factors</i>	66
7.3	LIMITATIONS	67

8	SVENSK SAMMANFATTNING	68
8.1	INLEDNING	68
8.2	SYFTE OCH FORSKNINGSFRÅGOR	69
8.3	FRÅN STATISK TILL DYNAMISK PRISSÄTTNING	70
	8.3.1 <i>Skillnaden mellan statisk och dynamisk prissättning</i>	71
	8.3.2 <i>När fungerar dynamisk prissättning</i>	72
8.4	IDROTTSBILJETTER.....	73
8.5	TEORI OCH LITTERATUR ÖVERSIKT	77
8.6	METOD.....	80
8.7	RESULTAT.....	82
8.8	SLUTSATSER	83
9	BIBLIOGRAPHY	84
10	APPENDICES	89

LIST OF FIGURES

Figure 1: An estimation of the amount of data in the world by 2020.....	19
Figure 2: Inefficient fixed pricing.....	26
Figure 3: Two-tiered VTP.....	27
Figure 4: Multi-tiered VTP.....	27
Figure 5: Daily VTP.....	28
Figure 6: Call for first model.....	54
Figure 7: Summary of output for the first model.....	55
Figure 8: Call for step.model using the stepwise regression method.....	59
Figure 9: Summary of output for the stepwise model, including only statistically significant variables.....	60

LIST OF APPENDICES

Appendix 1: Dataset for analysis	89
Appendix 2: Summary of results full.model & step.model	90
Appendix 3: Full.model and Step.model normal distribution plots for residuals.....	92

SUMMARY

Purpose – The purpose of this thesis is to study attendance determinants at Tappara home games between 2014 and 2018. This thesis also explores the potential of adopting variable and dynamic pricing models within sports events in Finland. In order to support the adaptation of VTP and DTP, sports organizations must understand which factors affect their attendance the most.

Method – The approach chosen for this thesis is a quantitative analysis of attendance at Tappara home games, using a multiple linear regression model. Multiple independent variables were analyzed in order to explain changes in the dependent variable.

Findings – Attendance at Tappara home games was affected by factors identified in previous research. The findings show that factors such as opposition, time of the game and team performance affected attendance numbers during the 2014 to 2018 seasons.

Originality – This thesis studied attendance data from four regular seasons to determine what affects attendance at Tappara home games. The findings should be of interest when developing demand-based pricing strategies in the Finnish sports market.

Limitations – The study focused on attendance data from only one team during a time-period where the team performed similarly between the four regular seasons in the data set. Added teams and a broader time window would provide more comprehensive results

1 INTRODUCTION

1.1 BACKGROUND

My interest in sports dates all the way back to my childhood and youth. I have played different sports all my life, during which I have tried everything from ice-hockey, tennis, football and horseback riding. This interest has not been limited to me actually playing. During my studies, I have also developed a keen interest in the management of sports teams and organizations. Today, the sports industry is a global multibillion business with the biggest sports brands having millions of followers and fans around the world. This development has also led to sports organizations being run more professionally than ever. Passion and enthusiasm have taken a step back and been replaced by more business-oriented approaches, even here in Finland. This business-first type of mentality also plays a major role in the success teams are having on the sports fields. Better financial resources more often than not lead to better players etc. This is obviously not a guarantee for success, but a healthy economy certainly makes it easier to achieve. In the ever more competitive market of sports, teams are constantly looking for ways to maximize revenue streams. This includes the revenue generated by ticket sales. As more and more teams have embraced dynamic pricing of tickets in bigger sports markets, it should not come as a surprise that we should expect dynamic pricing in Finnish sports to take off in the future. Even today a handful of teams in Liiga, the premier ice hockey division in the country, have embraced dynamic pricing systems in an attempt to generate more revenue or maximize attendance.

The concept of real-time pricing has existed for a long time. Travel-related industries, such as hotels, car rentals, and airlines have employed this technique for years. Real-time pricing has also been implemented in the market for energy and insurance. The sports industry is different for various reasons and the demand across individual games tends to behave differently from industries that could be described as more traditional. Still, it is sensible to expect that the dynamic pricing of sports tickets should allow teams the ability to price their inventory in the most efficient way possible. There is considerable evidence that this can be done successfully, primarily in the North American market, where

multiple teams have been able to increase revenues using more efficient pricing techniques.

The sports industry has been slow in adopting more flexible pricing strategies. There are multiple reasons why the sports industry has only started to adopt dynamic pricing on a larger scale. One major reason are the supporters. Sports involves great passion, especially for the fans. Today, there is greater fan acceptance of real-time pricing in sports, as fans have become more accustomed to more aggressive pricing strategies in other industries. Also, the advancement of ticket pricing technologies has played a significant role. These advancements in both software and hardware has made it logistically possible to implement dynamic pricing. It is clear that the incentive for sports organizations to adopt DTP is money, as it boosts their revenue maximization goals. Still, there are also benefits for the consumers. They might be incentivized to purchase season-tickets in order to secure better price certainty. This might also give consumers the flexibility to acquire savings on low-demand games (Rishe, 2012).

The increased competition in Finnish sports has also led to a heightened demand for more business-oriented approaches. Finnish sports organizations are no different from bigger market organizations in that they are also looking for ways to maximize revenue streams in order to earn more money. The demand for more resources is universal and applies to organizations in Finland, whether they are involved in sports or not. Still, there has not been a widespread adaptation of dynamic pricing models in the Finnish sports industry. The reasons at this point can be speculatively explained by the sports industry being slow to embrace this sort of approach globally and also by the small resources of Finnish sports organizations. It should also be noted that dynamic pricing is a particularly complex process, requiring expert knowledge in fields such as mathematics and statistics. The process includes both technical challenges in addition to more emotional and human resources-related challenges. Change is more often difficult to implement and changing the way things have been done for years, in an industry and culture that has been traditionally reliant on experience and intuition, is a long and complicated process. The change in ticket pricing philosophies is no different. Luckily, many teams have already gone to VTP strategies and a handful of teams in the Finnish Liiga have adopted DTP. Spreading DTP strategies will require education of ticketing operations, but also the fans buying the tickets. The challenges are also technical in nature. Ticketing systems have

traditionally been quite inflexible and even simple changes in prices might have taken hours or even days to implement. Changing prices across every section and every seat in an arena would have taken significant amounts of time. With advances in technology and ticketing systems, organizations have the ability to change thousands of prices within seconds (Rishe, 2012).

During the last 40 years, the pricing of sports tickets has stayed largely the same. There have been little to no changes in the way sports organizations price their tickets. The traditional approach has been to maintain a fixed pricing structure where the main determinant for the ticket price has been the location of the seat. This is still the main approach to pricing tickets in the Finnish sports market. Ticket prices for each game are set in advance and are often static throughout the season, with little variation even between seasons. This leaves little to no opportunity to adjust prices based on consumer demand for each game. Evolving technology and the emergence of e-commerce in the 21st century has led to the development of secondary ticket markets, especially in the most popular sports markets, such as the United States. These secondary markets have been instrumental in developing models to maximize the profit of selling tickets by trying to determine the consumers' willingness to buy. The emergence of the secondary ticket market has forced sports organizations to rethink their pricing strategies in order to tap into the revenue streams caused by inefficiently priced tickets (Drayer & Shapiro, 2012).

After the shift of the millennium, there have been organizations experimenting with variable ticket pricing (VTP) where a certain number of games were identified as "premium" based on a variety of factors (Rascher, et al., 2007). The adaptation of VTP pricing was supported by the earlier research and the findings of McDonald and Rascher in 2000 (McDonald & Rascher, 2000). They studied more than 50 independent variables and their effect on attendance in Major League Baseball. The findings showed that variables such as day of the week, home and visiting teams' winning percentages and weather had an effect on attendances that could be considered statistically significant. The modern approach, however, has approached pricing from a different angle. Modern pricing strategies try to estimate consumer demand with the use of multiple market variables. This estimation is then used in an effort to optimally price tickets, based on the demand of each individual game. Research shows that these variables affect the consumer demand for the product. Prices of modern sports tickets can be adjusted based on this

demand. By automating this process sports teams have the possibility to earn extra revenue. According to Drayer and Shapiro (2012), previous literature on the subject shows that “present day ticket prices for sporting events vary as a result of a wide variety of quantifiable factors”. In order for Finnish teams to have the ability to move to dynamic pricing models, variables that affect attendance in their events have to be identified. This is critical in understanding how attendance in the Finnish ice-hockey market works and which variables affect attendance the most.

Despite many teams having adapted VTP, organizations in Finland are still setting ticket prices well before the start of the season. Even though organizations are well informed of their market, this type of pricing still runs the risk that actual consumer demand is not realistically reflected in the ticket prices. In bigger markets organizations have begun to embrace dynamic ticket pricing, as a response to this limitation. This is especially evident in the North American sports market (DTP) (Drayer & Shapiro, 2012).

The San Francisco Giants were the first team in professional sports to adopt a complete dynamic pricing strategy. This included prices that fluctuated daily based on their perceived demand in changing market conditions. During their first season, the Giants reported an increase of 7% in revenue. After this initial success, teams in the Major League Baseball (MLB), National Basketball Association (NBA) and National Hockey League have rapidly adopted dynamic pricing strategies. As of March 2013, 21 of the 30 teams in the MLB had implemented a form of DTP to some extent (Drayer & Shapiro, 2012).

With the successful emergence of DTP and documented increases in both revenue and attendance, the Finnish sports market is starting to take note. In order for Finnish organizations to successfully adapt DTP models, more research is needed to understand the factors that affect attendance in the context of the Finnish sports event market. According to Drayer and Shapiro (2012), “price setting in a demand-based environment is contingent upon understanding the variables that influence fluctuations in demand.” Ticket sellers have an increased need to understand attendance determinants in order to understand what factors affect attendance and to what extent. Empirical evidence of these determinants in the Finnish market is limited. Finnish sellers need to examine attendance determinants in order to maximize profits through efficient pricing strategies. Previous research has also examined organizational pricing determinants with traditionally priced

tickets that were priced prior to the beginning of the season (Reese & Mittelstaedt, 2001) (Rishe & Mondello, 2003) (Rishe & Mondello, 2004). Still the Finnish sports market has been researched even less, if at all. Research is needed in DTP models but also pricing and attendance determinants in context to the Finnish market.

Therefore, the purpose of this study was to examine Liiga attendance determinants in the primary market. By identifying the factors in the literature which traditionally influence attendance, exploratory models examining the factors influencing attendance were developed. An empirical investigation of the attendance determinants in the primary market provides ticket sellers a foundation when planning and implementing VTP and DTP strategies. According to Drayer and Shapiro (2012), a continued understanding of the factors affecting ticket prices and attendance is critical for revenue generation. This is due to the fact that both sellers in the primary and secondary markets continue to utilize demand-based strategies successfully.

1.2 PURPOSE

The objective for this thesis is to determine what has affected attendance at Tappara home games between 2014 and 2018. This thesis also explores the potential of adopting variable and dynamic pricing models within sports events in Finland. In order to support the adaptation of VTP and DTP, sports organizations must understand which factors affect their attendance the most. This thesis aims to support the adaptation of new pricing models and help organizations to realize the potential revenue increases that could be achieved by adopting dynamic pricing models.

1.3 RESEARCH QUESTIONS

In order to achieve the set objectives for this thesis, two separate research questions were developed:

RQ1: What factors affect attendance for Tappara in the Finnish Liiga?

RQ2: What factors can be considered significant when considering dynamic pricing strategies?

This thesis aims to support the adaptation of dynamic pricing models in the Finnish sports industry. The results and conclusions from this thesis should be beneficial to organizations looking to adopt more dynamic pricing models. This also includes how dynamic pricing might achieve higher revenues for Finnish sports organizations. The study should be of use to any ticketing operation in the biggest sports in Finland but also in the Nordic countries and even Europe.

1.4 CONTEXT

The study will be limited to Tappara men's hockey team, playing in the Finnish Liiga, the premier ice hockey league in Finland. This is due to the sheer size difference compared to other sports. Ice hockey is the premier sport in Finland, both in terms of money and attendance. This will result in bigger sample sizes when studying historical attendance records. I have chosen to concentrate the study on Tappara home games as it is my home town team and, therefore, I found it to be the most interesting direction for the analysis. The data required for this research will be publicly available. This includes attendance records for the team in the scope of the research in addition to any independent variables.

1.5 LIMITATIONS

The focus of this study is to determine what variables affect attendance at Tappara regular season games. This information should be important when designing and potentially implementing dynamic pricing strategies in the Finnish sports market. Attendance determinants are only studied for a single team and the data set only spans four seasons. This kind of analysis could for example be performed on all Liiga teams with further data from additional regular seasons. The analysis could also be performed in the context of other sports as attendance determinants might differ from ice hockey. The analysis also does not include any data from playoff games, where the demand is much higher.

This thesis only analyzes how different variables affect attendance at Tappara home games. Additionally, pricing determinants in a dynamic pricing context could be analyzed in the future as data from this type of pricing become available.

1.6 THESIS STRUCTURE

This thesis consists of nine main chapters. In the first chapter the topic of the thesis is presented along with the research questions, background information and the reasons why I have chosen to study this particular topic.

In the second chapter, in which, the evolution of pricing strategies is described. This involves the shift from static pricing to fully dynamic pricing models. I will also present industries that have acted as early adopters of dynamic pricing strategies. The chapter also discusses prerequisites for dynamic pricing to be successful.

The third chapter introduces how variable ticket pricing (VTP) and dynamic ticket pricing (DTP) have been adopted in the sports industry. Relevant background information regarding sports ticketing is presented.

The fourth chapter introduces the theoretical framework, general theory and literature review of pricing tickets in sports in addition to price and attendance determinants in the context of sports. This part is relevant in order to answer the research questions of the thesis.

The fifth chapter discusses the methodology of the thesis. The method used in the thesis is a quantitative analysis of 120 Tappara home games during the 2014-2018 regular seasons using a multiple regression analysis.

The results of the multiple regression analysis are presented in chapter six and conclusions from this thesis are followed in chapter seven. The conclusions discuss both theoretical and managerial conclusions of the thesis.

Chapter eight includes a complete summary of the thesis in Swedish. The ninth chapter is the bibliography of the thesis. Appendices are listed in the last and tenth chapter.

2 PRICING – FROM STATIC TO DYNAMIC

In this chapter, I will explain the concepts of different pricing strategies, ranging from traditional fixed pricing strategies to modern dynamic pricing strategies. I will also present the evolution of dynamic pricing, its history and relation to traditional industries that have acted as early adopters of this type of pricing. Later in the chapter, I will also explain how and under what circumstances dynamic pricing has been adopted by sports organizations and its relation to attendance determinants.

2.1 FIXED VS DYNAMIC PRICING STRATEGIES

Kokemuller (2018) defines fixed pricing as a strategy in which a price point is established and maintained for an extended period of time. Dynamic pricing means that the price of a product or service can change over time. It is imperative for any business to select an appropriate pricing strategy, as it has major implications in the effort to attract customers and reaching optimal profit margins (Kokemuller, 2018).

2.1.1 ADVANTAGES OF FIXED PRICING

The main strength of fixed pricing is that it attracts customers and clients that value price certainty. For example, in a project environment, a fixed price allows potential clients to estimate the costs of the project prior to any agreements. Another attribute of fixed pricing is its consistency. Customers get used to certain prices and companies have less risk of offending their customer base with fluctuating prices. Projecting sales and profits also becomes a simpler task when the price point is known (Kokemuller, 2018).

2.1.2 DISADVANTAGES OF FIXED PRICING

The main disadvantage of fixed pricing is its rigidity. Fixed pricing does not allow for adjustments when costs are higher than expected. This is especially true in the product and service delivery businesses. When a price is established beforehand, companies are not able to adjust their price regardless of changes in spent time or increased costs. This may lead to undercharging customers even with added work hours compared to the initial

estimate. In the event and entertainment businesses, fixed pricing does not allow managers to sell off extra inventory or available seats or tickets (Kokemuller, 2018).

2.1.3 ADVANTAGES OF DYNAMIC PRICING

Another term often associated with dynamic pricing is price discrimination. This is due to the fact that dynamic pricing allows for the maximization of profits from every customer. This approach is preferred in events like concerts or sports games. If demand is initially lower than expected, event managers can sell off open seats with discounts in order to generate any revenue that is possible. Another positive with dynamic pricing is that service projects can be priced according to the time and cost involved, or simply based on fluctuating demand. This is common practice also with seafood distributors and restaurants, who often vary their prices seasonally or based on inventory supply (Kokemuller, 2018).

2.1.4 DISADVANTAGES OF DYNAMIC PRICING

When prices are constantly changing, it is easy to alienate your customer base. If customers feel they have paid more than their peers for the same product or service, they might lash back. This can take the form of demanding their money back or spreading negative messages regarding the company. This kind of approach to pricing may also be viewed negatively by customers that value knowing the price up front before a purchase. Dynamic pricing also requires advanced pricing systems in order to optimize prices. The hospitality and entertainment industries often make use of advanced pricing algorithms to adjust prices in real time (Kokemuller, 2018).

2.2 DYNAMIC PRICING

As mentioned earlier, dynamic pricing is nothing new. According to Burger and Fuchs (2005) the main purpose of dynamic pricing is to offer products in accordance with various groups demand curves and price sensitivity. Arnoud den Boer (2013) describes dynamic pricing with learning as a combination of two research fields: statistical learning and price optimization, both of which have been around for a while. He goes on to describe dynamic pricing more specifically as the study of “determining optimal selling

prices of products and services, in a setting where prices can easily and frequently be adjusted”. Additionally, Dictionary.com defines the term as “commerce offering goods at a price that changes according to the level of demand, the type of customer, or the state of the weather”. What these definitions from seemingly different sources have in common, is that dynamic pricing is characterized by the ability to set optimal prices according to the perceived demand of a product or service, across changing conditions.

It is worth noting that dynamic pricing is not limited to e-commerce businesses or to vendors selling their products online. Digital price tags enable brick-and-mortar stores to make use of dynamic pricing in store. The use of digital technology is the common denominator. Technological advancements have enabled businesses to continuously adjust prices, according to changes in conditions and circumstances. Companies are now able to adjust prices in an instant, without incurring any costs or effort. Many times, this can be done automatically, with minimal human input. This type of dynamic pricing is widely used in different fields of business and has in many cases become an integral part of pricing policies (den Boer, 2013).

Price optimization (PO), also known as yield (YM) or revenue management (RM), assumes that the primary causal variable in customer purchase behavior is the price of a product or service. Arnoud den Boer further states that the key to the successful use of RM techniques is price elasticity. More specifically RM seeks to understand the response of buyers as the price of a product either increases or decreases. Therefore, these types of pricing techniques are looking to predict the behavior of demand under different circumstances. This is often done with the help of price elasticity curves which are constructed to help understand the impact of price across a range of changes and conditions (den Boer, 2013).

