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Creating a Demand-Based Ticket Model for Eliteserien

How revenue management could save the Norwegian league's attendance rates

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NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgments

This master thesis marks the end of my time at the Norwegian School of Economics. I look back at a time with ups and downs. Starting my masters in a new city under corona was difficult for me, and I learned a lot during this period. This thesis was both an accomplishment and a passion project for me. It has been frustrating at times, but I am proud of what I have achieved.

There are many people that I wish to show appreciation to. First of all, I want to thank the respondents of the survey I made, the ticket managers representing the different clubs. A special thanks to Joe Foster at Bodø/Glimt, that showed extra interest in my thesis. Further, I want to thank Terje Alstad at NTB and Thomas Torjusen at Norges toppfotball that made it possible for me to come in contact with the individual clubs. I also want to thank my supervisor Julio C. Goez for helping and guiding me in the field of revenue management. All the meetings we had on Teams were greatly appreciated. Last but not least, I want to thank my family for supporting me during the whole process and for always believing in me.

My thesis was written at the Norwegian School of Economics but also during my exchange at the University of Maastricht. I want to thank my friends in Bergen and Maastricht for the endless discussions about my master thesis topic and the inspiring words that kept me going. As a football enthusiast, it fits to end the acknowledgments with a quote from football legend Pelé that describes the whole process of writing the master thesis well:

“The more difficult the victory, the greater the happiness in winning”

Abstract

Dynamic pricing has been a pricing strategy used by many industries with shifting demands. However, sports have just recently started implementing such a strategy. From pricing experiments in the American baseball league MLB to mathematical models created for European sports teams. The currently available studies have focused exclusively on making models for big teams in major sports leagues, but not on a smaller scale with fewer supporters. Furthermore, previous papers have had their main point of attention on revenues, while this paper looks at how to increase attendance rates using dynamic pricing. This research paper will look at implementing such a strategy in the Norwegian top division for football called Eliteserien. The necessary information on the club's pricing strategies was realized by a survey answered by the majority of the league's ticket coordinators. Further, using previous prices and attendance rates combined with price experiments, we are able to find the consumers' price elasticity. Results indicate that consumers are far more price elastic now than they were in previous years. Based on this elasticity, we can make a dynamic model that charges different prices based on the point of purchase and demand. With an analytical model, clubs will be able to increase attendance rates by addressing customers' demands at several levels.

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1. Introduction

When football clubs set their prices, they usually utilize traditional pricing in the form of section-based pricing, or even pricing the whole stadium at the same price point (Drayer, Shapiro, & Lee, 2012). This frequently leads to one of two scenarios: tickets often have a large demand, and it will be hard to get a ticket or it will be easy to get into games because the demand is low. In sports, the teams often vary in popularity depending on their match form and how competitive they are. This makes it hard to set a fixed charge for the price setters at the club, especially since the price is fixed during the whole season for many clubs. This problem might be coming to an end as dynamic pricing is making an entrance into sports. Dynamic pricing makes your ticket vary according to the demand of a particular ticket. Now not only will the price of your flight ticket and your hotel room vary with the demand of the football weekend, but the match ticket will also vary with this demand.

The Norwegian football league, Eliteserien, has had a sinking attendance rate in the last ten years before the corona pandemic (Hjelseth, 2019). In fact, a report done by the CIES football observatory showed that Eliteserien was one of the leagues with the greatest decline in attendance in recent years. Out of the 26 leagues analyzed in the period 2008-2018, the Norwegian League came second to last with a decrease in attendance of 29% (Poli, Ravenel, & Besson, 2019). The Norwegian clubs have mainly utilized section-based pricing that is fixed for the whole season for their ticket pricing strategy. By applying dynamic pricing measures, clubs have a chance to appeal to consumers that previously were outpriced by the current pricing model. In addition, there are several other factors that further explain the trend of sinking attendance. By understanding the advantages of dynamic pricing, clubs do not only have the potential to increase attendance but also increase revenues in the long run. Higher attendance results in a larger number of tickets sold, meaning higher revenues even when a single ticket has a lower price point than before. Although dynamic pricing is a potent pricing tool for clubs, it is important that the method is correctly implemented in the market. By looking at examples from the Major Baseball league (MLB), the German Bundesliga, and the English championship (2nd division in English football) we can get a greater understanding of how to implement such a strategy. Furthermore, other research done on revenue management in different sectors helps us get a greater understanding of how such a mathematical model can be created.

This paper first looks at related literature and describes how dynamic pricing has become such a crease in the sporting world. This will be done by looking at advances in the sports sector in different countries. The fundamental theoretical foundations of revenue management and dynamic pricing are described second. The following step illustrates how we collect data from first-hand and secondary sources to generate a basis for model creation. By enabling this data, we can understand the pricing choices of different clubs as well as the demand of the supporters. Using this information, a dynamic pricing model in a particular pricing situation can be created. In the end, a conclusion summarizes the paper's main points and limitations.

2. Research question and objective

After having done a brief introduction to the topic of dynamic pricing and the Norwegian football league, my research question is the following:

"Is there potential for a dynamic ticket pricing model to increase attendance for clubs in the Norwegian football league?"

My objective with this master thesis is to find a possible connection between increasing attendance and applying a dynamic pricing strategy to the teams of the Norwegian football league. I want to look at how clubs price themselves and what pricing mechanisms they are using currently. Further, I want to look at the consumers and research their willingness to pay and how it has evolved in recent years.

Hypothesis

Before collecting data, I compiled some hypotheses concerning the making of a dynamic pricing model and the Norwegian league in general. These are central aspects I wanted to know more about, and I will try to falsify or confirm these during my thesis.

Hypothesis 1: *"Interest in the Norwegian league has decreased the last ten years."*

Hypothesis 2: *"Supporters are more price aware or more price elastic than in previous years"*

Hypothesis 3: *"Norwegian clubs are faced with a lot of challenges when it comes to creating a dynamic pricing model"*

Hypothesis 4: *"There are not enough countermeasures done by the clubs to stop the loss of attendees"*

3. Examples of dynamic pricing

To understand the concept of dynamic ticket pricing in professional sports, a few selected examples of implementation in other countries will be presented and discussed.

3.1 In other parts of the world

3.1.1 The American success story

Dynamic pricing of sports tickets became popular in the USA after an experiment done by the San Francisco Giants in 2009 where they let a segment of the stadium be priced by this new pricing method. Prices were changed daily to adapt to the varying demand. Factors that changed the price were weather, team performance, opponent, and others. In addition to the factors, historical trends were analyzed. The dynamic ticket strategy was implemented to reduce the uncertainty of consumer demand that could shift drastically throughout a six-month season (Shapiro & Drayer, 2012). The financial results were impressive, which led them to price their whole stadium dynamically in the next season, grossing a 7% increase in ticket revenue. After the success of the San Francisco Giants, dynamic pricing became a subject generating a significant amount of coverage for scientific research. Clubs and researchers tried to figure out how to get as much out of this new pricing technique.

A group of researchers looked at the benefits and challenges of developing a new pricing strategy for the Los Angeles Dodgers, another franchise in the Major Baseball League (MLB). The Dodgers had faced sinking attendance rates the last years, from forty-six to forty-three to only thirty-six thousand fans per game in 2012. In this period, the Dodgers had fallen from first in attendance to eleventh in the MLB. During the 2012 season, 17 of the total 30 MLB teams were using a dynamic ticket pricing strategy (Dunne, 2012). Most of them through a software pricing company called Qcue that recommended daily price changes based on market demand (Parris, Drayer, & Shapiro, 2012). Dodgers were facing several challenges with a fixed section-based pricing strategy. Since the stadium has a fixed capacity, the revenue from the seats that weren't sold would be permanently lost. They were competing against an increasing number of sports clubs in the already crowded Los Angeles market but also an expanding number of entertainment services outside of sports. In addition, secondary markets were capitalizing on the pricing inefficiencies and selling them closer to the actual market demand. In the years leading up to 2012, secondary market prices had gone down, and the number of tickets sold through them had gone up, causing a decrease in the perceived value of the tickets (Fisher, 2009). Results of dynamic ticket pricing showed that the ticket price would better reflect the one of the secondary ticket market, causing more of the revenue to stay in the club's books (Parris, Drayer, & Shapiro, 2012).

The dynamic ticket pricing method spread to several other leagues in America, like the National Hockey league, the National football league, and the National Basketball Association, after the success it had in the MLB. A research paper out of the University of Tulsa researched the dynamic pricing usage in American sports. They surveyed and interviewed a total of 72 managers and executives from the four major American sports leagues. Their findings were that even though the sports organizations apply dynamic pricing, their procedures lag. According to the report, 70 % of responders believe their organizations apply business analytics to dynamic prices, but only 30% update their prices daily. If prices are not updated daily or maybe even hourly, they face the risk of being priced wrong in relation to current market demand. For example, if the club announces that their star player is back from injury without updating their prices, they face the risk of selling out at a lower price than the demand will indicate. Another important result from the report was that just 50% of the organizations automate the decision process (Bouchet, Trolio, & Walkup, 2016). When the decision process is not automatically updated, clubs face the risk of being too late on their updates, meaning they would lag behind actual market demand. However, if the teams do not fully trust their algorithms or automatic pricing tools, they would be better off checking every price change that is suggested by the algorithm. The report suggests that there are still areas of improvement for sports teams in North America when it comes to their dynamic ticket-based pricing. Nufer and Fischer (2013) drew the conclusion that based on the success of dynamic pricing in North America, it was only a matter of time before it was applied by a major football team in Europe.

3.1.2 Implementation in the European football leagues

Researchers Christoph Breuer and Christoph Kemper (2016) wanted to see if dynamic pricing was viable for the biggest football club in Germany, Bayern Munich. In addition to being the biggest club in Germany, Bayern Munich is also considered the 3rd most valuable football club worldwide, according to Forbes (Ozanian, 2021). When Breuer and Kemper started their research of Bayern, they had a system similar to the clubs in Norway, where ticket prices depended on the seat category. Here a better seat, usually on the long side of the stadium would be more expensive than a ticket for a seat on the short side. The seats were categorized by numbers 1 to 4 according to their prices. In addition, the club had a 5-10€ increase in price if they were playing against a high-level opponent. They were categorized as A opponents and B opponents. Something that is not currently seen in Norway today. The researchers looked at reseller websites to determine the demand for the games and found out that A-games had a much higher demand. During their research, they found out that the tickets had surcharges between 75-225% at the reseller websites. Therefore, Breuer created a demand function for each section and found out that the club was selling their tickets at a low price, and an optimal fixed price would increase their revenue by over 100% for most categories. On top of that, a dynamic price for each category could reap even bigger revenues (Kemper & Breuer, 2016).

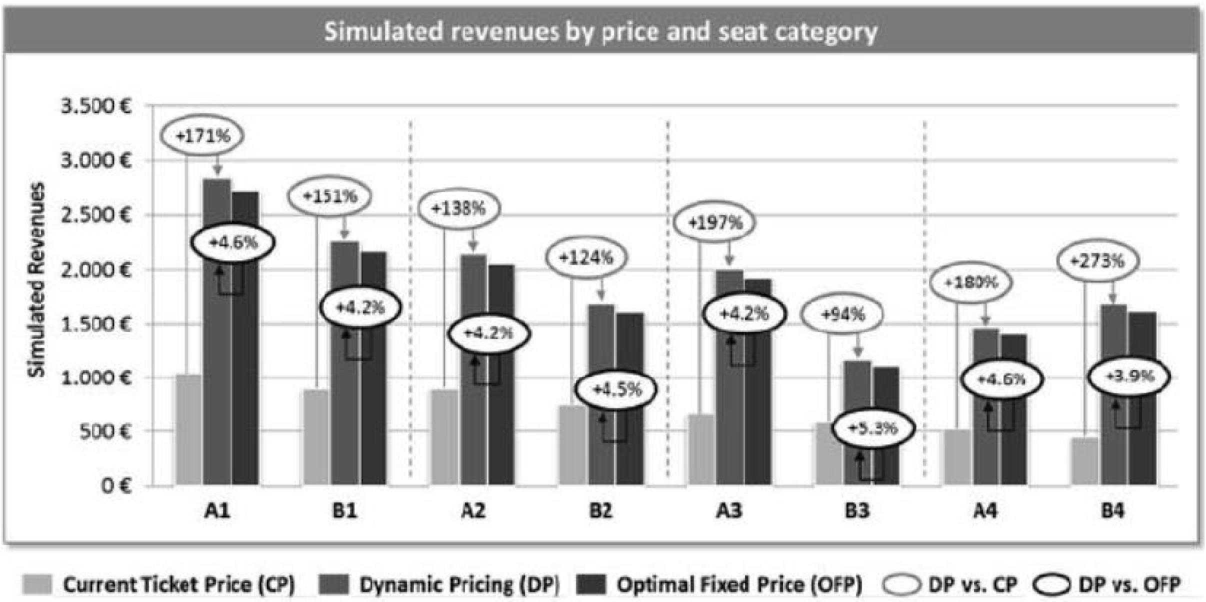

Figure 1: Simulated revenues (Kemper & Breuer, 2016)