In order for companies to make use of dynamic pricing algorithms, data and the application of analytics solutions are required. Pricing algorithms are often multifaceted and take multiple factors into account, such as competitors, time, supply and demand, customer profiles and several external market factors. The rise of digital sales environments has ensured that businesses are provided with an abundance of sales data. In fact, most estimates predict that there will be 45 zettabytes of data in the world by 2020. According to Cave (2017) some estimates go even further and predict that if certain circumstances are met, the world might be creating up to 160 zettabytes of data a year by

2025. This is a significant increase from the estimated 20 zettabytes of data in the world as of 2018.

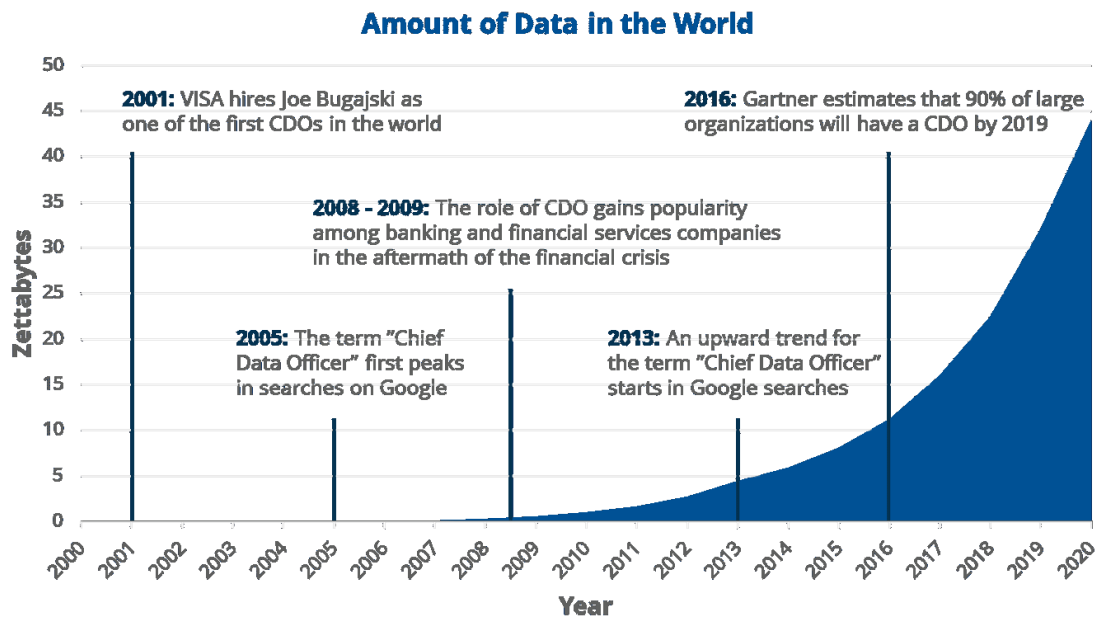


Figure 1: An estimation of the amount of data in the world by 2020.

Even if the most dramatic predictions don't come to fruition, it is safe to say that businesses will still have access to more data than ever before. This kind of data can contain important insights into consumer behavior. With the right type of analytical applications, this information can be turned into knowledge with potential competitive advantages. Arnoud den Boer describes the research of the field as following: "Exploiting the knowledge contained in the data and applying this to dynamic pricing policies may provide key competitive advantages, and knowledge of how this should be done is of highly practical relevance and theoretical interest. This consideration is one of the main drivers of research on dynamic pricing and learning: the study of optimal dynamic pricing in an uncertain environment where characteristics of consumer behavior can be learned from accumulating sales data" (den Boer, 2013).

The literature on dynamic pricing and learning has seen contributions from different scientific communities in recent years and has been growing rapidly in recent years. Fields such as operations research and management science, marketing, computer science and economics/econometrics are few of the fields that are contributing to research on the subject (den Boer, 2013).

2.3 PIONEERS OF DYNAMIC PRICING

Demand is stochastic by nature. Companies can draw benefits from this phenomenon by pricing dynamically. When prices are set dynamically, companies are delaying their pricing decisions until they know the prevailing market conditions and adjust their prices accordingly. In theory, companies that implement dynamic pricing should earn higher revenues than companies committing to fixed prices before learning what the actual demand is. The advantages seem obvious, but still, many companies are pricing their products and services without taking market conditions into consideration (Cachon & Feldman, 2010). This kind of pricing is exemplified by movie theaters charging a preset price without taking into regard the quality of the movie. Highly popular movies are usually also priced the same as movies with lower demand levels. Restaurants do not charge more when they are busy, and sports teams charge the same price, regardless of how well they have been playing, opposition or weather on the day of the game (Cachon & Feldman, 2010).

It is worth noting that companies do in fact take advantage of their consumers' heterogeneity. According to Cachon and Feldman (2010) this is done by segmenting the market and charging different prices from different customer segments. For example, movie theaters charge lower prices for daytime shows and weekdays. They also offer discounts for students and senior citizens. Restaurants offer different menus for lunch and dinner and some sports teams might charge different prices for seats before and after certain holidays. However, these pricing decisions are made before the realization of demand and consumers have knowledge of them in advance (Cachon & Feldman, 2010).

Even if some companies are still pricing their products more traditionally, dynamic pricing is already used by a large number of businesses operating in various industries. According to Davenport & Harris (2007) "companies are using analytics for a competitive advantage by pricing products appropriately, whether it is Wal-Mart's everyday low pricing or a hotelier's adjusting prices in response to customer demand." Analytics has enabled them to engage in dynamic pricing, allowing them to adjust prices on-the-fly in response to changing market conditions. These variables include factors such as demand, inventory level, competitor behavior and customer history. According to Davenport and Harris (2007), the use of analytically based pricing software is spreading among industries.

2.3.1 TRAVEL AND HOSPITALITY INDUSTRY

The concept of dynamic pricing was originally developed by the airline industry based on forecasted demand and inventory availability (Cross, 1997). This concept was called “yield management”. The yield management concept was later adopted by other industries, such as the hotel industry. The term “yield” was associated with the airline industry and therefore replaced with the term “revenue” (Drayer, et al., 2012 a). In this thesis, I will refer to “dynamic pricing” or “revenue management” throughout the study.

The nature of the travel and hospitality industries is suitable for dynamic pricing strategies. Hotel rooms are perishable assets and by setting the optimal prices dynamically, the revenue they generate can be maximized. This is also true for flight tickets. Customers also have the ability to change their purchase plans with the aim of paying as little as possible.

As with countless other industries, the emergence of the Internet has had a significant impact on both industries. Online booking sites provide greater price scrutiny than ever as relevant information is easy to access. Any given party has access to price information and can compare several alternatives with little effort. The rapid access to information and response inevitably has an effect on how hotels set their room prices (Abrate, et al., 2012).

2.3.2 RETAIL INDUSTRY

Before the adaptation of dynamic pricing, retailers set their prices based on intuition. With modern analytical software, retailers are able to price their products with speed and accuracy. This type of software will analyze a retailer’s point-of-sale data to determine factors such as price elasticity and cross-elasticity (Davenport & Harris, 2007). Price elasticity is a microeconomic measure for change in demand for a good when the price changes good substitute for another (Investopedia), whereas price cross-elasticity measures whether a good is a good substitute for another (Investopedia). These measures are used in algorithms that determine optimal prices to maximize sales and profits (Davenport & Harris, 2007).

A popular technique among retailers has been to use analytics to optimize mark-downs. This optimization has involved the question of when and by how much to lower prices.

Additional price optimization targets have been the analysis of promotions, category mix, along with the breadth and depth of assortments. According to Davenport and Harris (2007) “most retailers experience a 5 to 10 percent increase in gross margins as a result of using price optimization systems”. They continue with citing a report by Yankee Group, claiming some enterprises to have realized up to 20 percent profit improvements by using price management and profit optimization (PMPO) solutions.

JCPenney was one of the frontrunners in adopting price optimization software and processes within the retail business. The company has implemented analytics throughout their business, including merchandising, pricing optimization and the supply chain. According to Davenport and Harris (2007) “this approach helped the company add five points to gross margin, increase inventory turns by 10 percent, and grow top-line and comparative store sales for four consecutive years (2001 through 2004).”

Davenport and Harris (2007) present Dell as an additional case of achieving success with the use of dynamic pricing. When combined with other analytic data, dynamic pricing can provide strategic advantages. Dell managed to anticipate the economic downturn of 2000 and 2001, with the use of their forecasting system. This allowed them to prepare sufficiently by cutting costs and slashing prices. The company was able to weather the recession much better than their competition. Their sales only went down 2.3 percent in 2001, compared to Hewlett-Packard (sales down by 32 percent), Compaq (down 36 percent), and Gateway (down 62 percent). Dell also managed to increase their market share after the economy shifted (Davenport & Harris, 2007).

While it is important to recognize the possibilities that the use of dynamic pricing strategies can bring, it is also of equal importance to recognize the risks that come with it. Most consumers today are familiar and used to the idea of products and services being priced dynamically, according to prevailing market conditions. Davenport and Harris exemplify this with the case of Amazon.com. By examining price-elasticity of DVDs sold through their website, Amazon identified recurring customers and charged them higher. This was seen as morally wrong by many, and the company was forced to change their pricing strategies as a result of the backlash (Davenport & Harris, 2007).

2.4 ANALYTICS AND DYNAMIC PRICING

In this chapter, I will explain why analytics, data analysis and business intelligence exist and what purpose they serve in relation to DTP. I will briefly introduce their history, why their role has become so prominent in modern business and why their significance is expected to grow even further in the future.

2.4.1 WHEN DOES DYNAMIC PRICING WORK?

Revenue management systems combine information systems and pricing strategies with the aim of "determining prices according to predicted demand levels so that price-sensitive customers who are willing to purchase at off-peak times can do so at favorable prices, while price-insensitive customers who want to purchase at peak times will be able to do so" (Kimes, et al., 1998).

For dynamic pricing to work, certain conditions have to be met in the market. In 1989 Kimes (1989) studied the process of implementing RM systems in the hotel industry. In her study, she identified six prerequisite circumstances for the pricing strategy to work efficiently. These circumstances were discussed by Drayer et al. (2012 a) and their observations are listed below.

- 1. The ability to segment markets** – Marketing managers can make use of different marketing strategies and differentiate prices by segmenting their customer base into different groups.
- 2. Perishable inventory** – If inventory is perishable, managers are not able to sell any unsold products after they expire. Many industries, such as the tourism and hospitality industries face these kinds of issues.
- 3. Product sold in advance** – The issue deals with time and the uncertainty of sales. With the ability to make effective pricing decisions, some of this uncertainty is negated over time.
- 4. Low marginal sales costs** – When serving additional customers costs do not increase significantly. This means that organizations might be incentivized to change prices, in order to sell more of their remaining stock.

5. High marginal production costs – This criterion indicates that it is difficult, if not impossible for a manager to increase the inventory of the company. This applies for example to the travel and hotel industries, where it is virtually impossible or at least very expensive, for hotel and airline operators to add rooms or seats at hotels or airplanes respectively.

6. Fluctuating demand – RM systems are able to adjust prices based on fluctuations in demand. This might be the biggest advantage in their use. The travel and hospitality industries are characterized by the fluctuating demand. These changes in demand are based on season and the day of the week (Kimes, 1989) (Drayer, et al., 2012 a).

The initial set of 6 criteria, were perfected later by Kimes et al. in 1998 (Kimes, et al., 1998), when they added an additional criterion.

7. Predictable demand – The added criterion is closely related to the previous one. According to Drayer et al. (Drayer, et al., 2012 a) “demand makes it appropriate to charge different prices, while predictable demand makes it easier to identify when these fluctuations occur”.

Drayer et al. (Drayer, et al., 2012 a) conclude their discussion of Kimes' theories, by stating that her theories “on RM have been widely accepted in both academic and practitioner circles”. They still point out that the seven criteria identified, were originally written for the tourism and hospitality industries (Kimes, 1989) (Kimes, et al., 1998). Therefore, their suitability and usefulness in the context of sports tickets will be discussed in the next chapter.

3 SPORTS TICKETING

Predicting sales in the sports event market has traditionally been based on experience and intuition about historical patterns and data from comparable events. While teams have increased price differentiation across seats and even games, little is known how relative price changes affect a customer's choice amongst seating options. Variable and dynamic pricing requires an understanding of how customer willingness to pay relates to perceived event quality and time until the event (Drayer, et al., 2012 a).

Sports differ in certain areas from what could be described as traditional industries. Still, like in many other areas of business, large amounts of data and expensive human resources are readily available to sports organizations all over the world. Still, whether managing a regular business or a sports organization, both fields of operation have a need to optimize critical resources combined with the need to win. These factors are even more critical in the world of sports (Davenport & Harris, 2007).

The ever-increasing competition in professional sports, in combination with the constant search for success on the field, has led to sports organizations exploring new avenues to increase their revenue streams. This has also had an effect on the types of pricing strategies being employed. Sports teams have traditionally priced every game equally, or at least with little variety. This kind of pricing did not consider how attractive or unattractive a particular game was perceived. New technologies and other disruptive forces impacted the sports event ticket market, which not only opened up new markets for consumers but also forced sports organizations to reevaluate their ticket pricing strategies. For example, in 2006, all teams in the National Basketball League (NBA) priced their tickets statically with no price differences depending on the demand of the game. This static pricing strategy allowed sophisticated resellers to price the same tickets more accurately based on factors impacting demand, such as opponents or date. This kind of secondary ticket markets led to sports organizations losing some of the control over the pricing and sales of their tickets. To counter this loss of control most teams in the NBA and many in other sports leagues have begun to price tickets both variably and dynamically to make the most of the previously unexplored pricing opportunities (Harrison & Bukstein, 2017).

3.1 FIXED TICKET PRICING

In order to understand why DTP strategies are worth the investment of time and resources, we must also understand the inefficiency of so-called fixed pricing strategies. As mentioned earlier in the chapter, these traditional pricing strategies relied on setting static prices in advance, many times for the whole season. Additionally, variable ticket pricing is somewhere in between a completely static and fully dynamic pricing strategy. This type of pricing might involve charging a premium for games considered to be of better quality or charging more for seats that offer better views of the game (Broshears, 2016).

When running an attraction, demand usually varies widely from day to day. This is especially true for sports events, as demand between games might vary quite heavily. Usually, a single price that applies for the whole season is set in advance. When this type of pricing is graphed as demand vs. price, the inefficiency becomes apparent.

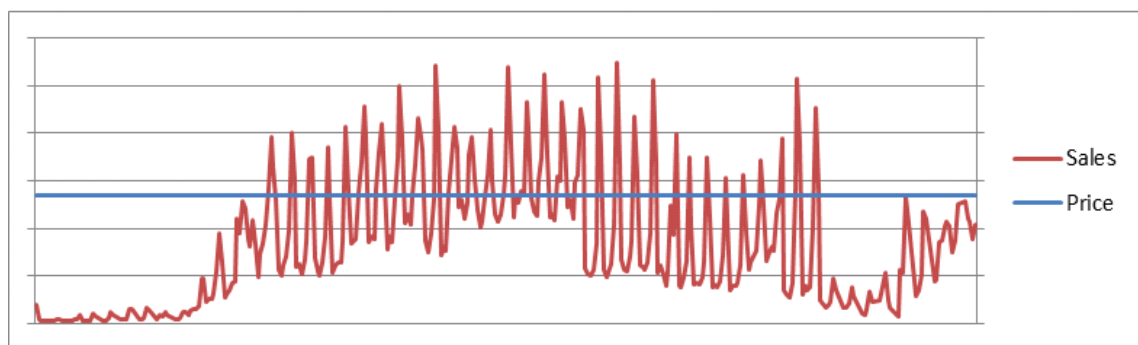


Figure 2: Inefficient fixed pricing

In this illustration, sales are used as a proxy for demand. This is overly simplified but works for the purposes of this illustration. In-depth analysis of demand is much more complex. As illustrated in the graph above, some days are much more popular than others, and admission is worth much more to the market. Still, the cost of a ticket on days when demand is higher is the same as tickets on lower-demand days. When tickets aren't considered as valuable, sales could be boosted by offering various discounts. It is worth noting that these discounts alone do not make use of the potential extra revenue from the high-demand days (Broshears, 2016).

3.2 VARIABLE TICKET PRICING (VTP)

The first step to becoming more dynamic is to adopt variable ticket pricing (VTP). As stated earlier, VTP is somewhere in between fixed pricing and completely dynamic pricing. In this type of pricing, the price for a ticket is still fixed for any given day, but admission is grouped into different categories based on the estimated demand. Usually, tickets are organized into 2-5 different price categories and every game of the season is placed in one of these categories. The prices are fixed for the duration of the season for each category (Broshears, 2016).

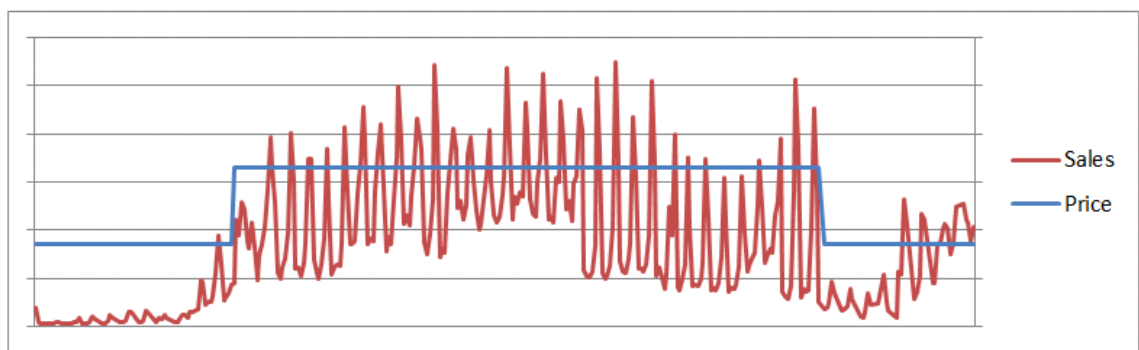


Figure 3: Two-tiered VTP

Variable pricing is illustrated in the graph above, using a simple two-tiered pricing strategy. Tickets are simply divided into normal and off-peak categories (Broshears, 2016).

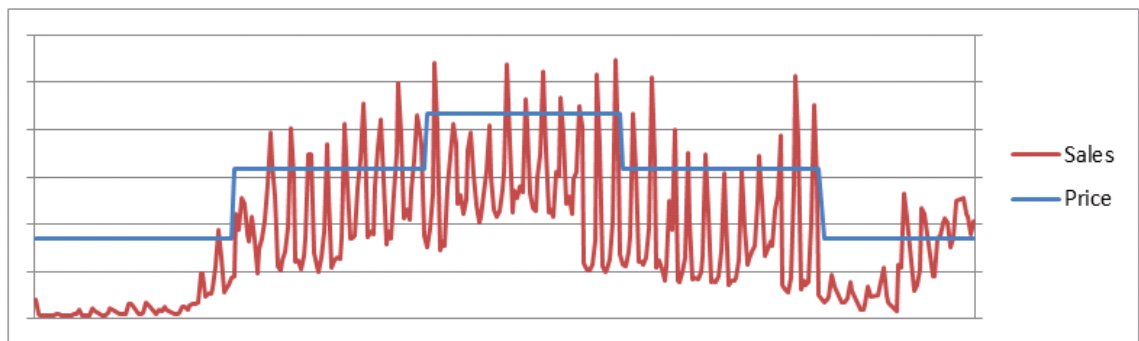


Figure 4: Multi-tiered VTP

More advanced VTP methods use multiple price categories. This added flexibility in pricing gives companies more opportunities to match their prices with the demand of their customers. A multi-tiered VTP strategy is illustrated in the graph above.

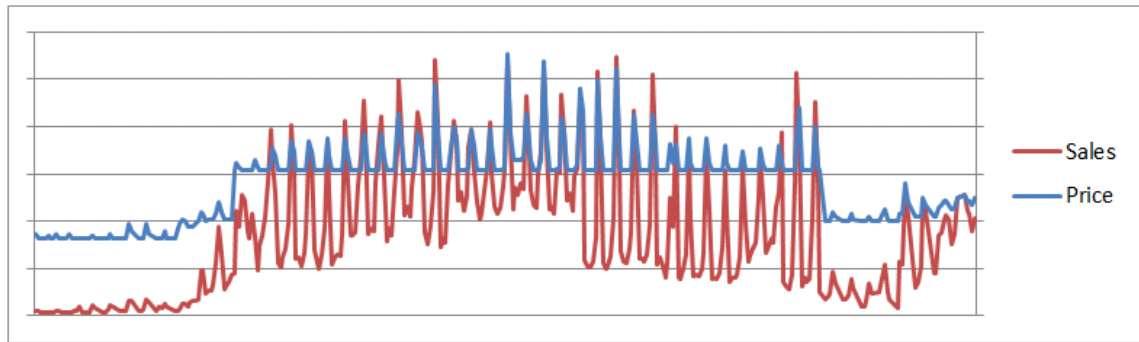


Figure 5: Daily VTP

The most flexible approach to VTP would involve the creation of different price tiers for each day of the year, for each game of the season. This would indeed enable sports teams to account for changes in demand during the course of the season as demand changes from game to game. The problem, however, with this kind of approach is that it is cumbersome to implement and uphold. It can be challenging to project demand before the season starts, even for only a handful of tiers, and having a different tier for each and every game of the season might be impossible for most teams to implement. These are the two main limitations of VTP strategies. There is a practical limit on how many different pricing tiers an organization can implement and uphold. The price for each tier is also fixed based on predictions made before the start of the season. There is no flexibility to adjust these prices when the conditions in the market change. This is where advanced pricing algorithms come in, as DTP with automation is able to overcome the main limitations of VTP (Broshears, 2016).

3.3 DTP AND SPORTS

In a dynamic pricing environment data are constantly gathered and evaluated. This allows for the adjustment of prices in real time with up-to-date demand forecasts for each day. It is worth noting that changing the prices for one game affects the demand for other games. DTP algorithms must be able to take this into account. Gathering and analyzing data is required in fixed, variable and dynamic pricing. What makes dynamic pricing the most efficient method of pricing?

- Dynamic pricing algorithms have superior data processing powers compared to individuals or even teams of individuals.

- Dynamic pricing algorithms are developed by highly specialized professionals. The algorithms make use of advanced statistical techniques and econometric theories. This type of knowledge is not accessible for most ticketing operations.
- Dynamic pricing algorithms are constantly at work while people employed at ticket operations also perform other tasks. Therefore, prices are constantly fine-tuned.

Even with all the strengths of DTP algorithms, it is worth noting that they do not have access to human experience and intuition which can be of critical importance in some cases. They also do not know the business or its customers as an experienced professional can, as this type of information can be difficult to quantify. This is why it is important that even the most automated pricing systems leave the opportunity for humans to review the suggested price adjustments before their implementation (Broshears, 2016).

3.3.1 SPORTS TICKETS AND DYNAMIC PRICING – A GOOD FIT?

Earlier in the last chapter, the seven criteria for successful RM implementation in the hotel industry were presented (Kimes, 1989) (Kimes, et al., 1998). When comparing these seven criteria for RM with the sports industry, it appears dynamic pricing and sports ticketing can be combined successfully. Drayer et al. (2012 a) discussed how these seven criteria are applicable to the sports industry. Their findings are discussed below.

1. The ability to segment markets - According to Drayer et al. (2012 a) there have been several studies in a sports management context, which suggest that market segmentation can be done in a sports context. This can be done with a variety of different characteristics, such as gender, education level or season ticket status.

2. Perishable inventory – Sports as a product is a perishable item. This means that any unsold tickets cannot be sold once the game has been played. In a 2009 study, Drayer and Shapiro identified the significance of the perceived value of a game. This impacts the price consumers are willing to pay for a certain ticket (Drayer & Shapiro, 2009) (Drayer, et al., 2012 a).

3. Product sold in advance – Tickets for sporting events are often sold right up until the last minutes before the event. Still, the initial date when tickets become available is often

months in advance. This means that consumers have a large time window to purchase tickets (Drayer, et al., 2012 a).

4. Low marginal sales costs – Most professional sports events draw crowds in the thousands and even the tens of thousands. This means that servicing additional attendants does not require a significant investment in the day-of-game operations. As the cost of additional fans is low, sports organizations have the opportunity to profit by selling additional tickets (Drayer, et al., 2012 a).

5. High marginal production costs – It is often unrealistic for sports organizations to add additional seats to their stadiums or arenas, either due to resource or space constraints. This makes the marginal production costs of additional seats often very high, as building a new arena, for example, is very expensive (Drayer, et al., 2012 a).

6. Fluctuating demand – As tickets for sporting events are sold during a large time window, the demand for particular games may experience significant shifts between the initial on-sale date and the day of the event. According to Drayer and Shapiro (2009) factors related to team and player performance change regularly, which in turn has an impact on consumer demand (Drayer, et al., 2012 a).

7. Predictable demand – According to Drayer et al. (2012 a) estimating demand in a professional sports setting is a manageable task. They argue that the statistical nature of many professional sports, in combination with easy access to other quantifiable demand factors enables sports organizations to estimate the demand for their product. Plenty of research has been done on the topic, and variance in demand for professional sports tickets has been explained by factors such as home field advantage, outcome uncertainty and labor strikes. Also, more traditional game-related variables, such as team and player performance, have been determined to explain changing levels of demand in sports event tickets (Drayer, et al., 2012 a).

As mentioned above, these seven criteria for successful RM implementation seem to be present in the sports ticket business. In addition to the aforementioned criteria, the presence of a vibrant secondary market in North America indicates that RM approaches are effective in the context of sports (Drayer, et al., 2012 a). In a 1998 research, Boyd and Boyd (1998) argued that whenever secondary market actors were able to sell event tickets with a profit, the tickets were not priced optimally. This notion is also supported by the

successful operation of scalpers and "ticket agents". These operators sell game tickets at prices significantly higher than the face value of the tickets. The existence of this kind of practices in all popular sports suggests that teams set prices too low in order to maximize profits. Sellouts and long waiting lists for season tickets, especially in the North American market, were also presented as evidence that many teams could increase profit by raising prices. It is characteristic for the Finnish sports market that the majority of the events are not sold out, even in the most popular sports like ice-hockey or football. These events have high numbers of unsold seats, indicating that tickets are priced too high, a potential source for additional revenues for many organizations. Research conducted by Rascher et al. (2007) and Drayer and Shapiro (2009) has revealed that teams could earn substantial additional revenue through more efficient pricing practices. These findings do not automatically translate to the Finnish sports market, as demand for sports tickets is lower. Still, there is sufficient room for more flexible pricing in the Finnish market and additional revenue can be gained by adjusting prices based on fluctuating demand.

When it comes to dynamic pricing and revenue management, the hotel industry's approach has focused on maximizing revenue by adjusting the price of room reservations. This approach has typically disregarded additional revenue streams generated by streams such as restaurants, gift shops etc. (Kimes, 1989). Conversely, the sports industry has traditionally maintained a focus on attendance maximization with revenue maximization not playing a major role. Prior research (Courty, 2003) suggests that sports organizations have an incentive to underprice tickets in order to maximize the number of tickets sold. In the study, he suggests that full arenas or stadiums bring significant additional benefits besides revenue from ticket sales. This includes revenue from parking, concessions and merchandise. More fans in the stands is also considered beneficial to the game day experience which enhances the experience for attending fans. The DTP method is more aggressive. DTP attempts to maximize both revenue and attendance, simultaneously.

It could be argued, at least in theory, that high-demand games can be priced higher without compromising attendance numbers. Low-demand games should be priced lower, which should attract more fans because of the lower ticket prices. Although ticket revenue will not be as high in the low-demand games, additional fans should still generate ancillary revenue streams during the event. Additional fans should also enhance the match day experience for everyone in attendance. However, Drayer et al. (Drayer, et al., 2012

a) still argue that every time organizations increase the prices of tickets, they run the risk of decreasing tickets sales. Therefore, organizations are still incentivized to underprice tickets in order to maximize attendance at every game (Drayer, et al., 2012 a).

3.4 MANAGERIAL CONSIDERATIONS

Based on the comparison in the previous section, between the seven prerequisites identified by Kimes and sports, DTP and the sports industry seem like a good fit. Still, before sports organizations are to implement any DTP pricing strategies, there are some factors that decision makers at sports organizations are to consider. These factors are discussed in the section below.

3.4.1 DATA MANAGEMENT AND PRICING DECISION

According to Drayer and Shapiro (2012 a) the San Francisco Giants pricing algorithm is based on historical data. This sort of data can be utilized for highly accurate insights. The problem with historical data is that the market is in a constant state of change. This means that the products sports organizations are offering are also constantly changing. Situational factors around the product, often challenging to even quantify, can change rapidly and dramatically. Drayer et al. (2012 a) exemplify this by comparing different data types sports organizations might use. While team and player performance might be easily quantifiable, factors such as fan expectation of team performance, or identifying the most important player statistics to consumers, might be significantly more challenging to quantify. Still, these factors could have a significant impact on the demand for certain games. While some variables, like economic conditions, might be applicable to the sports industry, factors affecting demand in sports are much more complicated and behave much differently than in many other markets (Drayer, et al., 2012 a).

Like any other organization, also sports teams have to make certain decisions regarding their pricing. Previous research in web-based industries has shown that consumers might respond negatively if they have to pay different prices for the same product (Kung, et al., 2002). This is due to the increased price sensitivity consumers have in the internet era (Kotler & Keller, 2016). Again, as mentioned in the previous section, demand in the

sports industry works differently. The unique nature of sports, as a product, makes it less price sensitive. In 2002 Nagle and Holden (2002) researched factors that were associated with lower price sensitivity. They were able to identify several factors that were related to the aforementioned phenomena. Their findings included factors such as; “a distinctive product, a low awareness of substitutes, an expenditure that is a small part of consumer's income; an expenditure that is a small part of the total cost of the end product; a product that is assumed to have more quality, prestige, or exclusiveness; and a product that cannot be stored (Drayer, et al., 2012 a). The most notable exception when it comes to sports tickets and the factors associated with lower price sensitivity is the criteria of expenditure being a small part of the consumer’s income. Sports fans are a diverse group of people and range from a wide variety of economic groups. For some consumers, sports tickets might be significant amount of money, yet still they might attend certain games (Drayer, et al., 2012 a). On the contrary, while some fans might feel that they are being priced out of attending games, Drayer et al. point out that economic theory still suggest that these consumers are not as price sensitive as expected (Howard & Crompton, 2004). Still, price setting has not been considered as important by sports organizations, as they have favored more traditional cost-based approaches when pricing their tickets (Reese & Mittelstaedt, 2001). Drayer et al. (2012 a) argue that the consequences of shifting to DTP must be carefully considered and analyzed by the practitioners themselves and the scientific community.

3.4.2 REVENUE MAXIMIZATION VS ATTENDANCE MAXIMIZATION

The traditional approach in the hotel industry when it comes to dynamic pricing has been focused on maximizing revenue from room reservations. Little or no emphasis has been put on so-called ancillary revenue streams from restaurants, gift shops or others. This phenomenon, called the ‘multiplier effect’ is more central to modern dynamic pricing methods. Nowadays dynamic pricing is used more as a tool to improve the profitability of the whole hotel or property, rather than solely concentrating on generating revenue through rooms (Drayer, et al., 2012 a).

The approach in the sports industry has traditionally been a bit different. Organizations have focused on attendance maximization, without maximizing revenue gained from tickets sales. This has many benefits and according to Drayer et al. (2012 a) previous

research has shown that sports organizations are incentivized to underprice their tickets in an effort to maximize the number of fans attending games. Research shows that by maximizing attendance, organizations are able to bring in ancillary revenue in the form of parking, concessions and merchandise. Furthermore, a full stadium also provides a better fan experience, which should lead to even more fans attending in the future. The DTP approach aims to bring the best of both worlds when it comes to ticket pricing, the idea is to simultaneously maximize revenue and attendance. The theory behind DTP is quite simple. For high-demand games, where higher ticket prices increase revenue, without affecting attendance numbers negatively, prices are set higher. For low-demand games, prices are set lower, in an attempt to draw more fans. This, in turn, should result in more ancillary revenue and an enhanced game-day experience for the fans (Drayer, et al., 2012 a). As discussed previously, any time prices are increased, organizations run the risk of decreasing attendance. Even with the recent trend of more aggressive ticket pricing and emphasis on revenue generation, this risk has led to many sports organizations still preferring to underprice their tickets, in an effort to maximize attendance (Drayer, et al., 2012 a).

3.4.3 SECONDARY MARKET SPONSORSHIPS

One significant factor that contributed to the emergence of VTP and DTP strategies was the fact that in the North American market, secondary market sellers were making big profits by reselling tickets to events to which they had made no contribution in organizing. Securing season-tickets has become a significant business for people not directly associated with sports organizations. Many season ticket holders only attend a few games a year, where after they sell the rest of their tickets for big profits. According to Drayer et al. (2012 a) these monetary profits, in fact, belong to the organizations and not the ticket-holders who only act as middle-men. The response was to charge higher prices for high-demand events, in an effort to recapture some of the revenue being lost to the secondary market.

The growth and perceived legitimacy of the secondary market has led to many collaborations between organizations, leagues and secondary market actors (Drayer & Martin, 2010). The common practice has been to agree sponsorship deals in which the teams and/or leagues receive compensatory flat fees, whereas the secondary market actors

receive the right to call themselves “official” secondary ticket marketplaces (Drayer, et al., 2012 a). According to Drayer et al., (Drayer, et al., 2012 a) in North America these deals are worth millions of dollars every year. If DTP can dig into the profitability of secondary ticket markets, this should lead to fewer people engaging in the reselling of their tickets. This, in turn, would drive down the value of the sponsorship deals being struck with the secondary market actors. Any decreases in the value of these deals should at least partly be offset by DTP approaches (Drayer, et al., 2012 a). Still, at the moment, these kinds of deals are non-existent in the Finnish ice-hockey market. Demand in Finland is much different and even the most popular Finnish teams only draw crowds that are much smaller than their North-American counterparts. Ticket reselling only ever happens with the most popular games and for example during the playoffs. DTP might be able to limit the profitability of ticket scalping even in Finland. Therefore, the effects on the secondary market should also be considered in the Finnish context.

3.4.4 TIME

The sports product can be described as very uncertain at times. Therefore, teams often consider their season ticket bases as one of their most valuable assets. These fans are not only the most dedicated, but more often than not, also pay for their tickets well in advance. This type of fixed revenue source is very beneficial as the demand for tickets can otherwise fluctuate quite heavily during the season. Not only does this help teams predict their income and generate revenue well before the season even starts, but also help in staffing events according to attendance levels. According to Drayer and Shapiro (2009) time is detrimental when it comes to ticket prices. As events get closer, prices in the secondary market were found to decrease. In theory, an organized group of ticket buyers could wait for the prices to fall as the event gets closer. In reality, this is not a very realistic scenario, but sports organizations have to understand the importance of time in DTP setting. According to Drayer et al. (2012 a) DTP can control many variables efficiently; DTP systems may never be able to account for time as a variable. They use the hotel industry as an example, where room rates tend to increase as the chosen night of stay approaches. If the room is still unsold at the very last-minute heavy discounting might occur. According to Kimes (2010) this type of discounting is in many cases, not recommended, as heavy drops in prices might affect the perceived value customers have of the product negatively. This is due to multiple reasons. For example, customers may

become dissatisfied if they are forced to pay the full price for a room they have previously managed to book for a heavily discounted price. In my personal opinion, this kind of purchase behavior is becoming a bit dated. A large part of modern online consumers is aware of potentially aggressive pricing strategies and understand how the fundamentals of dynamic pricing work. Therefore, they would consider the inability to get a deal which represents good value for them, a personal mistake, rather than being the fault of the seller or the chosen pricing strategy. Still, many customers might become upset if they feel prices are set unfairly. Dissatisfied customers are less likely to repeat purchases and often spread negative word-of-mouth, especially in the internet era. The hotel industry has combated this phenomenon by setting price-floors for rooms. According to Drayer et al. (2012 a) the setting of price floors may reduce room revenues in the short term but is more beneficial in the long run. They argue that the same kind of practice may be well suited to the sports industry in a DTP setting. The prices of tickets might change multiple times before the game, and prices tend to increase as the date of the event gets closer. To prevent heavy discounting just before the event, price floors could be set in order to set a minimum ticket price. Drayer et al. (2012 a) argue that this kind of practice should help fans to purchase tickets at an appropriate price while also keeping their level of satisfaction at a higher rate.

3.4.5 SEASON TICKET HOLDERS

As discussed above, the season ticket holders form a valuable asset to most sports organizations. As this group of fans, who more often than not are the most loyal, is an important source of revenue for organizations, the impact of DTP on them is crucial. Carefully crafted policies are vital in order to incentivize fans into buying season tickets, rather than buying single tickets when they are perceived as good deals. The most obvious scenario that might end up hurting an organizations relationship with their fans would be a low-demand game where DTP would set prices lower than season ticket holders have paid for them. It is important that organizations consider how to avoid this type of occurrences. There are certain steps that can be taken, like providing a price guarantee and crediting season ticket holders when prices drop below their pre-game cost. According to Drayer et al. (2012 a) “the money in this account could be used towards future ticket purchases or even day-of-game purchases such as concessions and merchandise. Additional value-added benefits provided specifically to season ticket

holders, such as parking benefits or invitations to visit with players and coaches, may also continue to incentivize potential consumers to buy full or partial ticket plans.” (Drayer, et al., 2012 a)

It seems that there are solutions that sports managers can rely upon, which they need to be aware of. These types of solutions must be monitored and provided when necessary. Furthermore, the loyalty of season ticket holders and their long-term relationship with the organization must be carefully considered in any DTP strategy. Drayer et al. (2012 a) suggest that any “negative long-term impact from losing loyal fans due to ill-managed DTP may be tremendous”. This claim is supported by literature on dynamic pricing in the hospitality industry (Lindenmeier & Tscheulin, 2008) which found that any negative perceptions of dynamic pricing practices with short-term perspective may cause dissatisfaction among customers and have damaging long-term consequences (Drayer, et al., 2012 a).

3.4.6 PRICE CEILINGS AND PRICE FLOORS

When planning DTP strategies and preparing for scenarios, like the one mentioned above, where a person attending a single game is paying less than a season ticket holder, price floors should be considered. As mentioned earlier, pricing tickets too low can potentially upset season ticket holders, but according to Zeithaml (1988) it also has the potential to devalue a product in the eyes of consumers. One option is to set a floor for each section in their arena that a ticket price could not fall below. This kind of pricing structure is not fully dynamic. In a dynamic approach as the game is starting, any empty seats would be given away essentially for free. In theory, this would be done in order to capitalize on any potential ancillary sales that might be generated through additional fans attending the game (Drayer, et al., 2012 a).

For games in high demand, a true DTP approach would make prices much higher than normal. This means that fans might be paying many times the normal amount for tickets, which again might lead to dissatisfaction among the fans buying tickets. For these high-demand games, organizations might implement price ceilings, in order to keep prices within a reasonable threshold. Drayer et al. (2012 a) argue that in order to build a passionate and loyal fan base, it is important for organizations to give consumers in the low and middle-income brackets, chances to attend games against premium opposition.

When raising prices for premium games, organizations also run the risk of overpricing their tickets, which in turn could lead to actually decreasing attendance levels (Drayer, et al., 2012 a).

If organizations were to implement any type of price ceilings or price floors, it would mean that demand-based fluctuations would be restricted. This could be considered as a sort of compromise between VTP, which is unable to factor in variables that change during the season and a fully dynamic pricing model based on aggressive price discrimination. The choice of pricing strategy is also largely dependent on the existence of any secondary ticket markets. Any price ceilings or price floors might deny teams additional revenue as fans would be scouring for better deals from secondary markets. This is also evident in the Finnish market, as tickets to high-demand games are often resold through secondary channels. Still, there are no secondary ticket market channels specially dedicated to selling tickets. Also, the secondary channels in Finland make no use of DTP strategies. Drayer et al. sum it up by stating that any teams considering implementing any form of DTP must decide whether the structure is going to be truly dynamic and consider all price points. The alternative is a strategy with a preset threshold of prices (Drayer, et al., 2012 a).