The numbers from figure 1 were found with a method called a Monte Carlo simulation. The method involves simulating an environment on a computer by taking a bunch of random draws from a demand distribution to replicate the randomness of demand over a large number of days (Bodea & Ferguson, 2014). In this study, supporters with varying willingness to pay for a ticket were drawn randomly from the estimated demand function. A ticket was sold if the ticket price set by the club was lower or the same as the fan's willingness to pay. If the price was higher than the willingness to pay of the fan, the ticket was not sold. This scenario was repeated 1000 times to find the optimal prices for each of the six categories shown in Figure 1. (Kemper & Breuer, 2016)

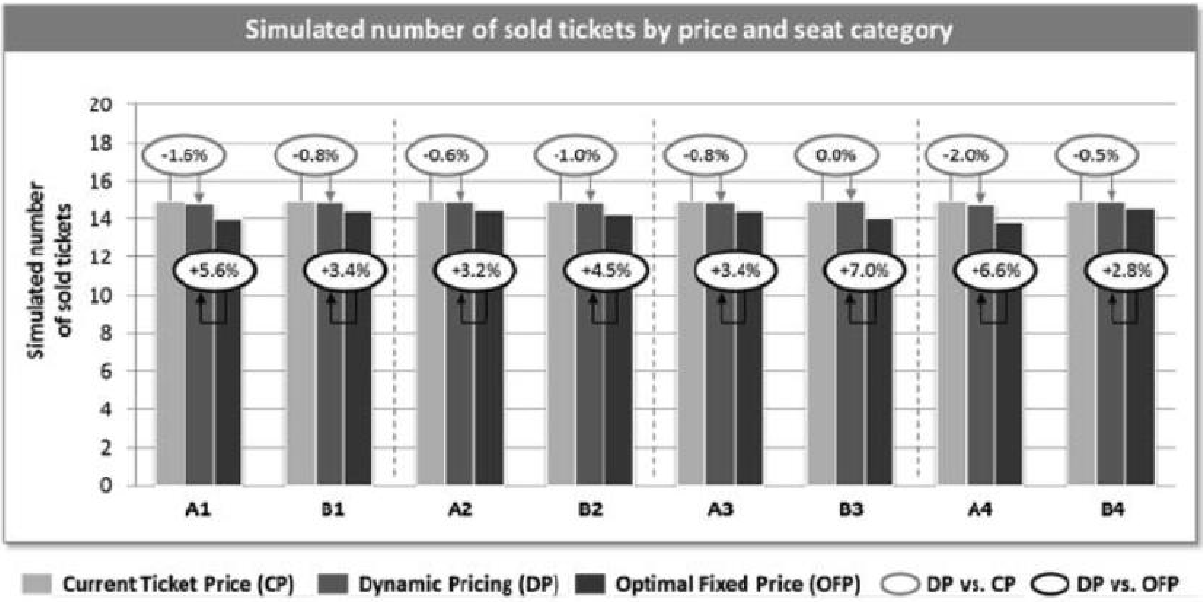

Figure 2: Simulated number of tickets sold (Kemper & Breuer, 2016)

Since Bayern Munich was selling its tickets far under market demand, every game was as close to sold out. Because the researchers wanted to keep up the stadium attendance, they looked at how an optimal fixed price and dynamic pricing would affect the current numbers of tickets sold. The results showed that with the dynamic pricing method, the number of tickets sold would be closer to today's number than with the optimal fixed price. With the dynamic pricing scheme, the biggest loss of tickets was not more than 2% in a seating category, as seen in Figure 2.

From the simulated example, it appears that dynamic pricing would be very beneficial for the club Bayern Munich. In Norway, we have to look at a similar but different approach if we want to implement dynamic pricing. That is because the demand for the tickets is not as high as in Germany. If we look at the prices before the new simulated price, we can draw from the research paper that the lowest price to go to a Bayern Munich match is a standing ticket of 15€. If we compare this price with the cheapest tickets the Norwegian clubs offer, we see that Bayern lands just below the average in the Norwegian league (157kr in 2017 and 165kr in 2018). This means that the cheapest ticket for the 3rd biggest club in Europe is lower than the average cheapest ticket in Eliteserien.

3.2 In the Norwegian league

The current pricing strategy in Norway is fixed section-based pricing. Prices are based on the section your seats are placed in. These prices are normally fixed for the whole season. In figure 3, we can see that the short sides of the stadiums are named "Byen" and "Havet." These are priced cheaper than the long sides with the names "SNN" and "LNS." We can observe that the long sides also have a greater number of sections than the short sides; that is because the clubs want to offer different price points for what is generally known as the best seats in the stadium (J.Foster, personal communication, January 11, 2022).

Figure 3: Example of a section-based pricing model in the Norwegian league (Bodø/Glimt, 2022)

In 2017 the Norwegian Football club Strømsgodset wanted to modify the section-based pricing strategy. According to an article in VG+, Strømsgodset implemented a varying price for their expensive tickets that year (Anthonessen, 2017). Their prices varied between 310 and 330 Norwegian kroner, depending on what opponent they were playing. By studying the effects of

Strømsgodsets implementation of this new pricing strategy, we can gain insight into how the Norwegian market might respond to dynamic pricing. By reviewing this example, we can look at how Strømsgodset failed to realize the potential of variable pricing. Furthermore, the addition of variable pricing, to a lesser degree, enables the club to answer to real market demand like the club can do with dynamic ticket pricing. Implementing a variable pricing strategy implies that prices are set months before the actual match and are not changed midseason depending on form, weather, and other factors that might change demand (Parris, Drayer, & Shapiro, 2012).