3.4.7 PRICE TRANSPARENCY

Another aspect of implementing DTP strategies is the decision regarding how transparent organizations want to be with their pricing. In the case of price ceilings and price floors, organizations must decide whether to inform their consumers of the existence of such price thresholds. Additionally, sports managers must then decide on whether to share the type of factors that drive their pricing. This is important for a number of reasons. According to Drayer et al. (2012 a) consumers feel entitled to consistent pricing and often demand prices that are in line with their previous transactions. If these unwritten rules are violated, many consumers might feel that they have been unfairly treated and decide to walk away from purchasing the product. As with any other business, customer dissatisfaction is undesirable.

Research in the hospitality industry has shown that when consumers feel that they have been unfairly treated, the feeling tends to decline over time (Wirtz & Kimes, 2007). Further Kimes' studies (1994) (2003) have shown that when consumers become more

familiar with the principles of dynamic pricing their attitudes and perceptions become more positive. This is a phenomenon that might well occur in the context of sports. The initial response to DTP implementations may well be negative, but the negative attitudes may diminish over time as fans become more familiar with the practice and the fundamentals behind it. Evidence from the hospitality industry has also shown that when consumers are provided with sufficient information on prices and the policies behind pricing, their perceptions of fairness tend to increase. Price is often the single most important factor when making purchase decisions, while detailed and accurate information about the price tends to increase perceived fairness and value. These types of results were found in a study conducted by Tanford et al. (2011), when researching the price transparency of bundled vacation packages. Drayer et al. (2012 a) summarize their findings, by stating that “price was the most important factor in choice of vacation packages; however, providing detailed information about the price of each component of the package (as opposed to a single price for the entire package) increased perceptions of fairness and value.” In an additional study, Choi and Mattila (2005) found that customers have a tendency to perceive dynamic pricing practices as fairer the more information they are provided. Key decisions facing the managers of sports organizations when it comes to price transparency revolve naturally around how much information should be shared with the customer but also in training the staff in the fundamentals of the pricing system. The staff is tasked with the explanation of how the pricing works to any inquiring customers. Drayer et al. (2012 a) point out that the staff must clearly understand how the system works, but also preferably completely buy into the philosophy of the pricing model. If the staff do not perceive DTP practices to be fair, they might have trouble in educating and convincing customers to its benefits.

3.4.8 FACE VALUE

Face value refers to the printed value of tickets. In a DTP environment, the prices can potentially change every day, or even from minute to minute. This raises the question of whether or not the value of the ticket should be printed. The idea of removing a printed face value is to minimize the scenario where attendants sitting beside each other compare the prices of their respective tickets. If the other party has paid significantly more, they might feel disappointed and unfairly treated. The removal of a printed face value is not as straightforward though. According to Drayer et al. (2012 a) in some cases, laws require

event promoters to print the price on sold tickets. The price printed on the ticket also affects the perceived value of the ticket, in the eyes of the customer (Drayer & Shapiro, 2011). The effect of the printed price on perceived value is not always negative. In some cases, a printed price might increase the value of the ticket in the eyes of the customer. According to Drayer and Shapiro (2011) “a consumer’s perception of the value of the ticket in relation to the actual price is a primary determinant of the consumer’s evaluation of price fairness.” This means that whether or not a consumer considers a price to be fair is dependent on how valuable a consumer perceives the ticket to be in relation to the actual price. This, of course, differs between different customers and events. In some cases, consumers might perceive prices that are many times the original value to be fair whereas sometimes even slight increases in price might be greeted with a strong backlash from the consumers.

4 REVIEW OF LITERATURE

In this chapter, I will present previous research on VTP and DTP in a sports context. Most common theories regarding attendance and price determinants will also be presented in order to provide the reader with a theoretical background on factors that affect attendance and the price of sports tickets.

4.1 VTP AND DTP IN SPORTS

Dynamic ticket pricing (DTP) has only recently started being adopted in the sports industry. From fixed to variable ticket pricing, there are still many organizations, even in North America that are using dated pricing strategies. The situation in Finland is leaning even more towards traditional ticket pricing strategies. The hotel and airline industries have been using real-time pricing approaches, often referred to as revenue management, for much longer. Real-time pricing is based on the idea of taking advantage of high-demand seasons and boosting sales when demand is low. The main idea behind VTP and DTP is being flexible with ticket prices that allow organizations to price their inventory of tickets to better reflect the value perceived by customers. VTP and DTP approaches allow sellers to separate the games that consumers are willing to pay more for by examining certain variables. According to prior research revenue management is suited to environments where there is a fixed capacity of products and perishable inventory. As stated earlier, revenue management strategies have been pioneered by the airline and hotel industries (Drayer & Shapiro, 2012).

Research on real-time pricing within the sports market context is still limited. This is largely due to the fact that the earliest implementations of DTP and VTP in sports occurred as late as 2009 and 2000 respectively (Drayer & Shapiro, 2012). Drayer and Shapiro (2012) also argue that as a concept, DTP and sports tickets are a good fit. The findings regarding dynamic pricing and the seven criteria established by Kimes (1989) also support the idea that sporting events and tickets sales are a good fit with real-time pricing techniques. Drayer and Shapiro (2012) mention that “these criteria include a relatively fixed capacity, a perishable inventory sold in advance, the ability to segment a market, and fluctuating demand, all of which occur in the spectator sports industry.”

In a separate study (Drayer, et al., 2012 a) noted the significance of data management when making pricing decisions. A pricing strategy, VTP or DTP, allows for organizations to more accurately assess consumer demand for individual games in combination to factoring in changing market conditions. This has led to more efficient pricing decisions and increased revenue streams. In North America, due to the bigger demand for sports event tickets, at least in the major sports league context, the growth of secondary ticket markets has forced organizations to rethink their pricing strategies. Many organizations have therefore adopted the more flexible VTP and DTP pricing methods, emulating the success achieved by the secondary ticket market companies (Drayer, et al., 2012 a).

4.2 ATTENDANCE DETERMINANTS

In terms of attendance determinants, not much research has been done in the Finnish market. Still, it is reasonable to assume that many of the same variables that affect ticket sales in North America, also apply in the Finnish market. Rishe and Mondello (2004) (2003) researched the traditional cost-based pricing methods, in major North American sports leagues.

Factors that affect attendance have been thoroughly discussed across all fields and levels of sports. By examining previous research, we can gain a better understanding of what affects attendance in sports events. In the context of this study, it is important to understand what types of variables have been researched before, in order to develop a set of variables to be analyzed. Studies presented below have been conducted in the North American market on a professional level focusing on the biggest Major League organizations.

Hockey is not a particularly big sport and it is mostly played in cold weather countries. As of 2018, the International Ice Hockey Federation (IIHF) has 76-member countries: 56 full members, 19 associate members and one affiliate member (International Ice Hockey Federation, 2018). Therefore, the sport of hockey is not as researched as many of the more popular sports in the world. This applies to the research of hockey attendance as well which has not been studied quite as much, as more popular counterparts. According to Paul et al. (2016) the study of ice hockey attendance has mostly focused on the effects of fighting and rule changes. These include the studies of Jones (1984), Jones et al. (1993), Jones et al. (1996) and Paul (2003). All of the aforementioned studies are in the context

of the National Hockey League, based in the USA and Canada. More recent studies with a more general focus have also been conducted by Hong (2009) and Rascher et al. (2009). Hong studied the differences between casual and more avid fans attraction to hockey games. Rascher, on the other hand, researched how the 2004-2005 NHL lockout affected the NBA and minor hockey leagues. In 2011 Paul and Weinbach (Paul & Weinbach, 2011) expanded the study of ice hockey attendance into the Quebec Major Junior Hockey League, one of the premier junior hockey leagues in the world. This study researched how winning, scoring and fighting affect attendance in a semi-professional junior hockey league setting. A more recent study by Paul et al. (2016) studied financial betting data as a measure of uncertainty of outcome and how it affects hockey attendance. The study was conducted in the context of the three top European leagues, the KHL, SHL, and Liiga. According to Paul et al. this was the first study of European hockey to use betting market odds to estimate the impact of home team win probability and uncertainty of outcome on attendance.

4.2.1 VENUE QUALITY AND LOCATION

In the context of attendance research, a lot of focus has been on the location and quality of venues where teams are playing. A lot of the research mention the so-called “honeymoon effect” or the “novelty effect”. The honeymoon effect involves increased attendance numbers when moving into a new facility, but as times passes the effects wear off and attendance normalizes over time (McEvoy, et al., 2005). The novelty effect operates under the assumption that arenas themselves are attractions and more attractive arenas lead to more attendance, regardless of how the local team is playing (Soebbing, et al., 2016). A 2005 study by Coates and Humphreys (2005) researched the effects on attendance when professional sports teams moved to new venues between 1969 and 2001. Their findings suggest that there is an increase in attendance, but that the effects vary between sports. They also argue that the effects of the new stadiums wear off over time. Other studies have been conducted on the honeymoon effect, which deals with the same phenomenon. A 2005 study by McEvoy et. Al. researched the attendance records of facilities during their lifespans and compared them to new facilities. They also found an increase in attendance during the first years of their lifespan, which later dropped during subsequent years. They also found that attendance fell systematically as the facilities grew older, but that the attendance slightly increased during the final years of a facility’s

lifespan (McEvoy, et al., 2005). In two separate studies in 2005 and 2006, Leadley and Zygmunt (2005) (2006) studied the honeymoon effect in both the NBA and NHL between the years 1970-2003. The study showed a “honeymoon effect” between attendance and ticket price in a new venue.

Even though the honeymoon and novelty effects are not relevant for this particular study, as Tappara has played in the same arena since 1965, it is worth noting the effect of these phenomena and how they affect attendance. This might become relevant even for Tappara as there are advanced plans to build a new arena in the city of Tampere, which would act as the new home stadium for the team. In this context, the heightened demand caused by a new arena becomes relevant, especially in regard to DTP.

4.2.2 EFFECT OF PROMOTIONS

Another important aspect when analyzing attendances during sports events are the effects of promotions and marketing on attendance during specific games. Boyd and Krehbiel have done multiple studies on the effects of promotions in the context of their type and timing (Boyd & Krehbiel, 1999) (Boyd & Krehbiel, 2003) (Boyd & Krehbiel, 2006). The 1999 study focused on the timing of promotions in the MLB and ran promotions on different days of the week. The study found that promotions were more effective on games that were played during the day and weekend games. The 2003 study focused on the attractiveness of different types of promotions in the MLB and how they affect attendance. Promotions were run on three different times, against three different opponents, on three different days of the week. The results suggested that promotions should not be run too densely and should not be combined with factors that might otherwise increase attendance. The 2006 study focused on which type of promotions should be run on given nights. They examined all games that were played during the 2002 MLB season. The results from their multiple regression analysis suggested that it was the most beneficial to run promotions during night games (Boyd & Krehbiel, 2006). Another study on the marginal impact of promotions on attendance in the MLB, found that a promotion increases attendance by about 14%. It is worth noting that the increase in promotions negatively impacts the marginal effect of each promotion. According to MacDonald and Rascher (2000) the gain in attendance is still worth the watered-down effect.

4.2.3 GAME-RELATED FACTORS

Another area considered to affect fan attendance are different game-related variables. These include the winning percentage of the organization and outcome uncertainty. The assumption is that fans want to see their team perform well and therefore attend games when the winning percentage of the organization is higher. A 2008 study (Davis, 2008) confirms these findings. Another assumption is that uncertainty regarding result has a positive effect on attendance. Having a competitive league is not only important for television ratings, but also for in-person attendance. Paul et. al. researched how outcome uncertainty affects attendance in the Russian KHL, Swedish SHL and the Finnish Liiga. They concluded that uncertainty has an effect in all leagues, but the importance varies across leagues. The fans in the KHL and SHL had a stronger preference to see the home team win but also displayed a preference for outcome uncertainty. This means that they attended games when the home team was winning but the outcome still was uncertain. In Finland, the Liiga attendance numbers suggested a similar preference for the home team winning but the fans did not have as strong of a preference for outcome uncertainty. According to the authors, this differs from recent findings in the sport of baseball and from previous findings in the NHL (Paul, et al., 2016). In other studies, concerning outcome uncertainty, Coates and Humphreys (2012) found that attendance increases when fans expect the home team to win, but holding this constant, attendance falls for games expected to be close. They argue that there is an asymmetric relationship between expected game outcomes and attendance. The study also suggests that the definition of the uncertainty of outcome hypothesis should be expanded, in a way that it would include consumer decision making under uncertainty (Coates & Humphreys, 2012). A 2018 study by Young (2018) concluded that many game related variables affect attendance records in the MLB. These factors were related to the offensive capabilities of both the home and visiting team.

4.2.4 OTHER FACTORS

Another important factor to consider when analyzing attendance determinants is the relation between ticket prices and attendance. This is especially important in the context of DTP, as it is important to understand how changes in ticket prices affect attendance in sports events. A few studies have focused on the relation between ticket price and

attendance. It could be argued that price would be the single most important factor in regard to attendance and therefore this topic should be studied further. A study focusing on MLB, NBA and NFL teams, found that ticket prices are fairly inelastic; meaning that fans are willing to pay larger amounts for certain tickets. According to the analysis, attendance demand is inelastic and therefore the inelastic portion of the demand curve is consistent with the revenue maximization goals of sports franchises. The study also concludes that prices of related goods and services, such as parking and concessions, are elastic in their nature. This means that any changes in price will also have an effect on the number of fans that purchase goods or services (Coates & Humphreys, 2007).

The aforementioned studies show there are factors that affect attendance at sporting events and that there are measures that can be taken in order to increase either revenues or attendances. Through the analysis of data collected from the 2014-2018 seasons, this study sought out to find what variables affect attendance at Tappara regular season home games.

4.3 PRICE DETERMINANTS

Most of the research and literature related to price determinants has been focused on the primary market and traditional fixed ticket pricing models. Some studies have been done regarding the secondary ticket market. Analyzing what affects prices in a DTP context is relevant to this study as it helps us understand what factors affect the price in a dynamic pricing environment (Reese & Mittelstaedt, 2001) (Rishe & Mondello, 2003). Pricing determinants were initially researched by Reese & Mittelstaedt (2001). They conducted a research regarding price determinants of NFL tickets. Their findings suggested that organizations made use of factors such as previous year's team performance, organizational revenue needs, public relations, fan tolerance to price increases, and average league ticket prices in order to determine a price suited to the demand of the tickets. It is worth noting that this research was done before the implementation of demand-based pricing strategies (VTP and DTP). After determining appropriate prices, organizations were unable to change prices during the season and therefore also unable to adjust their prices according to changes in demand.

An investigation into price determinants by Rishe and Mondello (2003) also supported previous findings. They found factors such as previous year's performance, fan income

level and playing in a new stadium to have a statistical significance that influenced ticket prices. The significance of playing in new stadiums was also confirmed in later research done on attendance determinants by McEvoy et. al. (2005) and Soebbing et. al. (2016). This phenomenon is often referred to as the “honeymoon” or “novelty” effect. In 2004 Rishe and Mondello (2004) extended their research to include all four major sports leagues in North America. The findings in the latter study were consistent with the previous findings conducted on ticket prices in the NFL. Again, they found that ticket prices were affected by previous year’s performance, a new venue, previous price increases and fan income. The research also suggested a positive correlation between price and the size of the market where the team was playing, with the exception of the NFL, where according to Drayer and Shapiro (2012) sell-outs are common, regardless of the size of the market where the team is playing. They also make the notion that this research was conducted when demand-based pricing was still relatively new, limited and untried. They argue that while some of the variables used in the aforementioned research could be considered “demand related”, the prices were still set in advance and therefore ignored changes in demand during the season.

Drayer and Shapiro (2009) were the first to research price determinants in the secondary market. According to Drayer et. al. (2012 a) this research had limitations, as it was conducted by observing eBay auctions, where some variables were specific only to this resale format. They also state that the research was limited to the NFL playoffs, where demand and consequentially also prices start at a higher level. Demand also stays high during the playoffs, which is not reflective of demand during a whole regular season. In 2012 Drayer et. al. (2012 b) examined the prices of NFL regular season tickets. The study was conducted on a more conventional secondary market channel. Again, the results suggested similar outcomes, where many team performance variables were deemed to impact ticket prices. According to Drayer and Shapiro (2012) they also deemed variables such as; “seat quality, point spread, percentage of capacity sold, and new stadium as statistically significant.”

This type of research is not completely relevant when it comes to the Finnish market as most tickets are sold via primary channels. The secondary market in Finland consists of online auction sites such as “Huuto.net” and “Tori.fi” where the amount of tickets is low. Also, the resale of tickets revolves around the playoffs or occasional high-demand games.

Sellouts are rare, and tickets are often available through the primary ticket market. Still, this type of research on secondary market prices provides some insight into what affects prices in these markets and may be of use when determining significant variables in the Finnish market.

Drayer and Shapiro (2012) point out that even though the research discussed above, provides a foundation for examining ticket prices and the factors affecting them, they have not studied price determinants in the primary market in a DTP context. In 2012 they conducted a study “to examine pricing determinants and identify factors that affect demand-based pricing in the primary ticket market through DTP, and within the secondary ticket market through StubHub” (Drayer & Shapiro, 2012). This study found a combination of time-related, game-related, environmental, team-performance, player-performance, ticket-related and model specific variables to explain over 90 and 70 percent of price changes in two separate models. The models differed in that the other included data with season ticket and secondary market price, while the other dataset did not include season ticket and secondary market prices (Drayer & Shapiro, 2012).

Drayer and Shapiro (2012) argue that one of the most crucial elements for a successful implementation of a DTP strategy is to understand factors influencing consumer demand. There have been a number of studies focusing on the subject. Moe et al. (2011) studied the consumer decision-making process in a professional sports context. The results of the study indicated that factors such as performance, the perceived attractiveness of the opponent, seat location and time left to the game were all factors which affected ticket sales. This study was different in that it did not touch on the subject of ticket price. The aforementioned findings suggest that it is important to understand the factors affecting attendance in order to successfully implement DTP strategies.

To summarize, the literature has studied the shift from cost-based pricing to demand-based pricing. These studies have focused on the development of DTP, which has shown to impact organizational profitability and consumer resale in the sports market. This literature has focused on the North American market. Literature is still limited as the topic of dynamic pricing is still new in the context of sports. Additionally, previous studies have been able to identify factors that influence ticket prices in both primary (Reese & Mittelstaedt, 2001) (Rishe & Mondello, 2003) (Rishe & Mondello, 2004) and secondary ticket markets (Drayer & Shapiro, 2009). These studies found that factors such as team

performance, opponent information, demographics, economic characteristics, game day and time impact the price of sports tickets in a dynamic pricing environment.

5 METHOD

The purpose of this chapter is to present the method used to answer the research questions of this thesis.

5.1 RESEARCH DESIGN

As most data for the analysis of attendance records in the Finnish Liiga was readily available, a quantitative approach was chosen as the main empirical evidence in this study. This seemed natural, as data was readily available and easy to quantify. By examining previous research and studied variables, two research questions were developed to examine attendance during the 2014–2018 Tappara home games.

RQ1: What factors influenced game attendance for Tappara during the 2014–2018 regular seasons?

RQ2: What factors can be deemed significant when considering dynamic pricing strategies?

A single team was purposefully chosen for this study. Teams in different cities and markets might have very dissimilar demand curves which might distort eventual results. Also, as this study is only a preliminary dip into the research of attendance determinants and eventually price determinants in the Finnish hockey market, a simple approach was deemed suitable. A single team was deemed as a simple enough data set which could still be regarded as statistically significant. Data from four different regular seasons were collected, which consisted of 120 home games.

Based on previous research and by examining the kinds of variables that were available for analysis, an initial set of variables were gathered. A correlational design was used to assess the relationships between various factors and attendance at Tappara home games during four Liiga regular seasons between 2014 and 2018. According to Metsämuuronen (2006) multiple linear regression can be used when studying the effect of multiple explanatory variables on one dependent variable (Metsämuuronen, 2006). As all variables in the collected data are known, multiple linear regression will be used for descriptive modeling. This method effective in finding out which independent variables have the strongest impact on the researched dependent variable, in other words, to see which of

the variables explain most of the changes in attendance at Tappara home games during the 2014-2018 seasons.

The initial model consisted of 19 variables. This model was created in order to examine the factors that affected attendance at the 120 home games during the season. Following initial model, a more streamlined model was created in order to achieve statistical significance. The variables for the new model were chosen with an automatic and iterative method called stepwise regression, a built-in function in R-studio. The analysis along with results will be presented in depth in chapter six.

5.2 DATA COLLECTION

Tappara game attendance data were collected for regular season games throughout the 2014-2015 until the 2017-2018 season, four seasons in total. The dataset consisted of 120 home games and accounted for 19 variables. These variables were broken down into categories based on their characteristics; such as time-related, game-related, environmental and team performance-related variables. The variables chosen for the initial model are presented below.

5.3 DEPENDENT VARIABLE

Attendance (Att): A variable defining the amount people attending each game. This number is the official amount given by the Liiga website.

5.4 INDEPENDENT VARIABLES

5.4.1 TIME-RELATED VARIABLES

Game number (Num): The running number of the game played. 60 games are played by each team during the regular season.

Part of the season (PoS): A categorical variable identifying at which point during the season a specific game was played. This variable was broken down into three categories (Early Season: September–October; Mid-Season: November-January; and Late Season: February–March).

Weekday/weekend ('WdWe'): A categorical variable identifying whether the game was played on a weekday (Monday–Thursday) or weekend (Friday–Sunday). Games in the Finnish Liiga are played on Tuesdays, Wednesdays, Thursdays, Fridays and Saturdays. Some games can exceptionally be played on Mondays or Sundays.

Time of the game ('ToG'): A categorical variable identifying game time (15.00, 17.00 or 18.30). It is worth noting that only one game had a 15.00 start time. Games are starting at 18.30 on weekdays and 17.00 during weekends.

5.4.2 GAME-RELATED VARIABLES

Opposition ('Opp'): Variable indicating the opponent that Tappara faced during each observation. Each opponent was dummy coded in the data.

Liiga average attendance ('LAA'): A continuous variable measuring the monthly average attendance at Liiga games during the month of the observation. Data were collected from the official Liiga website.

5.4.3 ENVIRONMENTAL

Temperature ('Temp'): A variable measuring the temperature observation in degrees (Celsius) on game-day as a daily average. The observations used in the analysis were from the Tampere Tampella weather observation station in downtown Tampere. If data was unavailable the Härmälä observation data was used. Data were collected from the open data portal of the Finnish Meteorological Institute (FMI).

Precipitation ('Prec'): A variable measuring the precipitation (amount of rain or snow) on game-day. The observations used in the analysis were from the Tampere Härmälä weather observation station. Data were collected from the open data portal of the FMI.

Snow on the ground ('Snw'): A variable measuring the amount of snow on the ground during game-day. The observations used in the analysis were from the Tampere Härmälä weather observation station. Data were collected from the open data portal of the FMI.

5.4.4 TEAM PERFORMANCE VARIABLES

Winning percentage ('WP'): A continuous variable measuring Tappara winning percentage for the season on game-day.

Winning percentage in the last 5 games ('WP5'): A continuous variable measuring the winning percentage in the last 5 games at the time of the observation. The first percentages are calculated with the available observations until a winning percentage for the last five games can be calculated.

Winning percentage in last 10 games ('WP10'): A continuous variable measuring the winning percentage in the last 10 games at the time of the observation. The first percentages are calculated with the available observations until a winning percentage for the last five games can be calculated.

Games played ('GP'): Measuring the number of games Tappara has played during the season.

5.5 DATA ANALYSIS

Data were analyzed using the R-studio software. The variables were chosen with the so-called "stepwise regression" method. Stepwise regression (or stepwise selection) consists of iteratively adding and removing predictors, in the predictive model, in order to find the subset of variables in the data set resulting in the best performing model, that is a model that lowers prediction error (Kassambara, 2018). The software does this automatically and produces a set of variables that perform the best in predicting changes in the dependent variable.

The complete analysis can be found in Appendix 2. The results and the analysis will be presented in detail in chapter 6.

6 RESULTS

This chapter will present the results of the multiple regression analysis and the stepwise regression method.

6.1 MULTIPLE LINEAR REGRESSION

For the analysis of attendance data, a multiple linear regression model was performed. A regression with multiple explanatory variables is called a multiple regression. This analysis was done in order to determine the variables that have the most effect on attendance at Tappara home games. The analysis itself was performed with the free, open-source analytics software R-studio. The method chosen was a stepwise regression, which iteratively adds and removes variables, in order to find the best set of variables for the model. Stepwise regression is suitable for this purpose as it eliminates variables from the model until it only includes variables that have a statistically significant effect on the dependent variable. This method is able to create a model of predictors that can explain the changes in the dependent variable. In order to understand the output of the multiple regression model, each of the output components are defined below:

Formula Call

This is the first output from the multiple regression analysis in R-studio. This is simply the formula used to fit the data. The formula consists of the response, i.e. the dependent variable attendance ('Att') and the predictors, i.e. the independent variables used to explain changes in attendance. The formula call also includes the data set being used 'Tap14-18_coded2' (Rego, 2015) (Draper & Smith, 1998).

The initial set of variables called "full.model" was created based on previous research and literature. The initial model is presented below:

```
Call:
lm(formula = Att ~ Num + WdWe + ToG + PoS + LAA + Temp + Prep +
    Snw + WP + WP5 + WP10 + Assat + HIFK + HPK + Ilves + Jukurit +
    JYP + KalPa + Karpas + KooKoo + Lukko + Pelicans + SaiPa +
    Sport + TPS, data = Tap14_18coded2)
```

Figure 6: Call for the first model

For the purpose of this study, the variable attendance (Att) was analyzed. This means that attendance is the dependent variable of the analysis. The remaining variables are the independent variables, which are used to explain the changes in attendance numbers. As stated above, the variables for the model were chosen by examining previous research and literature of attendance and price determinants in sports. The initial goal was to gather an extensive set of variables which could explain changes in the number of people attending Tappara home games. This initial model was later streamlined in order to develop a statistically significant model. The model consisted of 1 dependent variable and 12 independent variables. The results from the preliminary model (full.model) are presented below:

```

Residuals:
    Min       1Q   Median       3Q      Max
-1395.7  -371.5  -103.5   277.3  1963.6

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  778.8326  1559.7679   0.499 0.618716
Num          -1.8059    12.5554  -0.144 0.885938
WdWe         596.7012   171.0627   3.488 0.000742 ***
ToG          418.6341   159.9641   2.617 0.010336 *
PoS          197.2336   242.6015   0.813 0.418276
LAA           0.8680     0.3679   2.359 0.020392 *
Temp        -2.6403    12.7817  -0.207 0.836795
Prep         20.2954    23.8821   0.850 0.397585
Snw          -6.7616     9.8572  -0.686 0.494427
WP           94.8390    849.4003   0.112 0.911336
WP5          420.0463   468.8534   0.896 0.372594
WP10        -109.6063   722.9228  -0.152 0.879815
Assat        740.8881   418.4865   1.770 0.079903 .
HIFK         971.5742   415.6685   2.337 0.021542 *
HPK         -337.4804   408.3882  -0.826 0.410686
Ilves       1587.0465   387.2284   4.098 8.82e-05 ***
Jukurit      216.8402   487.3504   0.445 0.657388
JYP          330.6895   426.5047   0.775 0.440080
KalPa       -227.0197   405.3849  -0.560 0.576804
Karpas       807.0703   404.0626   1.997 0.048674 *
KooKoo      -422.4636   435.7812  -0.969 0.334814
Lukko       -155.0134   411.5260  -0.377 0.707261
Pelicans    -767.9369   413.7215  -1.856 0.066562 .
SaiPa       -612.5719   408.8088  -1.498 0.137372
Sport       -397.6222   397.3804  -1.001 0.319585
TPS          44.3181    417.8873   0.106 0.915767
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 643.2 on 94 degrees of freedom
Multiple R-squared:  0.6825,    Adjusted R-squared:  0.5981
F-statistic: 8.083 on 25 and 94 DF,  p-value: 2.694e-14

```

Figure 7: Summary of output for the first model

6.1.1 FIT OF THE MODEL

In order to understand how well the independent variables can explain changes in the dependent variable, the performance of the initial model was assessed. This performance is referred to as the fit of the model. The fit of the initial model was determined by examining certain values of the model summary output.

Residuals

The residual values are the difference between the actual observed response values (attendance) and the predicted response values. This section is broken down into five different points. When assessing the fit of the model a symmetrical distribution of these points on the mean value zero (0) is preferred.

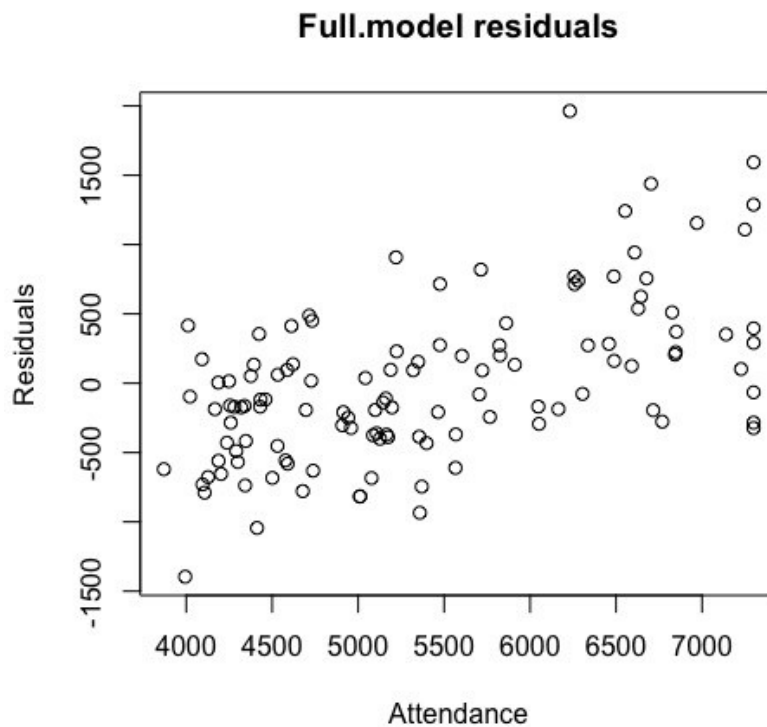


Figure 8: Full.model residuals

The residuals for the initial model were plotted in R-studio in order to visualize their distribution. The distribution did not appear strongly symmetrical. This meant that the initial model predicted certain points that differ from the actual observations. This suggested that a better performing model should be created (Rego, 2015) (Draper & Smith, 1998).

Coefficients

The R-studio output consists of the coefficients 'Estimate', 'Standard Error', 'T-value', 'Pr(>t)', 'Residual Standard Error', 'Multiple R-squared, Adjusted R-squared' and the 'F-statistic'. Before analyzing individual coefficients, the fit of the model was to be assessed in order to determine its statistical significance. The values of interest in the determining the fit of the model in multiple linear regression are the t-value, the probability of observing any value equal or larger than t, (Pr(>t)), and the adjusted R-squared value (Rego, 2015) (Draper & Smith, 1998).

The coefficient t-value measures how many standard deviations the coefficient estimate is away from zero. The T-value is calculated by dividing the estimate value of a variable with its respective standard deviation. Ideally, this number should be as far away from zero as possible, as this enables us to reject the null hypothesis. By rejecting the null hypothesis, we can declare that a relationship exists between attendance and the independent variables. In the initial model, the t-values are quite close to zero and small compared to the standard deviations. This indicates that while some relationship exists, the model could perform better (Rego, 2015) (Draper & Smith, 1998).

Pr(>t) is an acronym for the probability of observing any value equal to or larger than t. This means that a smaller p-value indicates a smaller likelihood of observing a relationship between the attendance and any independent variable is due to chance. In other words, a smaller p-value indicates a higher statistical significance. Usually, a p-value of 5 % or less is considered as the cut-off point. In R-studio the following levels of significance are used:

- $p < 0,001$ statistically very significant (***)
- $0,001 \leq p < 0,01$ statistically significant (**)
- $0,01 \leq p < 0,05$ somewhat statistically significant (*)
- $0,05 \leq p < 0,10$ statistically direction giving

Three stars indicate a highly significant p-value. In the initial model, only one variable reached this level of significance. Only six variables were considered statistically significant with a p-value under 5 % (Rego, 2015) (Draper & Smith, 1998).

The R-squared (R^2) value is a measure of how well the model fits the actual data. R^2 indicates a linear relationship between the dependent variable and independent variables. The R^2 value is always between zero and 1. An R^2 value close to zero indicates a model that does not explain variance in the dependent variable, while a number close one does explain the variance. The R^2 value of the initial model is 0,5833. This indicates that the set of explanatory variables can explain 59 % of the changes in the dependent variable attendance (Rego, 2015) (Draper & Smith, 1998).

The last indicator in assessing the fit of the initial model is the F-value. This value indicates whether there is a relationship between the dependent variable and the independent variables. A larger F-value indicates a stronger relationship. Note that the F-value is affected by the number of observations and variables used in the model. This means that a model with a large number of observations and multiple variables, an F-value that is over one is considered sufficient to reject the null hypothesis. In the initial model, the F-value was 8,08 which can be considered relatively larger than 1 given the number of observations and variables used in the analysis (Rego, 2015) (Draper & Smith, 1998).

The results of the initial model indicate that some relationship exists between the attendance and the variables used to explain the changes in the dependent variable. Still, the performance of the model is not optimal according to some of the assessed values. The following step was to construct a new set of variables, that are able to perform better in explaining changes in attendance.

6.2 STEPWISE REGRESSION

The new model was created using stepwise regression. With this method, a number of variables that were deemed unnecessary were dropped. This method was used in order to create the best performing model. The independent variables left in the model amounted to 5. The variables left in the model were deemed significant by the method and are presented below:

Call:

```
lm(formula = Att ~ WdWe + ToG + LAA + WP5 + Assat + HIFK + HPK +  
    Ilves + KalPa + Karpat + KooKoo + Lukko + Pelicans + SaiPa +  
    Sport, data = Tap14_18coded2)
```

Figure 9: Call for step.model using the stepwise regression method

The variables selected using the stepwise method were:

- Opposition related (11)
- Weekday/weekend
- Time of the Game
- League Average Attendance
- Winning percentage in the last 5 games

The summary of the output for the stepwise regression model (step.model) are presented below:

```

Residuals:
      Min       1Q   Median       3Q      Max
-1559.20 -334.83  -81.14   325.50  2034.48

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  502.5774   1113.1871    0.451 0.652587
WdWe         540.9107    139.4720    3.878 0.000185 ***
ToG          466.5224    142.2814    3.279 0.001418 **
LAA           0.9922     0.2605    3.809 0.000236 ***
WP5          455.3126    264.2921    1.723 0.087904 .
Assat        578.2499    259.8458    2.225 0.028216 *
HIFK         774.3801    258.1907    2.999 0.003387 **
HPK          -570.3822    258.3982   -2.207 0.029485 *
Ilves       1391.4827    227.3378    6.121 1.67e-08 ***
KalPa       -391.3336    246.7416   -1.586 0.115774
Karpát       554.2776    257.5496    2.152 0.033701 *
KooKoo      -686.0745    286.7032   -2.393 0.018506 *
Lukko       -383.3728    256.8808   -1.492 0.138618
Pelicans    -934.4485    249.6148   -3.744 0.000298 ***
SaiPa       -802.1392    250.7946   -3.198 0.001832 **
Sport       -573.4214    228.9568   -2.504 0.013816 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 624.9 on 104 degrees of freedom
Multiple R-squared:  0.6684,    Adjusted R-squared:  0.6206
F-statistic: 13.98 on 15 and 104 DF,  p-value: < 2.2e-16

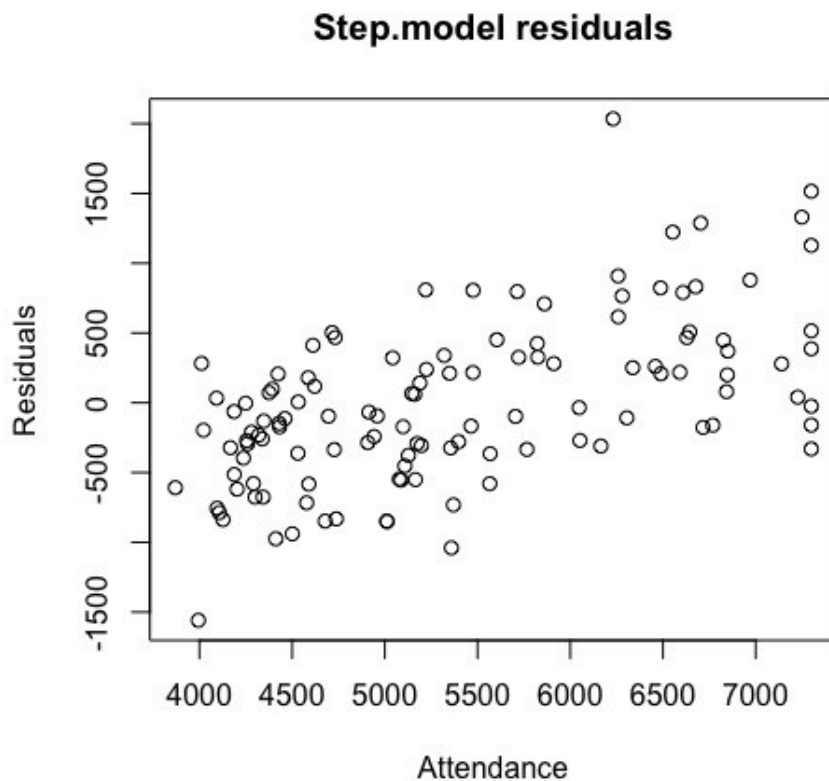
```

Figure 10: Summary of output for the stepwise model, including only statistically significant variables

6.2.1 FIT OF THE MODEL

The assumption of the multiple regression analysis is that the explanatory variables have an effect on the dependent variable. The null hypothesis is, therefore, the opposite, where the explanatory variables would have no effect on the dependent variable. After assessing the fit of the new model, we can determine if the null hypothesis can be rejected. Thereafter the individual coefficients can be assessed.

Residuals



The residuals for the second model were plotted in R-studio in order to visualize their distribution. The distribution did appear more symmetrical than in the initial model. This meant that the new model performed better in predicting certain points in the data (Rego, 2015) (Draper & Smith, 1998).

Coefficients

We begin by testing whether the explanatory variables collectively have an effect on the dependent variable. The results of the new model show an increase in the T-values of the output as they are further away from zero. This is an indication that the model is performing better. The output also shows that $Pr(>t)$ are also performing better. Four variables were deemed statistically very significant, with three stars. The output also shows that $F = 13,98$ ($p < 2.2e-16$). The F-value has increased from 8,08 to 13,98 and the p-value decreased to 2.2e-16. The R²-value also increased from 0,5833 to 0,6206. It seems that by all aforementioned measures the new model is performing better with more

statistical significance. Therefore, we can reject the null hypothesis that the variables collectively have no effect on attendance ('Att').