First, we look at how implementing variable pricing might have affected the attendance of the club. In 2016 the year before the pricing change, the club averaged an attendance of 6826. In 2017 with variable pricing, Strømsgodset had an average of 6272 at home games, and in 2018 without variable pricing, the attendance was lowered to 5939. However, the decrease between 2017 and 2018 could also be an effect of the cheapest tickets increasing by 120 kr. After the 2017 season, Strømsgodset returned to a fixed price on the expensive tickets of 340 kr, 10 kr over the highest amount of the year before with a variable pricing strategy.

If we compare the successful example of The San Francisco Giants with the less successful Strømsgodset project, we see some major differences in the implementation. First, Strømsgodset did not base their prices on demand like with dynamic ticket pricing, but on what opponents they were playing. It is reasonable to think that a match against a higher-rated opponent or more popular opponent would increase demands, but restricting the prices to what the club believes is a reasonable price will not allow the market to show its full effects. For example, 310 kr might be too high for a match against a bottom league team, and 330 kr might be too low for a game against their biggest rivals. A 330-310 kr range will have a low price elasticity, meaning that the prices in this range do not change demand by a significant amount. But, for example, a range between 350-200 kr would be much more price elastic, leaving room for changes in demand. The varying price experiment of Strømsgodset had little to no effect on demand, and considering that Strømsgodset also abandoned the strategy one year later shows that it most likely didn’t work as well as they had hoped.

For Strømsgodset’s pricing model to work to the best of its abilities, the club should have left the ticket price to an automatic pricing model that always calculates the optimal price at any given point. However, when studying the American sports clubs only 50% of them did this as well (Bouchet, Trolio, & Walkup, 2016). With or without an automatic pricing model, there should be a lower border that hinders the prices from being cheaper than the season ticket amount that is set for that game. For Strømsgodset, this was not a problem since their tickets were already priced high and had a low range of change. If all tickets were priced at the lower bound of 310 kr, it would still be more expensive than the season ticket. But if buying each ticket individually each game is cheaper than the season ticket, it will remove the purpose of a season ticket overall. The amount set for each game in season ticket would also vary with both a dynamic and a variable pricing strategy. Just dividing the number of games by the price of the season ticket would not make sense when the prices for each game changes. A low demand game might set 100kr from the season ticket, but then a higher demand game might have 200kr set from the season ticket. An example from the Championship, the 2nd division in England, a 300£ season ticket would set three games at 17£, seven games at 15£, eight games at 13.25£ and five games at 7£. Meaning that the season ticket holder also pays a dynamic amount for each game. The prices for the non-season ticket holders would then not go lower than this price. (Rostance, 2012).

4. Theory

In this chapter, I will present the theoretical framework and concepts that will be used in this thesis. Understanding these concepts will help getting more knowledgeable about the subject and will be valuable in solving the problem statement of this thesis.

4.1 Revenue Management

Revenue management, also called yield management, is a business technique employed by several industries today. A simple definition of revenue management is:

"The process of allocating the right type of capacity to the right kind of customer at the right price so as to maximize revenue or yield" (Kimes, The Basics of Yield Management, 1989).

Kimes, Chase, Choi, Lee, and Ngonzi (1998) built upon Kimes' definition by defining revenue management as controlling the four Cs in order to obtain a fifth C, customer demand. The four Cs offered by the group were:

- Calendar - how far in advance the reservations are made,
- Clock - the time of day service is offered,
- Capacity - the inventory of service resources and
- Cost - the price of the service

Since then, many researchers have tried to define RM, but there is no clear agreed upon definition today. The reason for that is because revenue management has been steadily evolving since the definition of Kimes and have been adapted differently to various industries. What is described in all definitions of RM however is the time-perishable nature that many service industries operate in and the necessity to understand advanced level of demand and pricing (McGee, 2016).

Revenue management started gaining traction in late 1985 when American Airlines developed a revenue management program based on differentiating prices between business and leisure travelers. The implementation of this strategy was in response to low-fare airlines challenging Americans Airlines on their core routes. They implemented a yield management system that used algorithms to determine the number of seats to protect for later booking. Meaning they would sell early-bookers a ticket for a low fee but then hold spots for the later-booking business passengers. With this strategy, American Airlines could split its customer base into two different categories, known as a price discrimination strategy. (Phillips, 2021). Revenue management has become an industry standard for airlines but has also ventured to other industries, like the hotel-, cruise- and transportation industry.

Although a strategy like revenue management might look feasible, there are certain criteria for such a strategy to work. According to Robert L. Philips (2021), revenue management is only applicable when these conditions are met:

- Capacity is limited and perishable. (Meaning one could not store an empty seat for a later date. There is a limit, and this counts for every flight/booking)
- Customers book capacity ahead of time. (Customers book ahead of time to make sure there is capacity for the individual. This makes it so the companies can adjust for demand for future periods)
- Prices are changed by opening and closing predefined booking classes. (The company can segment different people into booking classes, making it possible to adjust prices for different classes.)

Those last two points are easier to fulfill in recent times with the growth of e-commerce. E-commerce is buying or selling goods or services over the internet. With e-commerce, tickets can be adjusted on the fly, making it easier to perform revenue management. This is one of the reasons we see an increased adaptation of revenue management in recent years (Boyd & Bilegan, 2003; Bodega & Ferguson, 2014)

Another criterion that is crucial for a revenue management strategy to work is that the company is highly profit-orientated and that the business has freedom of action. This means that they can and will charge someone more for a ticket at a later date than someone booking earlier without it being immoral. An industry might be opposed to such behavior at the start, but consumers become more conformed to it after a while (Phillips, 2021)

We often discuss three levels of revenue management decisions:

Level	Description	Frequency
Strategic	Segment marketing and differentiate prices	Quarterly or annually
Tactical	Calculate and update booking limits	Daily or weekly
Booking control	Determine which bookings to accept and which to reject	Real time

Table 1: Three levels of revenue management decisions (Phillips, 2021)

The strategic level in table 1 consists of identifying customer segments and establishing products directed at these segments (Philips, 2021). A typical example of this in revenue management is the airline industry, where one differentiates between leisure and business customers. A leisure customer is more price sensitive and more flexible with flights at different times of the day and weekend flights. In contrast, business customers are booking late, and stricter to the requirements of the flight. The company can then differentiate them into different segments. Revenue management is the art of utilizing these differences to achieve higher profits. Their different requirements create differences in willingness to pay. To take advantage of this, one must make use of price discrimination.