The new model suggests that explanatory variables Weekday/Weekend Time of Game ('ToG'), League Average Attendance ('LAA'), Winning Percentage in the last 5 games ('WP5') and opposition ('Assat', 'HIFK', 'HPK', 'Ilves', 'KalPa', 'Karpas', 'KooKoo', 'Lukko', 'Pelicans', 'SaiPa', 'Sport') perform the best in explaining changes in the dependent variable. Of the variables mentioned above 'WdWe', 'LAA', 'Ilves', Pelicans were over the set threshold for being statistically very significant with p -values under 0,001. Variables 'ToG', 'HIFK', and 'SaiPA' were above the threshold for being statistically significant with p -values under 0,01. The adjusted R-squared value of the model improved from 0,5891 to 0,6206. This set of variables is able to explain 62 % of the changes in the dependent variable.

The findings of the analysis imply, that the variables mentioned above have a statistically significant effect on attendance at Tappara home games. The results are also in line with previous research and analysis where factors such as time of the game, opposition and team performance were identified as significant attendance determinants.

7 CONCLUSIONS

This study aims to determine the factors that affect attendance at Tappara home games in the Finnish premier ice hockey league Liiga. This knowledge is intended to be beneficial in the development and eventual adaption of fully dynamic pricing strategies within the league and Finnish sports in general. By analyzing explanatory variables, it was possible to establish a set of variables that affected attendance at Tappara home games. This also allowed for the identification of factors that could be considered significant when planning dynamic pricing algorithms. Match data from Tappara home games during the 2014–2018 seasons were used for quantification and validation of the results.

7.1 THEORETICAL CONCLUSIONS

The findings from the statistical analysis of Tappara attendance data suggest that opposition, along with the time of the game and team performance, are factors that impact attendance numbers. The results are in line with previous research and literature in the field of attendance and price determinants. Previous research suggests that variables relating to the opposition, time of the game and team performance are important when it comes to determining the demand for individual games.

7.2 MANAGERIAL CONCLUSIONS

The results of this study have many areas of interest from a managerial perspective. The findings suggest that opposition is statistically a very significant attendance determinant. This is also true for whether the game is being played on a weekday or weekend. The findings also highlight the inefficiencies of current pricing strategies and the potential economic benefits that dynamic pricing strategies offer. These economic benefits consist of additional revenue from ticket sales for high-demand games and additional sales from more fans attending low-demand games.

7.2.1 OPPOSITION

The results of the analysis suggest that opposition had a big effect on attendance at Tappara home games. At the moment the organization employs a pricing strategy that could be described as variable ticket pricing. The ticket prices are set in advance for the whole season and for the current 2018–2019 season games against Ilves, HIFK and Kärpät have a price premium incorporated. This means that fans are paying a slight premium on games that are played against opponents that are deemed of added interest. This added demand is also vindicated by the results of the analysis as the findings suggest a positive relationship between games against Ilves, HIFK and Kärpät respectively. The estimates suggest attendances to increase by 1391,48 against Ilves, 774,38 against HIFK and by 554,27 against Kärpät. This indicates that the Tappara organization is correctly pricing these games higher, because of the heightened demand. Still, the added premium of around three euros per price category seems quite conservative. This price increase only applies to certain sections of the arena. The premium is around 7 % increase in price for the most expensive group of tickets. It is also worth noting that the rest of the opposition is priced in the same price category. This would suggest that Tappara divides their opposition into two or three different price categories which resembles a two-tiered variable pricing strategy. Tickets are simply divided into normal and off-peak categories (Broshears, 2016) based on opposition. Additionally, there seem to be differences in demand inside the price category for “normally” priced opponents. Games against Ässät, HPK, Jukurit, JYP, KalPa, KooKoo, Lukko, Pelicans, SaiPa, Sport and TPS are all in the same price category. Still the results indicate a negative relationship between games against HPK (-570,38), KalPa (-391,33), Lukko (-383,37), KooKoo (-686,07), Pelicans (-934,44), SaiPa (-802,13) and Sport (-573,42) and attendance. Within the same category games against Ässät have a positive relationship with attendance (578,24). Jukurit, JYP and TPS have not been included in the final stepwise model. This is likely due to the fact that the attendance numbers against these teams are close to the baseline attendance numbers. The results, however, suggest that some of the less interesting teams could be priced differently. Especially games against Pelicans and SaiPa could potentially benefit from lowered ticket prices, which could lead to additional fans attending games and potentially extra revenue through ancillary sales.

7.2.2 WEEKDAY VERSUS WEEKENDS

Another important insight from the analysis is the heightened demand for games played on weekends. Again, the results indicate a positive relationship for games played during weekends ('WdWE') and attendance ('Att') as the estimate indicates 540,91 more fans attending games on weekends than during weekdays. This heightened demand is not accounted for in the Tappara pricing strategy as games during both weekdays and weekends are priced the same. As mentioned earlier the only price differentiation is done based on the opposition. This again presents an opportunity to gain additional revenue by pricing weekend games higher than games during weekdays. Also, some weekday games might even benefit from discounted ticket prices as fans might be more willing to attend games during the week if they were offered tickets at discounted prices. As an example, a Tuesday night game against Pelicans is likely to generate significantly less interest than a Saturday night game against local rivals Ilves. If the ticket prices for a Tuesday night against Pelicans was to be discounted a few days before the game or during the day of the game, based on the estimated demand, Tappara might be able to draw in additional fans to the arena. Even if the additional tickets sold would not generate any significant extra revenue the added fans should enhance the game experience and generate some extra revenue from parking and ancillary sales at the arena. As mentioned earlier in the thesis any discounted prices have to be carefully considered as underpricing tickets can have some negative consequences for the organization. Still, it is important to recognize the potential and inefficiencies in how games are not priced differently for weekdays and weekends. At the time of writing the Tampere Theatre is selling tickets to its new show called Rainman, where tickets for Saturday night shows are starting at 39 euros, whereas tickets for shows during the week are starting at 10 euros. This shows that in some industries products or services are already being priced based on time, also in Tampere. The sports industry should harness the potential of these efficient pricing decisions.

7.2.3 TEAM PERFORMANCE

The third insight gained from the analysis relates to the performance of the home team, in this case, Tappara. Previous research has shown that team performance has an effect on both ticket prices in a dynamic pricing environment and attendance numbers. In other words, team performance affects the demand for sports events. The results suggest a

positive relationship between the winning percentage in the last five games ('WP5) and attendance ('Att'). It is worth noting that the stepwise regression method did not include the variables winning percentage in the last 10 games ('WP10') and for the whole season ('WP'). The results suggest that team performance in the short term have a positive effect on attendance Tappara attendance. This again is of potential use for sports organizations looking to make use of DTP. Short term success on the ice seems to lead to a heightened demand, at least in this case. If Tappara were looking to implement their own DTP strategies, they should consider a variable that measures the team's short-term performance on the ice.

7.2.4 OTHER FACTORS

The attendance determinants that have the most effect according to the analysis relate to opposition, time of the game and team performance. Some variables that were included in the initial model seemed to have no or limited effect on Tappara attendance numbers. For example, weather-related variables were not included in the stepwise regression model. These variables consisted of temperature ('Temp') and precipitation ('Prep') and amount of snow ('Snw'). It seems that neither temperature, the amount of precipitation or snow on the ground affected attendance numbers in a statistically significant manner. Besides from the fact that ice-hockey is played inside, in cover for weather effects, the hockey regular season runs from September to March. During this time the weather in southern Finland is often rainy and cold. People are also used to snowfall and cold weathers during the winters. It seems that these variables do not affect attendance numbers.

The variables measuring more long-term team performance like winning percentage in the last 10 games and winning percentage for the whole season were not deemed significant determinants of attendance. It is worth noting that the Tappara team was quite successful each of the seasons in the dataset and future research is needed into how less successful seasons affect attendance. The assumption is that a significantly lower winning percentage for the season would affect attendance negatively.

Based on the results of this study sports organization should explore the potential benefits of dynamic pricing strategies. The analysis of Tappara attendance data suggests that there are factors that affect the demand for games with different levels of demand between

different games. This means that there should be potential for additional revenue by making more efficient pricing decisions. This study should be of interest when determining what affects attendance Finnish ice-hockey.

7.3 LIMITATIONS

The results of this study are in line with previous research regarding price and attendance determinants within sports. The opposition, time of the game and team performance factors have all been previously identified to affect attendance and price of sports tickets. Still, this study has some limitations that any stakeholders and future research should take into consideration.

The main limitation is that this study only analyzed attendance data from one team. A broader selection of teams will provide more insight into the results of the analysis. Additional teams, in combination with additional observed seasons would be especially beneficial for team performance analysis in the long-term. Tappara performed well in each of the regular seasons included in the study and therefore variables measuring the winning percentage in the last 10 games and for the whole season were similar between games. More teams would add variety to the performance data as teams who perform both well and badly would be represented in the data. This effect would also be spread through several seasons. This should provide a more comprehensive and complete view of attendance determinants in the Finnish hockey market. The analysis of attendance determinants would also largely benefit from pricing and sales data for different categories in the arenas. This would enable a more thorough analysis of how demand behaves across different sections at sports events.

Another limitation of the study is the lack of player performance data. Previous research has identified the effect of star players. Star players and especially talented young players can have a positive effect on the demand of a certain team. This study did not take this kind of factors into account.

8 SVENSK SAMMANFATTNING

Determinanter för deltagande vid idrottsevenemang

8.1 INLEDNING

Mitt intresse för sport och idrott väcktes redan tidigt i barndomen. Jag har varit aktiv inom idrott hela mitt och haft chansen att pröva bland annat ishockey, fotboll, tennis och ridning. Detta intresse har inte varit begränsat till mitt eget aktiva deltagande. Speciellt under senare år har jag utvecklat ett starkt intresse för hur idrottsorganisationer leds och förvaltas. Idrottsbranschen har utvecklats till en global marknad som är värd flera miljarder euro. De största idrottsorganisationerna har flera miljoner följare och anhängare runtom hela världen. Denna utveckling har lett till att idrottslag och organisationer leds mer professionellt och ekonomiorienterat än tidigare. Dessa organisationer leds inte längre med passion, entusiasm och intuition som primära drivkrafter, utan mer ekonomiorienterade ledningskulturer har uppstått. Denna utveckling är uppenbar också i Finland. Ett mer affärsorienterat tillvägagångssätt spelar naturligtvis en stor roll också på idrottsplanen. Matematiken bakom detta tankesätt är relativt enkel. Större finansiella tillgångar leder ofta till t.ex. bättre spelare och idrottsanläggningar. Mera pengar är förstås inte en garanti för framgång, men en välmående ekonomi har definitivt en positiv inverkan.

På en allt mer konkurrenskraftig idrottsmarknad har organisationer ett ständigt behov av att öka sina inkomster. Detta inkluderar även intäkter från biljettförsäljning. Eftersom fler och fler lag framgångsrikt har antagit dynamiska prissättningssystem för biljetter inom större idrottsmarknader, speciellt i Nordamerika, är förväntningen att dynamisk prissättning också kan implementeras framgångsrikt inom finländsk idrott. Idag har endast några finska lag som spelar i Liiga, den främsta ishockeydivisionen i Finland, antagit dynamiska prissättningssystem. Eftersom flera lag redan nu har ont om resurser är det viktigt att skapa alternativa inkomstkällor för att säkerställa konkurrenskraften i framtiden.

Att prissätta produkter i realtid är inget nytt. Reserelaterade industrier så som hotell-, biluthyrnings- och flygbolagsbranschen har redan länge prissatt sina tjänster och

produkter i realtid. Denna typ av prissättning har också dykt upp på energi- och försäkringsmarknaden. Idrottsbranschen är annorlunda på grund av flera orsaker. Efterfrågan på enskilda matcher tenderar att bete sig annorlunda än på mer traditionella tjänster och produkter. Det är ändå rimligt att förvänta sig att dynamiska prissättningsystem kan effektivisera också prissättningen och försäljningen av biljetter för sportevenemang. Det finns betydande bevis för att detta kan ske framgångsrikt, främst från den nordamerikanska marknaden, där flera lag har kunnat öka sina intäkter med hjälp av effektivare prissättningsteknik.

8.2 SYFTE OCH FORSKNINGSPRÅG

Avhandlingens syfte är att studera vilka faktorer som påverkar mängden åskådare i Tapparas hemmamatcher. Vidare studeras också dynamisk prissättning och huruvida organisationer inom finsk idrott kunde öka sin omsättning genom antagandet av dynamiska prissättningsstrategier. Denna typ av analys är viktig i kontexten av dynamiska prissättningsstrategier. Utifrån avhandlingens syften, utvecklades följande forskningsfrågor:

FF1: Vilka faktorer påverkade mängden åskådare i Tapparas hemmamatcher under grundserien åren 2014 och 2018?

FF2: Vilka faktorer kan användas vid antagningen av dynamiska prissättningsstrategier inom finsk ishockey?

Avhandlingen kommer att svara på ovannämnda forskningsfrågor men strävar också efter att skapa en omfattande helhetsbild av hur dynamisk prissättning fungerar både inom traditionella industrier och inom sportvärlden. Avhandlingen kommer också att förklara hur dynamisk prissättning har förändrat försäljningen av biljetter till sportevenemang och vilka nyttor finska organisationer eventuellt kunde nå genom att anta dynamiska prissättningsstrategier.

Avhandlingens struktur

Avhandlingen består av sju huvudkapitel. I första kapitlet introduceras ämnet som en helhet. I kapitel två och tre presenteras relevant bakgrundsinformation om prissättning generellt och prissättning av idrottsbiljetter. Dessa två kapitel fokuserar på skillnaden

mellan mer traditionella prissättningsstrategier och moderna dynamiska prissättningsstrategier. Kapitel fyra presenterar tidigare forskning inom prissättning av idrottsevenemang och determinanter för deltagande inom idrott. I kapitel fem presenteras avhandlingens metod. Detta följs av kapitel sex, där resultaten diskuteras i relation till forskningsfrågorna och tidigare forskning. I följande kapitel sammanfattas avhandlingens slutsatser och förslag till fortsatt forskning presenteras. Kapitel åtta sammanfattar avhandlingen på svenska. Kapitel nio och tio innehåller källförteckningen och bilagor.

8.3 FRÅN STATISK TILL DYNAMISK PRISSÄTTNING

Som tidigare nämnts är dynamisk prissättning av produkter och tjänster inget nytt. Ett stort antal företag prissätter sina produkter och tjänster utifrån deras efterfrågan vid olika omständigheter. Idén med dynamisk prissättning är relativt enkel. Enligt Burger och Fuchs (2005) är syftet att erbjuda produktsortiment som överensstämmer med olika grupperns skilda efterfrågekurvor och priskänslighet. Dynamisk prissättning har traditionellt utnyttjats speciellt av flyg- och hotellindustrin. Priser justeras i realtid, ofta flera gånger per dygn, timme eller t.o.m. sekund, utan mänskligt påverkande. Ett underliggande mål är att maximera lönsamheten. Detta kan nås genom att optimera intäkterna och kapacitetsutnyttjandet. Arnoud den Boer (2013) beskriver dynamisk prissättning som en kombination av två forskningsområden: statistisk lärande och prisoptimering, som båda har funnits redan en längre tid. Vidare beskriver han dynamisk prissättning som forskningen av optimala försäljningspriser för produkter och tjänster i omständigheter där priser kan justeras med liten ansträngning. Vad som är kännetecknande för båda definitionerna är att dynamisk prissättning karaktäriseras av att ha en förmåga att sätta optimala priser på basis av den upplevda efterfrågan för en produkt eller tjänst i föränderliga omständigheter.

Dynamisk prissättning utvecklades ursprungligen av flygbranschen. Deras prissättning baserade sig på prognostiserad efterfrågan och tillgängligheten av lager (Cross, 1997). Inom flygbranschen kallades detta koncept för ”yield management”, alltså avkastningshantering. Avkastningshanteringens grundprinciper antogs senare av andra branscher som till exempel hotellindustrin. Avkastningshantering associerades dock fortfarande starkt med flygbranschen, och därför började man använda en ny benämning:

”revenue management”, alltså inkomsthantering. (Drayer, et al., 2012 a). I denna avhandling kommer jag att hänvisa till ”dynamisk prissättning” genom hela studien.

Idag används dynamisk prissättning av ett stort antal företag som verkar inom olika branscher. Enligt Davenport och Harris (2007) använder företag dataanalys för att nå konkurrensfördelar genom att prissätta sina tjänster och produkter mer effektivt. Denna typ av prissättning gäller både Walmarts dagliga lågprissättningar och anpassning av rumspriser på basis av efterfrågan på hotell. Dataanalys och dynamisk prissättning har gett företag möjligheten att justera sina priser i realtid, som svar på förändringar i marknadsförhållanden. Dessa prissättningsalgoritmer beaktar variabler som t.ex. efterfrågan, lagernivå, konkurrentbeteende och kundhistoria. Enligt Davenport och Harris (2007) sprids användningen av analytiskt baserade prissättningsprogram i alla branscher.

8.3.1 SKILLNADEN MELLAN STATISK OCH DYNAMISK PRISSÄTTNING

Enligt Kokemuller (2018) är statisk prissättning en strategi där produkters prispunkter etableras och upprätthålls under en längre tidsperiod. Detta skiljer sig från dynamisk prissättning där priset på en produkt eller tjänst kan ändras med tiden. Eftersom prissättning spelar en stor roll i företags strävan efter nya kunder och optimala vinstmarginaler är det viktigt att företag väljer en lämplig prissättningsstrategi.

Fördelar med statisk prissättning

Statisk prissättning lockar kunder och klienter som värderar prissäkerhet. Till exempel i fråga om projektledning ger ett fast pris säkerhet för en potentiell kund. Detta betyder att kunden kan i förväg veta hur mycket arbetet kostar. Eftersom den fasta prissättningen är konsekvent, blir kunderna vana vid priserna och därför löper företagen mindre risk att orsaka missnöje bland sina kunder. Det är också enklare att prognostisera försäljning och vinster när prispunkten är bestämd i förväg (Kokemuller, 2018).

Nackdelar med statisk prissättning

Risken med statisk prissättning är dess stelhet. Fasta priser betyder att företag inte kan justera priserna för sina produkter eller tjänster ifall kostnadsbasen blir större än förväntat. Kunden betalar ett pris som är bestämt i förväg, oavsett om företaget måste förbruka

ytterligare tid eller kostnader för att tillverka produkten eller tjänsten. Detta kan leda till underprissättning av produkter och tjänster när produktionskostnaderna stiger oväntat. Statisk prissättning tillåter inte justeringar i pris för att sälja extra lager eller lediga platser till underhållning eller andra typer av evenemang (Kokemuller, 2018).

Fördelar med dynamisk prissättning

Dynamisk prissättning kallas ofta prisdiskriminering eftersom det ger företag en möjlighet att få ut maximal vinst för varje kund. Detta är speciellt vanligt med evenemang. Om efterfrågan är låg, kan anläggnings- eller evenemangsarrangörer sälja överlops biljetter för att generera så mycket intäkter som möjligt. En ytterligare styrka med dynamisk prissättning är att det ger möjligheten att anpassa priser för projekt eller produkter på basis av tid, kostnader eller förändringar i efterfrågan. Till exempel leverantörer av fisk och skaldjur eller restauranger justerar ofta sina priser säsongmässigt och på basis av efterfrågan (Kokemuller, 2018).

Nackdelar med dynamisk prissättning

Kunder reagerar inte alltid positivt på snabba prisförändringar. Dynamisk prissättning kan leda till motreaktioner inom kundkretsen. Om kunderna inser att de har betalat högre priser än andra för samma produkt, kan de begära tillbaka sina pengar eller sprida negativ återkoppling. Dynamisk prissättning kan också vara fränstötande för kunder som vill veta priset de betalar på förhand. En annan utmaning för företag är behovet av avancerade prissättningsystem för optimering av prisjusteringar. Underhållnings- och resebranschen har traditionellt använt sig av invecklade mjukvarulösningar som anpassar priserna i realtid utifrån efterfrågan (Kokemuller, 2018).