At the tactical level, the company must set and update limits on how much of a particular product can be sold at a particular price to each segment for a specific period of time. These are often updated daily or weekly, as shown in table 1. Tactical revenue management is often called the "brains" of the operation. That is because it is at this level the future demand is forecasted, algorithms are optimized, and booking limits are updated (Phillips, 2021).

The booking control level in table 1 refers to the point in time where booking requests made by customers are accepted or rejected. This is a rather simple process of checking that the booking can be accepted with the booking limits in mind. A successful implementation of revenue management incorporates all three levels and requires them to flawlessly respond to changes in one of the three levels. To understand revenue management as a whole, we must understand some of the different methods used by the strategy.

4.1.1 Price discrimination

Price discrimination or price differentiation is the practice of charging individuals or groups of customers different prices for the same or similar products (Pindyck & Rubinfeld, 2018). The two terms are often used interchangeably, but price differentiation can also refer to other pricing mechanics like regional pricing and product versioning. In addition, price discrimination has a bad reputation because of the negative associations related to the word 'discrimination' (Phillips, 2021). Here they are both referring to the previous definition.

We often separate between three types of price discrimination:

1) First-degree price discrimination means pricing a product after what the customer's willingness to pay is for that product. This type of price discrimination is also called perfect price discrimination. This type of price discrimination is hard to achieve in practice since it demands that the company have all information available about every customer to be able to determine with certainty each customer's willingness to pay.

2) Second-degree price discrimination means that a company prices its products after what quantity each customer buys. For example, a person buying a quantity of 50 would pay a lower price per product than a customer buying just one.

3) Third-degree price discrimination splits the customer base into groups with different demand curves. This type of price discrimination is the most used. For example, can customers be split into groups based on age, like youth, students, and seniors. Following this example, a student would then pay less for a bus ticket than an adult.

(Pindyck & Rubinfeld, 2018)

From this point on, when the thesis mentions price discrimination, it will refer to what is described as third-degree price discrimination. To be able to perform price discrimination, the company needs to split its customer base into segments. The segments must have different price elasticities, meaning they respond uniquely to price changes. Additionally, the company needs to have sufficient market power to be able to change the price of the product.

Price discrimination also has limitations that can cause the positive effect of the method to dwindle or, in the worst case, have negative consequences. The limits can be described as

- *Imperfect segmentation*: We are not always able to precisely determine each customer’s willingness to pay. Therefore, it can be hard to split the different segments correctly.
- *Cannibalization*. There is a high motivation for customers in high-price segments to find a way to pay a lower price than they currently are paying. Customers will try to lure their way into a lower-paying segment.
- *Arbitrage*. Differences in price create a strong incentive for arbitrageurs to find a way to buy the product at a low price and resell it to high willingness to pay customers below the market price, keeping the difference for themselves

(Phillips, 2021)

4.1.2 Dynamic pricing

A pricing tactic similar to price discrimination that is also used in revenue management is called dynamic pricing. Dynamic pricing will say that the price of a product or a service is based on the demand of the product, but it fluctuates over time. The point of dynamic pricing is to always find the best price for each time period. Meaning that an item could decrease in price if the demand were sinking in order to save the revenue. An important factor of dynamic pricing is that the prices should always fluctuate and be controlled by a pricing algorithm or computer, such that the price always will be the best one for each circumstance.

Dynamic pricing is a phenomenon in several unrelated industries. The company Uber uses dynamic pricing on their services when they calculate the prices of their trips. If there is a low amount of drivers in the area and there is high demand for a driver, the price increases for that specific trip. With dynamic pricing there is no personal information needed, like in personal pricing. The price depends only on the activity surrounding the product. However, dynamic pricing isn’t always as popular with the consumers. This is because it makes it more challenging for consumers to shop rationally in a market where prices are continually changing, sometimes without the customer knowing the reason for the changes (Berg, 2019)

There are different opinions on dynamic pricing and revenue management, whereas some professors' opinions are that they are "alternative concepts of equal value" (Boyd & Bilegan, 2003). Others have made them more descriptive and split them into two different categories. They distinguish between quality-based revenue management and price-based revenue management. (Tscheulin & Lindenmeier, 2003). Quantity-based revenue is more allocated to the classic form of revenue management. A classic form of revenue management is closely related to the airline example, where one's job is to segment the market based on customers' differences in willingness to pay. Then update booking limits to whether they should accept or reject the inquiry. While price-based revenue management is focused on the variation in price, that can change differences in demand for a product. This method is more price-focused rather than on the capacity limit. One example could be low-cost airlines that only charge one price, which varies over time. Quantity-based revenue management is closely related to price discrimination, while price-based revenue management resembles dynamic pricing.

4.1.3 The price-response function

To be able to create a dynamic pricing model there are several integral steps that have to be completed in order for it to be satisfying.

The first step in finding the optimal pricing strategy is to look at a price-response function. A price-response function uses historical data and numbers where one seller is faced with selling a product with a negative sloped demand function. The function shows how a market will respond to price changes (Bodea & Ferguson, 2014). Different firms have different response functions, even if they are in the same industry. In the circumstance of a perfect competitive market where all the information about prices is known and every company is selling homogenous products, the company will be faced by a price-response function with a vertical line. In this case, the company will not be able to go over the market set price since another company will take over its market share, causing the demand for its product to drop to zero (Phillips, 2021). However, this is just a theoretical occurrence and will not happen in the real world. To summarize, for the price-response function to be helpful, there have to be differences in the market that cause changes in demand.

In the industry of sports price ticketing, there are capacity constraints that limit the range of the price-response curve. Each sports stadium has a different capacity limit or a limit of seats available for purchase. The club must therefore set a price that is optimal considering the capacity constraint. The result of a constraint is that the new profit-maxing price is always greater or equal to the unconstrained profit-maxing price (Phillips, 2021). This is because the optimal point of the price-response curve is the same as before the constraint or that the club has to increase the price for demand to creep under the constraint in capacity.

4.1.4 Elasticity

The price-response curve can be useful for finding the price sensitivity in the market. Finding the correct price sensitivity in the market is important to figure out how dynamic pricing should be implemented for a company. Price sensitivity is the degree to which demand changes when the cost of a product or service changes (Kagan, 2020). The simplest way to figure out the price sensitivity is to look at the slope of the price-response function. Though the slope has problems when it comes to the units of measure, they have to be the same for both price and demand. Therefore, price elasticity is a more accurate measurement. Price elasticity is defined as the ratio of percentage change in demand to the percentage change in price. Since it describes a change in percentage, its value is independent of the units of measurement (Phillips, 2021). The formula for price elasticity is:

$$\varepsilon(p_1, p_2) = \frac{\left[p_1 * \left(d(p_2) - d(p_1)\right)\right]}{\left[(p_2 - p_1) * d(p_1)\right]}$$

$\varepsilon(p_1, p_2)$ is the elasticity of a price change from p_1 to p_2. Since the demand function is always sloping downwards, meaning a higher price is resulting in lower demand, the $\varepsilon(p_1, p_2)$ will always be less than 0.

For a smaller, local estimate of elasticity it is possible to use the formula of point elasticity. This shows us changes in demand over a small area (Bodea & Ferguson, 2014).

$$\varepsilon(p) = p * d'(p)/d(p)$$

Low elasticity $|\varepsilon| < 1$ means that the consumers are price insensitive. Implying that a change in price has little effect on the demand. While high elasticity $|\varepsilon| > 1$ means that the consumers are price sensitive. Implying that a change in price has a large effect. There are also differences in short- and long run elasticity. Short-run elasticity is usually lower because buyers are able to afford the changes and are more flexible in the short run.

By looking at price elasticity, we can see how applicable a dynamic pricing strategy would be for a certain business. If they are faced with high elasticity, it means that pricing variably will have an effect on the demand of the customer. Therefore, measuring elasticity is an integral part of creating a dynamic pricing model.

4.1.5 Time of purchase

When going to an event, whether it is a concert, sporting event, or just a train ticket, customers purchase tickets at different times. For example, when buying train tickets, “purchases become more frequent about one month prior to departure, accelerating one week prior to departure, and with a peak of tickets bought one day prior to departure.” (Yuan, 2020)

We can show a relationship between tickets sold and time:

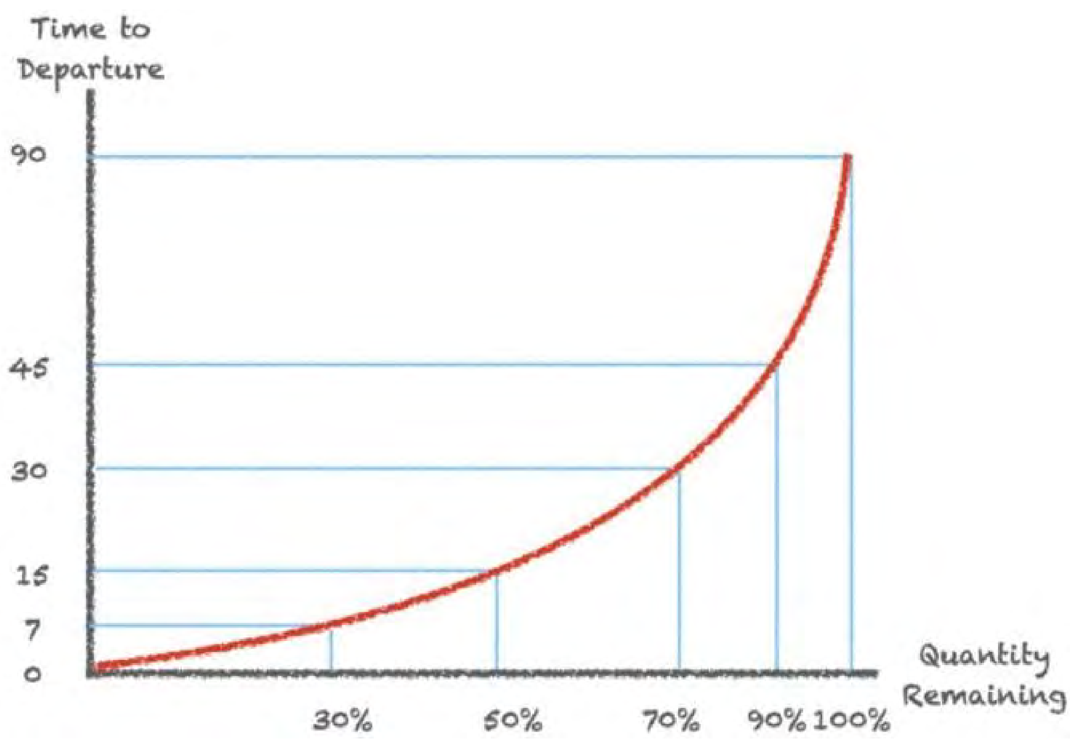

Figure 4: Relationship between time to departure and quantity remaining (Yuan, 2020)

Figure 4 must be read from right to left to fully grasp the meaning of the graph. From figure 4, we see that when time edges closer to departure, ticket sales increase, and the quantity remaining decreases accordingly. This gives the graph an exponential downward slope. By analyzing the interval between 90 and 45 days to departure, the graph depicts that only 10% of the quantity is sold. However, when looking at any interval closer to departure, we see that more tickets are being sold than in the previous interval.

In addition to the quantity of tickets bought increasing, the later a customer buys a ticket, the less price sensitive the customer gets. This points back to the difference between leisure and business customers in the aviation industry. For a firm to fully capitalize on the revenues in a dynamic pricing scheme, they need to know when the customers usually buy a ticket for one of their events and how their willingness-to-pay changes with the factor of time.