8.3.2 NÄR FUNGERAR DYNAMISK PRISSÄTTNING

För att dynamisk prissättning ska fungera måste vissa marknadsvillkor uppfyllas. Kimes (1989) studerade implementeringsprocessen av dynamiska prissättningsystem i hotellbranschen. Hon identifierade sex villkor för en lyckad implementering av dynamiska prissättningsstrategier. Dessa villkor kompletterades senare med ytterligare ett villkor (Kimes, et al., 1998). Dessa sju villkor är möjligheten att segmentera

marknaden, försvinnande lager, produkten säljs i förväg, låga marginalkostnader, höga marginalkostnader för produktion, fluktuerande efterfrågan, förutsägbar efterfrågan.

8.4 IDROTTSBILJETTER

Implementering av dynamiska prissättningssystem kräver investeringar i form av tid, pengar och andra resurser. För att kunna motivera dessa investeringar måste vi förstå varför så kallade statiska prissättningsstrategier är ineffektiva. Statisk prissättning innebär att priser fastställs innan säsongen börjar utifrån estimat på efterfrågan. Detta innebär att priserna inte kan justeras på basis av ändringar i marknadsvillkoren. Mellan statisk och fullt dynamisk prissättning finns så kallad ”variable ticket pricing” (VTP) där biljetter delas t.ex. in i flera priskategorier. Denna typ av prissättning innebär att kunder betalar t.ex. en premie för spel som anses vara av bättre kvalitet, eller för biljetter med en bättre överblick över matchen (Broshears, 2016).

Statisk prissättning

Efterfrågan på biljetter till idrottsevenemang tenderar att variera från dag till dag och match till match. Vissa dagar är biljetter mer eftersökta och därmed är inträdet värt mer på marknaden. Nackdelen med statisk prissättning är att även om biljetterna är mer efterfrågade är priset fastställt i förväg. Därmed kan organisationer inte dra nytta av den högre efterfrågan i form av ytterligare intäkter. När efterfrågan på biljetter är mindre kan försäljningen dock förbättras genom att erbjuda rabatter. Det är dock värt att notera att dessa rabatter inte kan utnyttja den stigande efterfrågan i form av ytterligare inkomster (Broshears, 2016).

Varierande prissättning

Första steget till mer dynamisk prissättning av biljetter är att anta varierande prissättning. Som tidigare nämnts ligger VTP någonstans mellan totalt fast prissättning och fullt dynamisk prissättning. I VTP är biljettpriserna ännu fastställda i förväg, men biljetterna delas in i olika priskategorier utifrån estimerad efterfrågan. Det är vanligt att det finns mellan två till fem olika priskategorier och varje match som spelas under säsongen placeras i en kategori. Genom denna typ av prissättning kan organisationer relativt enkelt

dra nytta av matcher som har en större efterfrågan och eventuellt sälja mera biljetter till matcher som inte är lika efterfrågade. Vanligtvis är priserna för varje kategori dock fastställda under säsongen (Broshears, 2016).

Dynamisk prissättning

En förutsättning för dynamisk prissättning är kontinuerlig insamling och utvärdering av data. Detta möjliggör justeringen av priser i realtid på basis av uppdaterade efterfrågeprognoser. Det är värt att notera att justeringar i priset för en match påverkar också efterfrågan på andra matcher. Prissättningsalgoritmerna måste ta också detta i beaktande. Även om statisk och varierande prissättning också kräver insamling och analys av data, har dynamiska prissättningssystem betydliga fördelar gentemot ovannämnda strategier:

- Dynamiska prisalgoritmer är överlägsna jämfört med människor i databehandlingsnabbhet och -kraft.
- Dynamiska prisalgoritmer utvecklas av högt specialiserade yrkesverksamma. Dessa system använder sig av avancerade statistiska tekniker och ekonometriska teorier. Denna typ av kunskap är inte tillgänglig för flesta idrottsorganisationer.
- Dynamiska prisalgoritmer jobbar ständigt medan anställda vid biljettoperationer utför flera andra uppgifter. Priser hålls ständigt uppdaterade utifrån senaste marknadsdata.

Även med dessa fördelar är det viktigt att komma ihåg att dynamiska prissättningsalgoritmer inte har tillgång till mänsklig erfarenhet eller intuition. Detta kan i vissa fall vara av avgörande betydelse. Prissättningssystem känner inte till verksamheten eller sina kunder som en erfaren människa. Denna typ av mänsklig kunskap kan vara svår om inte omöjlig att kvantifiera. Därför är det viktigt att även de längst automatiserade prissättningssystemen bibehåller möjligheten för människor att gå igenom föreslagna prisjusteringar före de genomförs (Broshears, 2016).

Kan idrottsbiljetter prissättas dynamiskt?

Tidigare i avhandlingen presenterades Kimes sju marknadskriterier för implementering av dynamisk prissättning inom hotellindustrin (Kimes, 1994) (Kimes, et al., 1998). För att dynamisk prissättning kan implementeras inom idrottsevenemang måste dessa

kriterier också uppfyllas inom marknaden för idrottsbiljetter. Drayer et al. (2012 a) diskuterade huruvida dessa kriterier är tillämpliga inom sportbranschen. Deras studier tyder på att dynamisk prissättning och försäljningen av biljetter till sportevenemang kan kombineras framgångsrikt. Deras observationer diskuteras nedan:

- **Marknad som går att segmentera** – Det finns flera studier och betydande bevis som tyder på att marknadssegmentering kan genomföras i en sportkontext. Segmenteringen kan ske på basis av kön, utbildningsnivå eller säsongkortsstatus (Drayer, et al., 2012 a).
- **Försvinnande produkt** – Sportevenemang är produkter som försvinner då de förbrukas. Detta betyder att en biljett är i princip värdelös efter att matchen har spelats. I en studie år 2009 (Drayer & Shapiro, 2009) identifierade Drayer och Shapiro betydelsen av det upplevda värdet av en match. Detta har en inverkan på priset som konsumenter är villiga att betala för en viss biljett (Drayer, et al., 2012 a).
- **Produkten säljs i förväg** – Biljetter till sportevenemang säljs ofta fram till sista minuten. Ändå sker biljettsläppen ofta månader i förväg. Detta innebär att konsumenter har ett brett tidsfönster för att köpa biljetter (Drayer, et al., 2012 a).
- **Låga marginalkostnader för försäljning** – De flesta professionella idrottsevenemang lockar till sig tusentals om inte tiotusentals åskådare. Låga marginalkostnader för försäljning innebär att flera sålda biljetter inte kräver betydande investeringar i t.ex. ytterligare personal. Eftersom kostnaden för att sälja ytterligare biljetter är låg har organisationer möjligheten att förtjäna extra genom försäljningen av ytterligare biljetter (Drayer, et al., 2012 a).
- **Höga marginalkostnader för produktion** – Det är ofta orealistiskt för idrottsorganisationer att öka på kapaciteten på sina stadion eller arenor. Detta är antingen på grund av resurs- eller rumsbegränsningar. Byggandet av nya arenor eller stadion kräver även större investeringar. Detta betyder att marginalkostnaderna för att producera ytterligare platser som kan säljas är mycket höga (Drayer, et al., 2012 a).

- **Fluktuerande efterfrågan** – Eftersom biljetter till sportevenemang säljs under ett brett tidsfönster kan efterfrågan för individuella matcher variera starkt mellan första biljettsläppet och själva matchdagen. Enligt Drayer och Shapiro (2009) ändrar faktorer som är relaterade till exempel lagets och spelarnas prestation ständigt. Detta kan i sin tur påverka matchens upplevda värde i konsumenternas ögon (Drayer, et al., 2012 a).
- **Förutsägbar efterfrågan** – Enligt Drayer et al. (2012 a) är efterfrågan på sportevenemang en faktor som går att estimera. De hävdar att den statistiska karaktären av flera professionella idrottsgrenar, i samband med enkel tillgång till andra kvantifierbara efterfrågefaktorer, som möjliggör estimeringen efterfrågan på denna typ av produkt. Variation i efterfrågan på sportevenemang undersökts i flera olika studier. Dessa studier har förklarat variationen med faktorer som till exempel ifall matchen spelas på hemmaplan och osäkerhet av utfall. Dessutom har mer traditionella matchrelaterade variabler som t.ex. lag- och spelarprestation förklarat en del av förändringarna i efterfrågan (Drayer, et al., 2012 a)

8.5 TEORI OCH LITTERATUR ÖVERSIKT

Dynamisk prissättning av biljetter har nyligen börjat antas inom idrottsbranschen. Även om nya prissättningsmodeller har visat sig vara framgångsrika, använder en stor del organisationer fortfarande fasta och varierande biljettpriser. Detta gäller även för nordamerikanska sportorganisationer. I Finland litar man i även större grad på traditionella prissättningsstrategier.

Forskningen inom dynamisk prissättning av idrottsevenemang och idrottsbiljetter är fortfarande relativt begränsad. Detta beror till en stor del på att de tidigaste implementeringarna av varierande- och dynamisk prissättning inom sportbranschen skedde så sent som år 2000 och 2009. Drayer och Shapiro hävdar ändå att dynamisk prissättning och biljetter till sportevenemang passar bra ihop. De argumenterar att tidigare forskning inom intäkts hantering och hotellbranschen i kombination med Kimes (1989) sju kriterier stöder idén om att biljetter till sportevenemang kan prissättas dynamiskt (Drayer & Shapiro, 2012).

I en separat studie (Drayer, et al., 2012 a) identifierades betydelsen av datahantering vid prissättningsbeslut. Varierande och dynamiska prissättningsstrategier ger möjligheten att mer noggrant evaluera konsumenternas efterfrågan för enskilda matcher och justera priser på basis av denna information. Flera organisationer har lyckats effektivisera sina prisbeslut och därmed ökat sina intäkter. I de största nordamerikanska idrottsgrenarna har den enormt höga efterfrågan gett upphov till uppväxten av så kallade ”sekundära biljettmarknader”. Detta har tvingat flera organisationer att omvärdera sina prissättningsstrategier. Enligt Drayer och Shapiro är uppkomsten av den sekundära marknaden ett bevis på att biljetter har prissatts ineffektivt. Flera organisationer har antagit mer flexibla prissättningsmetoder för att få sin del av intäkterna som de gått miste om på grund av sekundära biljettmarknader (Drayer, et al., 2012 a).

Determinanter för deltagande

Faktorer som påverkar närvaro vid idrottsevenemang har inte studerats mycket inom finsk idrott. Det är anmärkningsvärt att flera av de faktorer som påverkar biljettförsäljningen i Nordamerika, borde i teorin gälla även i Finland. Rishe och Mondello (2003) (2004) undersökte traditionella kostnadsbaserade prissättningsmetoder i nordamerikanska sportligor. Forskningen av åskådarmängder inom ishockey har fokuserat främst på effekten av slagsmål och regeländringar (Paul, et al., 2016). Dessa inkluderar studier av Jones (1984) (1993) (1996), och Paul (2003). Ovannämnda studier fokuserar på nordamerikanska ishockeyligan NHL, i USA och Kanada. Studier med ett mer allmänt fokus har genomförts av Hong (2009) och Rascher et al. (2009). Hong studerade skillnaderna på efterfrågan för ishockey mellan kasuella och mer ivriga anhängare. Rascher et al. undersökte hur NHL-strejken mellan 2004 och 2005 påverkade efterfrågan i den nordamerikanska korgbollsligan NBA och mindre hockeyligor som AHL och CHL i USA och Kanada. År 2011 studerade Paul och Weinbach (Paul & Weinbach, 2011) efterfrågan i Quebec Major Junior Hockey League, en av de främsta juniorligorna i världen. Studien fokuserade på effekten av vinster, mål och slagsmål i mängden åskådare i en semi-professionell liga. I en senare studie av Paul et al. (2016) studerades hur resultatösakerhet påverkade åskådarmängder i KHL, SHL och Liiga. I studien användes vadsagningsodds som mått för hur svårt det är att förutspå resultaten av en match. Detta var första studien inom europeisk ishockey som har använt vadsagningsdata som mått

för sannolikheten att hemmalaget vinner och resultatösäkerhet för att uppskatta mängden åskådare.

Prisdeterminanter

Största delen av undersökningen och litteraturen inom prisdeterminanter har fokuserat på studier av primära biljettmarknader och traditionella prissättningsmetoder (Rishe & Mondello, 2003) (Rishe & Mondello, 2004). Deras studier visade att faktorer som lagets tidigare prestation, kundernas inkomstnivå och åldern av arenan hade en inverkan på biljettpriserna. Den positiva effekten av nya arenor på mängden åskådare har senare bekräftats av McEvoy et al. och Soebbing et al (McEvoy, et al., 2005) (Soebbing, et al., 2016). Senare har också Drayer och Shapiro, samt Drayer et al. studerat prisdeterminanter i sekundära biljettmarknader (Drayer & Shapiro, 2009) (Drayer & Shapiro, 2012) (Drayer, et al., 2012 b). För att analysera effekten av dynamisk prissättning måste man förstå vilka faktorer som har en effekt på priset när produkter och tjänster prissätts dynamiskt. Reese och Mittelstaedt (2001) var bland de första som undersökte prisdeterminanter inom sportevenemang. Deras undersökning visade att idrottsorganisationer använde flera olika faktorer när de bestämde priser för sina biljetter. Det är värt att notera att denna forskning gjordes före genomförandet av efterfrågebaserade prissättningsstrategier (VTP och DTP).

Överlag kan man konstatera att forskningen har skiftat från kostnadsbaserad prissättning till efterfrågebaserad prissättning. Litteraturen har fokuserat på utvecklingen av dynamisk prissättning, som visat sig vara ett effektivt verktyg för ökade intäkter för sportorganisationer och vidare försäljningen av biljetter för sportevenemang. Största delen av forskningen har fokuserat sig på den nordamerikanska marknaden. Reese och Mittelstaedt, Rishe och Mondello och Paul et al. har studerat prisdeterminanter i primära biljettmarknader, medan Drayer och Shapiro har studerat prisdeterminanter i sekundära biljettmarknader. Dessa studier visade att faktorer som lagets prestation, motståndare, demografi, dagen och tiden då matchen spelas och vissa ekonomiska faktorer alla påverkar biljettpriser när biljetter prissätts dynamiskt.

8.6 METOD

Största delen av data för analysen av publikmängder i finska Liiga fanns offentligt tillgängligt. Detta ledde till att en kvantitativ metod valdes för denna studie. Genom att undersöka tidigare forskning utvecklades två forskningsfrågor för denna studie:

FF1: Vilka faktorer påverkade mängden åskådare för Tapparas hemmamatcher under grundserien mellan 2014 och 2018?

FF2: Vilka faktorer kan användas vid antagningen av dynamiska prissättningsstrategier inom finsk ishockey?

För att svara på de ovannämnda forskningsfrågorna, samlades matchdata från grundserier mellan 2014 och 2018. Data omfattade fyra säsonger och 120 grundseriematcher mellan åren 2014 och 2018. Den första modellen omfattade 19 olika variabler. Dessa variabler organiserades i olika kategorier utifrån deras egenskaper. Dessa kategorier var tids-, spel-, miljö- och prestationsrelaterade variabler. Variablerna för den första modellen presenteras nedan:

Beroende variabel

- **Publikmängd ('Att'):** Mängden åskådare per match på Tapparas hemmamatcher. Siffrorna har hämtats från Liigas officiella webbsida.

Oberoende variabel

- **Matchnummer ('Num'):** Ordningssiffran för matchen ifråga. Varje lag spelar 60 matcher under grundserien.
- **Del av säsong ('PoS'):** Variabel som kategoriserar matcher under vilken del av säsongen de har spelats. Säsongen delades i tre olika delar: (säsongstart: september–oktober; mellansäsong: november–januari; slutsäsong: februari–mars).
- **Veckodag/veckoslut ('WdWe'):** En kategorisk variabel som delar in matcherna enligt veckodag (måndag-torsdag) eller veckoslut (fredag-söndag).

- **Starttid ('ToG')**: Variabel som delade matcherna in i kategorier enligt starttid (15.00, 17.00 eller 18.30). Det är värt att notera att endast två matcher startade klockan 15.00 av 120 observationer). Matcherna startar klockan 18.30 på veckodagar och 17.00 under veckoslut.
- **Motståndare ('Opp')**: Variabel som indikerar motståndaren i respektive match.
- **Liiga publiksnitt ('LAA')**: Variabel som mäter ligans publiksnitt per månad. Data hämtades från ligans officiella webbsida.
- **Temperatur ('Temp')**: Variabel som mäter medeltemperaturen i Celsius för matchdagen i Tammerfors. Observationerna hämtades från Meteorologiska institutets portal.
- **Nederbörd ('Prec')**: Variabel som mäter mängden regn eller snöfall under matchdagen. Observationerna hämtades från Meteorologiska institutets portal.
- **Snö ('Snw')**: Variabel som mäter mängden snö på marken under matchdagen. Observationerna hämtades från Meteorologiska institutets portal.
- **Vinstprocent ('WP')**: Variabel som mäter vinstprocenten för Tappara under hela säsongen.
- **Vinstprocent i de sista fem matcherna ('WP5')**: Variabel som mäter vinstprocenten för Tappara under de senaste fem matcherna.
- **Vinstprocent i de sista tio matcherna ('WP10')**: Variabel som mäter vinstprocenten för Tappara under de senaste tio matcherna.

Data analyserades med analysprogrammet R-studio. Variablerna för den slutliga modellen valdes genom stegvis regression. Metoden innebär att programmet iterativt adderar och subtraherar variabler för att hitta den bäst presterande modellen, dvs. en modell med lägsta chansen för fel. Programmet gör detta automatiskt för att hitta en kombination variabler som bäst förklarar ändringarna i den bestående variabeln.

Den första modellen bestod av 19 olika variabler. Modellen skapades för att undersöka faktorer som påverkar publikmängder på Tapparas hemmamatcher under de 120

hemmamatcherna inkluderade i analysen. Efter den ursprungliga modellen skapades en mer strömlinjeformad modell för att uppnå högre statistisk signifikans. Variablerna för den nya modellen valdes med en automatisk och iterativ metod som kallas stegvis regression, en inbyggd funktion i R-studio. Analysen tillsammans med resultaten presenteras i nästa kapitel.

8.7 RESULTAT

Efter den första modellen skapades en ny modell för att öka prestationen. Sammanfattningen av den nya modellens resultat visar att den nya modellen presterar bättre än den första modellen.

Det justerade R²-värdet, som mäter prestationen av modellen, steg från 0,5833 till 0,6206. Detta betyder att den andra modellen kan förklara 62 % av ändringarna i den beroende variabeln. Enskilda variabelernas *t*-värden är längre ifrån 0, vilket tyder på att modellen presterar bättre än den första. *P*-värden för enskilda variabler sjönk drastiskt och fyra variabler var under 0,001 för att klassas som statistiskt mycket signifikanta. *F*-värdet ökade från 8,08 till 13,98. Modellens *p*-värde minskade till 2.2e-16.

Resultaten visar att oberoende variablerna 'WdWe', 'ToG', 'LAA' and 'WP5' och oppositionsrelaterade variablerna 'Assat', 'HIFK', 'HPK', 'Ilves', 'KalPa', 'Karpas', 'KooKoo', 'Lukka', 'Pelicans', 'SaiPa' och 'Sport' inkluderades i den stegvisa regressionsmodellen. Av ovannämnda variablerna var 'WdWe', 'LAA', 'Ilves' och 'Pelicans' över gränsen för att räknas som statistiskt väldigt signifikanta. Dessa variabler hade *p*-värden under 0,001. Variablerna 'ToG', 'HIFK' och SaiPa var under gränsen för att räknas som statistiskt signifikanta, med *p*-värden under 0,01.