5. Methodology

In this study, we will look at the Norwegian football league called Eliteserien and see if it is beneficial to implement a dynamic pricing scheme. An extensive amount of information had to be collected to try to answer such a question. The collection of data was firstly through the internet and other open sources I could find. In the latter stages of the process, I came in contact with a higher-up in Norwegian football, which made it possible to get in contact with the different football clubs through a survey. The data collection made it possible to gain both quantitative and qualitative information from secondary sources like information on the internet and primary sources like the survey taken by the different clubs. The use of existing and new information enables us to create new data and graphs to look at our hypothesis and our main research question from a different point of view.

5.1 Collection of data

The data collected corresponds to the years 2017 and 2018. The reason that these years were selected was that they were recent in time, so they were affected by the drop in supporter demand, but they were also not that close in time that they were affected by other externalities like the coronavirus. The data consisted of prices for game tickets and the average attendance rates during these years. Price guides made by newspapers stood for the primary source of data on prices of tickets. The attendance rates however are made public by Norges Toppfotball each year in an excel spreadsheet where key figures about the attendance behavior are calculated.

The price guides from 2017 and 2018 were made by two different news outlets and had placed the tickets into different categories. The prices of tickets for each individual club in 2018 were split into four different categories:

- The hardcore supporter,
- The away supporter,
- The cheapest available ticket and
- The luxurious or well-placed tickets (Dahl, 2018).

Further, prices of tickets from 2017 were categorized under:

- The expensive seats,
- The cheapest seats and
- The cheapest family prices (Anthonessen, 2017).

Since prices for each of the two seasons were taken from different sites, there is a margin of error in this study, and that has to be taken into account when analyzing the results. The categories that are consistent across the two data plots are the cheapest section and the most expensive section. Therefore, these are the only ticket categories considered in the thesis.

In the Norwegian top division in football there are two or three teams that go down a division each season. Since we wanted to compare the two seasons, we only selected the teams that were in the top division in both seasons. We made a table (see appendix 1) and plotted the numbers to get an overview of the prices. In addition, we also wanted to see if there was a trend in prices following the number of attendees and the other way around.

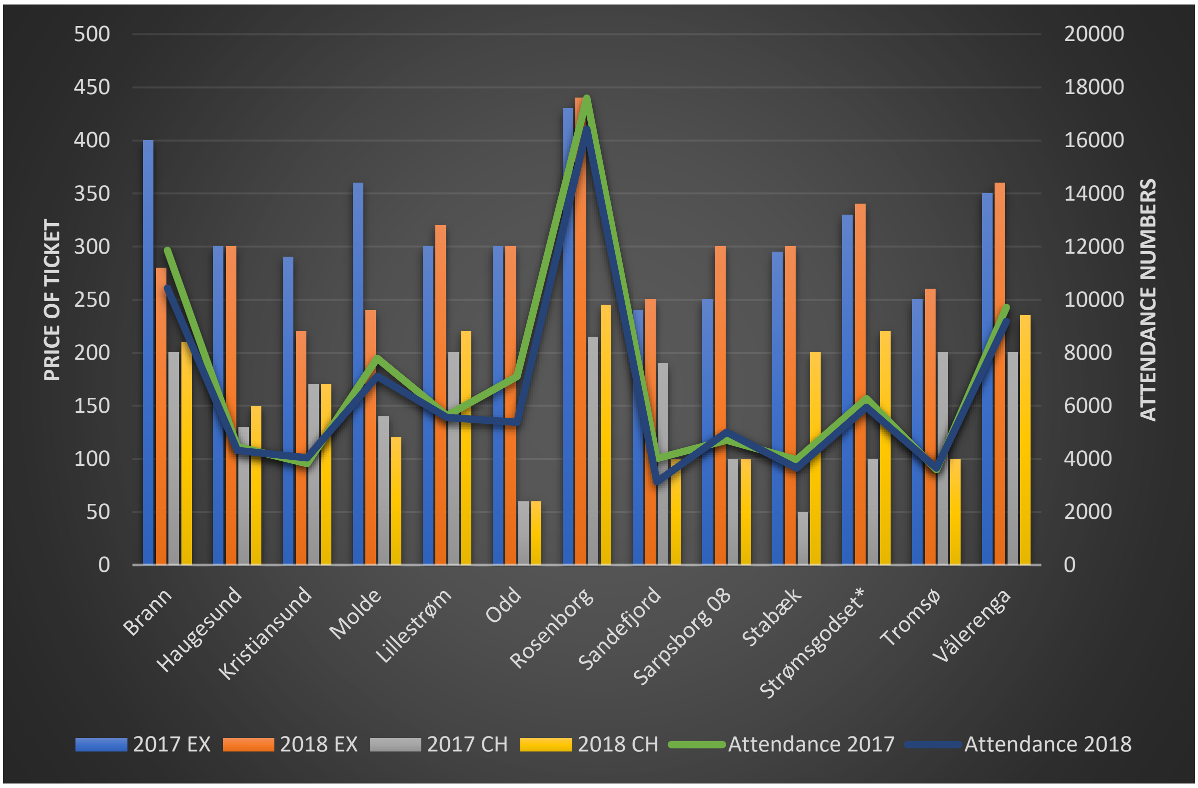

Figure 5: Expensive and cheap tickets in 2017 and 2018 compared with the attendances for the same years (EX = Expensive ticket and CH = Cheap ticket). Left axis: Price of tickets. Right axis: Attendance numbers.

From the data that was collected we made figure 5 showing the prices of the different seats in the two years and compared them with the attendance for each club in the two years. The blue (2017) and the brown (2018) cylinders are showing the ticket prices for the expensive ticket for their respective years. The two other cylinders to the right colored grey (2017) and yellow (2018) are showing the price for the cheap tickets. All these cylinders are measured against the left vertical axis "price of tickets." In addition to the ticket prices the figure has an additional second vertical axis on the right displaying the attendance numbers. The two colored lines show the average number of attendance, the green one for 2017 and the blue one for 2018.

From figure 5 we see examples showing that a decrease in the price will increase the attendance. For example, Kristiansund reduced the price of their expensive tickets by 70 kr and thereby increased the average attendance by more than 200. However, we see that other clubs have had other outcomes. From figure 5 we can see that Odd lost a considerable number of attendees from 2017 to 2018, but their prices stayed the same. Molde reduced their prices on both the expensive option and the cheap option and lost over 600 average attendees from 2017 to 2018. In total the average attendance decreased from 2017 to 2018 (see appendix 1 for table). By just looking at and plotting the data there is no conclusion that can be made with certainty. Therefore, we must analyze the data further.