Resultaten av analysen visar att ovannämnda variablerna har en inverkan på publikmängderna i Tapparas hemmamatcher. Resultaten stämmer också överens med tidigare forskning i ämnet, som identifierat matchtid, motståndare och lagets prestation som faktorer som påverkar publikmängder inom professionell idrott.

8.8 SLUTSATSER

Denna studie har som mål att identifiera faktorer som påverkade publikmängden för Tapparas hemmamatcher i den finska elitserien Liiga.

Resultaten från dataanalysen av Tapparas hemmamatcher visar att faktorer som motståndare, tidpunkten för matchen och lagets prestation under säsongen har en inverkan på publikmängden. Resultaten stämmer också med tidigare undersökning inom ämnet, som identifierat likande faktorer t.ex. inom den nordamerikanska idrottsmarknaden.

Resultaten av denna studie har flera intressanta aspekter för finska idrottsorganisationer och deras ledningsgrupper. I analysen har motstånd identifierats som en faktor med stor inverkan på publikmängd. Efterfrågan mellan motståndare som t.ex. Ilves, HIFK, Pelicans och SaiPa varierade starkt. Resultaten visade en positiv relation mellan publikmängderna för matcher mot Ilves och HIFK medan relationen var starkt negativ för Pelicans och SaiPa. Dessa fynd kan potentiellt utnyttjas ifall dynamisk prissättning planeras. Ifall matchen spelas under veckan eller ett veckoslut identifierades som en betydande faktor. En dynamisk prissättningsalgoritm kunde eventuellt prissätta veckoslutsmatcher mot Ilves högre än exempelvis en tisdagsmatch mot Pelicans. Studien diskuterade också ineffektiviteten hos kostnadsbaserade prissättningsmetoder som används ännu allmänt inom finsk idrott och potentiella ekonomiska nyttor som dynamisk prissättning erbjuder.

Som tidigare nämnts stämmer resultaten av denna studie överens med tidigare undersökning inom ämnet. Motståndare, plats och tidpunkt, samt lagets tidigare prestation spelar en roll i hur intressant diverse matcher anses vara. Det är dock värt att notera att denna studie har vissa begränsningar som eventuella intressenter måste ta i beaktande. Analysen gjordes på basis av matchdata från endast ett lag. Ifall data från flera lag skulle analyseras skulle resultaten ge en noggrannare inblick i hur efterfrågan bland olika lag formas. Data från flera lag skulle vara nyttigt för att analysera hur lagets prestation påverkar efterfrågan bland lag som presterar olika. I denna analys analyserades endast ett lag som presterade relativt bra under alla fyra säsonger som inkluderades i analysen. Pris- och försäljningsinformation kunde också användas i analysen för att förstå hur biljetter i olika prisgrupper säljs. I denna analys användes endast information om hur många biljetter sålts för hela matchen.

9 BIBLIOGRAPHY

Abrate, G., Fraquelli, G. & Viglia, G., 2012. Dynamic pricing strategies: Evidence from European hotels. *International Journal of Hospitality Management*, Volume 31, pp. 160-168.

Alamar, B., 2013 b. *Sports Analytics, A Guide for coaches, Managers and Other Decision Makers*. Chichester, New York: Columbia University Press.

Alamar, B. & Mehrotra, V., 2011. [Online]
Available at: <http://www.analytics-magazine.org/special-articles/391-beyond-moneyball-the-rapidly-evolving-world-of-sports-analytics-part-i>

Boyd, D. W. & Boyd, L. A., 1998. The Home Field Advantage: Implications for the Pricing of Tickets to Professional Team Sporting Events. *Journal of Economics and Finance*, 22(2-3), pp. 169-179.

Boyd, T. & Krehbiel, T., 1999. The effect of promotion timing on major league baseball attendance. *Sport Marketing Quarterly*, 8(4), pp. 23-34.

Boyd, T. & Krehbiel, T., 2003. Promotion timing in major league baseball and the stacking effects of factors that increase game attractiveness. *Sport Marketing Quarterly*, 12(3), pp. 173-183.

Boyd, T. & Krehbiel, T., 2006. An analysis of the effects of specific promotion types on attendance at major league baseball games. *Mid-American Journal of Business*, 21(2), pp. 21-33.

BrightPlanet, 2012. *brightplanet.com*. [Online]
Available at: <https://brightplanet.com/2012/06/structured-vs-unstructured-data/>

Broshears, C., 2016. *digonex.com*. [Online]
Available at: <https://www.digonex.com/how-does-dynamic-pricing-work/>
[Accessed 27 September 2018].

Burger, B. & Fuchs, M., 2005. Dynamic Pricing - A future airline business model. *Journal of Revenue & Pricing Management*, Volume 4, pp. 39-53.

Cachon, G. & Feldman, P., 2010. *Dynamic versus Static Pricing in the Presence of Strategic Consumers*, Philadelphia, USA: Department of Operations and Information Management, The Wharton School, University of Pennsylvania.

Carr, N., 2003. IT Doesn't Matter. *Harvard Business Review*.

Cave, A., 2017. *Forbes*. [Online]
Available at: <https://www.forbes.com/sites/andrewcave/2017/04/13/what-will-we-do-when-the-worlds-data-hits-163-zettabytes-in-2025/#4c415544349a>
[Accessed 8 June 2018].

Choi, S. & Mattila, A., 2005. Impact of Information on Customer Fairness Perceptions of Hotel Revenue Management. *Cornell Hotel and Restaurant Administration Quarterly*, 46(4), pp. 444-451.

- Coates, D. & Humphreys, B., 2005. Novelty Effect Of New Facilities On Attendance At Professional Sporting Events. *Contemporary Economic Policy*, 23(3), pp. 436-455.
- Coates, D. & Humphreys, B., 2007. Ticket Prices, Concessions and Attendance at Professional Sporting Events. *International Journal of Sport Finance*, Volume 2, pp. 161-170.
- Coates, D. & Humphreys, B., 2012. Game Attendance and Outcome Uncertainty in the National Hockey League. *Journal of Sports Economics*, 13(4), pp. 364-377.
- Courty, P., 2003. Some Economics of Ticket Resale. *Journal of Economic Perspectives*, 17(2), pp. 85-97.
- Cross, R., 1997. Revenue Management: Hard-core tactics for market domination. *Cornell Hotel and Restaurant Administration Quarterly*, 38(2).
- Davenport, T. H. & Harris, J. G., 2007. *Competing on Analytics, The New Science of Winning*. Boston: Harvard Business School Publishing Corporation.
- Davis, M., 2008. The interaction between baseball attendance and winning percentage: A VAR analysis. *International Journal of Sport Finance*, 3(1), pp. 58-73.
- den Boer, A., 2013. *Dynamic Pricing and Learning: Historical Origins, Current Research, and New Directions*, Twente: University of Twente.
- Draper, N. & Smith, H., 1998. *Applied Regression Analysis*. 3 ed. s.l.:John Wiley & Sons, Incorporated.
- Drayer, J. & Martin, N., 2010. Establishing legitimacy in the secondary ticket market: A case study of an NFL market. *Sport Management Review*, 13(1), pp. 39-49.
- Drayer, J., Rascher, D. & McEvoy, C., 2012 b. An examination of underlying consumer demand and sport pricing using secondary market data. *Sport Management Review*, 15(4), pp. 448-460.
- Drayer, J. & Shapiro, S., 2009. Value Determination in the Secondary Ticket Market: A Quantitative Analysis of the NFL Playoffs. *Sports Marketing Quarterly*, 12(1), pp. 5-13.
- Drayer, J. & Shapiro, S. L., 2011. An examination into the factors that influence consumers' perceptions of value. *Sport Management Review*, p. 1.
- Drayer, J. & Shapiro, S. L., 2012. An examination of dynamic ticket pricing and secondary market price determinants in Major League Baseball. *Sport Management Review*.
- Drayer, J., Shapiro, S. L. & Lee, S., 2012 a. Dynamic Ticket Pricing in Sport: An Agenda for Research and Practice. *Sport Marketing Quarterly*.
- Hall, J., O'Mahony, B. & Vieceli, J., 2010. An empirical model of attendance factors at major sporting events. *International Journal of Hospitality Management*, 29(2), pp. 328-334.

- Harrison, C. K. & Bukstein, S., 2017. *Sports Business Analytics - Using Data to Increase Revenue and Improve Operational Efficiency*, Boca Raton: CRC Press Taylor & Francis Group.
- Hong, J., 2009. A comparison of motivational factors affecting attendance between avid and casual fans at minor hockey games. *International Journal of Sport Management and Marketing*, 5(1-2), pp. 115-131.
- Howard, D. & Crompton, J., 2004. Tactics used by sports organizations in the United States to increase ticket sales.. *Managing Leisure*, 9(2), pp. 87-95.
- Hurwitz, J., Nugent, A., Halper, D. F. & Kaufman, M., 2013. *Big Data For Dummies*.. New Jersey: John Wiley & Sons, Inc..
- International Ice Hockey Federation, 2018. *iihf.com*. [Online] Available at: <http://www.iihf.com/iihf-home/the-iihf/members/> [Accessed 05 September 2018].
- Investopedia, n.d. *Investopedia.com*. [Online] Available at: <https://www.investopedia.com/terms/c/cross-elasticity-demand.asp> [Accessed 22 March 2018].
- Investopedia, n.d. *Investopedia.com*. [Online] Available at: <https://www.investopedia.com/exam-guide/cfa-level-1/microeconomics/price-elasticity.asp> [Accessed 22 March 2018].
- Jones, J., 1984. Winners, losers, and hosers: demand and survival in the National Hockey League. *Atlantic Economic Journal*, 12(3), pp. 54-63.
- Jones, J., Ferguson, D. & Stewart, K., 1993. Blood sports and cherry pie: some economics of violence in the National Hockey League. *American Journal of Economics and Sociology*, 52(1), pp. 87-101.
- Jones, J., Stewart, K. & Sunderman, R., 1996. From the arena into the streets: hockey violence, economic incentives, and public policy. *American Journal of Economics and Sociology*, 55(2), pp. 231-249.
- Kassambara, A., 2018. *Statistical tools for high-throughput data analysis*. [Online] Available at: <http://www.sthda.com/english/articles/37-model-selection-essentials-in-r/154-stepwise-regression-essentials-in-r/> [Accessed 6 June 2018].
- Kimes, S., 1989. The Basics of Yield Management. *Cornell Hotel and Restaurant Administration Quarterly*, 30(3), pp. 14-19.
- Kimes, S., 1994. Perceived fairness of revenue management. *Cornell Hotel and Restaurant Administration Quarterly*, 35(1), pp. 22-29.
- Kimes, S., 2003. Revenue management: A retrospective. *Cornell Hotel and Restaurant Administration Quarterly*, 44(5-6), pp. 131-138.

- Kimes, S., 2010. Successful tactics for surviving an economic downturn: Results from an international study.. *Cornell Hospitality Report*, 10(7), pp. 4-14.
- Kimes, S. et al., 1998. Restaurant Revenue Management, Applying Yield Management to the Restaurant Industry. *Cornell Hotel and Restaurant Administration Quarterly*, pp. 32-39.
- Kokemuller, N., 2018. *eu.azcentral.com*. [Online]
Available at: <https://yourbusiness.azcentral.com/advantages-disadvantages-fixed-pricing-dynamic-pricing-13188.html>
[Accessed 26 September 2018].
- Kotler, P. & Keller, K., 2016. *Marketing management*. 15 ed. Boston: Pearson.
- Kung, M., Monroe, K. & Cox, J., 2002. Pricing on the Internet. *Journal of Product & Brand Management*, 11(5), pp. 274-288.
- Leadley, J. & Zygmunt, Z., 2005. When Is the Honeymoon Over? National Basketball Association Attendance 1971-2000. *Journal of Sports Economics*, 6(2), pp. 203-221.
- Leadley, J. & Zygmunt, Z., 2006. When Is The Honeymoon over? National Hockey League Attendance, 1970-2003. *Canadian Public Policy*, 32(2), p. 213.
- Lindenmeier, J. & Tscheulin, D., 2008. The effects of inventory control and denied boarding on customer satisfaction: The case of capacitybased airline revenue management. *Tourism Management*, 29(1), pp. 32-43.
- McDonald, M. & Rascher, D., 2000. Does Bat Day Make Cents? The effect of Promotions on the Demand for MLB.. *Journal of Sport Management*, Volume 14, pp. 8-27.
- McEvoy, C., Nagel, M., DeSchriver, T. & Brown, M., 2005. Facility Age and Attendance in Major League Baseball. *Sports Management Review*, 8(1), pp. 19-41.
- Metsämuuronen, J., 2006. *Laadullisen tutkimuksen käsikirja*. Helsinki: International Methelp Oy.
- Milton, M., 2009. *Head First Data Analysis; A Learner's Guide to Big Numbers, Statistics and Good Decisions..* Sebastopol: O'Reilly Media, Inc..
- Moe, W., Fader, P. & Kahn, B., 2011. *Buying Tickets: Capturing the Dynamic Factors that Drive Consumer Purchase Decisions for Sporting Events*. [Online]
Available at: <https://www.slideshare.net/sloansportsconf/buying-tickets-capturing-the-dynamic-factors-that-drive-consumer-purchase-decisions-for-sporting-events>
[Accessed 28 June 2018].
- Nagle, T. & Holden, R., 2002. *The strategy and tactics of pricing : a guide to profitable decision making*. 3rd Edition ed. Upper Saddle River, NJ: Prentice Hall.
- Paul, R., 2003. Variations in NHL attendance: the effect of violence, scoring, and regional rivalries.. *American Journal of Economics and Sociology*, Volume 62, pp. 345-364.

- Paul, R., Conetta, C. & Losak, J., 2016. Betting market prices, outcome uncertainty and hockey attendance in Russia, Sweden and Finland. *Emerald Group Publishing Limited*, 42(9), pp. 852-865.
- Paul, R. & Weinbach, A., 2011. Determinants of Attendance in the Quebec Major Junior Hockey League: Role of Winning, Scoring, and Fighting. *Atlantic Economic Journal*, Volume 39, pp. 303-311.
- Rascher, D., Brown, M., Nagel, M. & McEvoy, C., 2009. Where did National Hockey League fans go during the 2004–2005 lockout? An analysis of economic competition between leagues. *International Journal of Sport Management and Marketing*, 5(1-2), pp. 183-195.
- Rascher, McEvoy, Nagel & Brown, 2007. *Variable Ticket Pricing in Major League Baseball*, Munich: Munich Personal RePEc Archive.
- Reese, J. T. & Mittelstaedt, R. D., 2001. An Exploratory Study of the Criteria Used to Establish NFL Ticket Prices. *Sport Marketing Quarterly*, 10(4).
- Rego, F., 2015. *github.io*. [Online]
Available at: <https://feliperego.github.io/blog/2015/10/23/Interpreting-Model-Output-In-R>
[Accessed 13 October 2018].
- Rishe, P., 2012. *Dynamic Pricing: The Future of Ticket Pricing in Sports*. [Online]
Available at: <https://www.forbes.com/sites/prishe/2012/01/06/dynamic-pricing-the-future-of-ticket-pricing-in-sports/2/#750a230263ef>
[Accessed 16 December 2017].
- Rishe, P. & Mondello, M., 2003. Ticket Price Determination in the National Football League: A Quantitative Approach. *Sport Marketing Quarterly*, 12(2).
- Rishe, P. & Mondello, M., 2004. Ticket Price Determination in Professional Sports: An Empirical Analysis of the NBA, NFL, NHL and Major League Baseball. *Sport Marketing Quarterly*, 13(2).
- Soebbing, B., Mason, D. & Humphreys, B., 2016. Novelty effects and sports facilities in smaller cities: Evidence from Canadian hockey arenas. *Urban Studies*, 53(8), pp. 1674-1690.
- Tanford, S., Erdem, M. & Baloglu, S., 2011. Price Transparency of Bundled Vacation Packages. *Journal of Hospitality & Tourism Research*, 35(2), pp. 213-234.
- Wirtz, J. & Kimes, S., 2007. The moderating role of familiarity in fairness perceptions of revenue management pricing. *Journal of Service Research*, 9(3), pp. 229-240.
- Young, L., 2018. Common Factors in Major League Baseball Game Attendance. *Journal of Sports Economics*, 19(4), pp. 583-598.
- Zeithamel, V., 1988. Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence. *American Marketing Association*, 52(3), pp. 2-22.

Appendix 2: Summary of results full.model & step.model

Residuals:

Min	1Q	Median	3Q	Max
-1395.7	-371.5	-103.5	277.3	1963.6

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	778.8326	1559.7679	0.499	0.618716
Num	-1.8059	12.5554	-0.144	0.885938
WdWe	596.7012	171.0627	3.488	0.000742 ***
ToG	418.6341	159.9641	2.617	0.010336 *
PoS	197.2336	242.6015	0.813	0.418276
LAA	0.8680	0.3679	2.359	0.020392 *
Temp	-2.6403	12.7817	-0.207	0.836795
Prep	20.2954	23.8821	0.850	0.397585
Snw	-6.7616	9.8572	-0.686	0.494427
WP	94.8390	849.4003	0.112	0.911336
WPS	420.0463	468.8534	0.896	0.372594
WP10	-109.6063	722.9228	-0.152	0.879815
Assat	740.8881	418.4865	1.770	0.079903 .
HIFK	971.5742	415.6685	2.337	0.021542 *
HPK	-337.4804	408.3882	-0.826	0.410686
Ilves	1587.0465	387.2284	4.098	8.82e-05 ***
Jukurit	216.8402	487.3504	0.445	0.657388
JYP	330.6895	426.5047	0.775	0.440080
KalPa	-227.0197	405.3849	-0.560	0.576804
Karpat	807.0703	404.0626	1.997	0.048674 *
KooKoo	-422.4636	435.7812	-0.969	0.334814
Lukko	-155.0134	411.5260	-0.377	0.707261
Pelicans	-767.9369	413.7215	-1.856	0.066562 .
SaiPa	-612.5719	408.8088	-1.498	0.137372
Sport	-397.6222	397.3804	-1.001	0.319585
TPS	44.3181	417.8873	0.106	0.915767

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 643.2 on 94 degrees of freedom
 Multiple R-squared: 0.6825, Adjusted R-squared: 0.5981
 F-statistic: 8.083 on 25 and 94 DF, p-value: 2.694e-14

Residuals:

Min	1Q	Median	3Q	Max
-1559.20	-334.83	-81.14	325.50	2034.48

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	502.5774	1113.1871	0.451	0.652587	
WdWe	540.9107	139.4720	3.878	0.000185	***
ToG	466.5224	142.2814	3.279	0.001418	**
LAA	0.9922	0.2605	3.809	0.000236	***
WP5	455.3126	264.2921	1.723	0.087904	.
Assat	578.2499	259.8458	2.225	0.028216	*
HIFK	774.3801	258.1907	2.999	0.003387	**
HPK	-570.3822	258.3982	-2.207	0.029485	*
Ilves	1391.4827	227.3378	6.121	1.67e-08	***
KalPa	-391.3336	246.7416	-1.586	0.115774	
Karpat	554.2776	257.5496	2.152	0.033701	*
KooKoo	-686.0745	286.7032	-2.393	0.018506	*
Lukko	-383.3728	256.8808	-1.492	0.138618	
Pelicans	-934.4485	249.6148	-3.744	0.000298	***
SaiPa	-802.1392	250.7946	-3.198	0.001832	**
Sport	-573.4214	228.9568	-2.504	0.013816	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 624.9 on 104 degrees of freedom

Multiple R-squared: 0.6684, Adjusted R-squared: 0.6206

F-statistic: 13.98 on 15 and 104 DF, p-value: < 2.2e-16

Appendix 3: Full.model and Step.model normal distribution plots for residuals.