One interesting club from the data collected though is Strømsgodset. In 2017 they had a dynamic pricing model on their expensive tickets where they varied between 310 and 330kr based on their opponent. Further, in 2018 when they had fixed prices, they had less audience than in 2017. If this difference is because of the change in variable pricing or if it is because of the price change in the cheaper option is not something we can conclude with. There might also be other external effects causing this, like table position or the purchase of an attractive player. These questions piqued my interest in the subject. I wanted to look at the possibility of dynamic pricing in the Norwegian league and if it would be beneficial for the attendance rates of the clubs.

The first thing we need to know is what the goal of the individual clubs are. Is it to sell out the stadium, or is it to earn as much money as the club can (which is usually the goal in revenue management)? The popular German football club Borussia Dortmund famously price their tickets low so each match they play on their home ground is full. In an interview with BBC the marketing director of Dortmund, Carsten Cramer, said:

"Why are tickets cheap? Football is part of people's lives and we want to open the doors for all of society. We need the people, they spend their hearts, their emotions with us. They are the club's most important asset." (Smith, 2014).

A full stadium and high demand can cause 2nd hand selling however, which is usually something the clubs do not want. In America, a company called SeatGeek operates with this as their main task. "It culls and lists inventory from all major primary and reseller websites like TicketsNow, eBay and Ticketfly. It then allows buyers to create custom searches based on factors such as seating, price and venue. Its proprietary software, Deal Score, ranks these seats from "amazing to awful," based on a scale of zero to 100" (Ibrahim, 2014). Sites like these might only be profitable because the clubs are pricing the seats wrong. If customers are willing to pay a higher amount for a ticket than the price that the clubs offer, they should look at the prices they offer. Are the current prices really the most profitable for the clubs?

5.2 Survey

To get an understanding on what basis the different clubs in Eliteserien price their tickets. I constructed a survey for the clubs. I originally wanted to know the prices the different clubs had around their stadium. But after I found that through the secondary sources, I understood that I could use the survey for a different purpose. I wanted to know on what basis they price their tickets today. All the clubs in Eliteserien currently have fixed prices based on two categories, where the seats are placed, and what type of person that buys a ticket. Tickets on the long side of the stadium are more expensive than seats on the short side or in the corners. In addition, students, children and seniors normally pay less than regular adults.

5.2.1 Strategy

After coming in contact with people at Norsk Toppfotball (NTF). They showed large interest in my project. My main goal was to get in contact with the clubs, so together we decided that making a survey and then delivering them to the clubs in the Norwegian Eliteserien would be the best solution. Coming in contact with the clubs was a unique opportunity for such a research project. To be able to extract the most amount of information from such a survey I made a strategy.

It was important for me that the information collected was comparable between the clubs, so that I could measure them against each other, but also that each questionnaire had some individual input on each answer to the survey. The respondents to the survey were the ticket managers at the individual clubs. The survey was sent by email from my contact at Norsk Toppfotball, and the respondents were suggested to answer. To get respondents to answer, the survey had to be short and concise, it should be straight to the point. Ideally all the clubs in the league would answer for the survey to have a complete overview, but this is rather unrealistic (Stene, 1999).

My survey was made with anonymity ensuring answers didn’t include the names of the respondents, only the name of the club they were representing. In addition to anonymity there were other factors considered when making the questionnaire:

1) <u>The terms used in the questionnaire should be as close to everyday speech as possible</u>
   An example of this is under question 3 in the survey. Where academically it would be more precise to use price elasticity as a term, but it would be easier to understand the word price sensitivity (Prisfølsomhet in Norwegian.). In addition, the word was also explained in the survey.

2) <u>Making the survey in the native language (Norwegian)</u>
   Even though the level of English in Norway is at a very high proficiency according to EFs English proficiency index (2021), I wanted the possibility of more in-depth answers to the open questions. Having the survey in the native language would make it easier to do so.

3) <u>Make the survey short, but with some open questions so they could answer more in-depth if they want to</u>
   Since the survey is an extra task in the ticket managers workday, I suspected that most of the answers would be shorter, but if the respondent were really interested in the topic some questions had no word limit to them.

5.2.2 Goals of the survey

The survey had several goals in mind that were distributed along with the questions. First, I wanted to know the current state of the club's ticket pricing strategies. By understanding the clubs' ticketing strategies, I could measure the strategy of dynamic pricing against them. What the differences between them were and what benefits dynamic pricing could give the clubs that the current pricing strategy was incapable of doing. Secondly, I wanted to know how difficult implementing a dynamic pricing model would be for a Norwegian club. Therefore, I asked about the current association the clubs had with the price sensitivity of supporters and dynamic pricing in general. Based on these results I could paint myself a picture of how much data the clubs are gathering about the supporters and how hard it would be to implement a dynamic pricing strategy. Lastly, a question was asked about what the clubs have done specifically to their prices to change the trend of sinking attendance. The goal of this question was to give the ticket managers a chance to explain what pricing attempts that were made to reverse the trend of sinking attendance. The question was made open intentionally since I wanted more personal input than in other questions.

The questions in the survey were made with the data previously collected in mind. The answers the ticket managers gave in the survey are helping in the creation of our dynamic pricing model. By adding the answers of the survey to our data we get a stronger position when discussing our results.

6. Results

6.1 Survey

To make a foundation for a dynamic pricing model, data was gathered directly from the clubs through a survey. The survey's goal was to get to know the status of how the different clubs in Eliteserien priced their tickets.

In total there were 12 respondents to the survey, these were collected in two waves, the first wave had four respondents and the second one eight respondents. The survey was distributed through Thomas Torjusen at Norsk toppfotball to the ticket coordinators at the clubs. Of the total 12 respondents three teams answered the survey twice, Vålerenga, Stabæk and Bodø/Glimt. While this made the open questions more detailed, the yes and no data pools became skewed, so the data had to be modified to get the correct overview of the league. To summarize, 9 clubs of the total 16 answered the survey making the survey very representable for the league.

The survey had five questions, where one of them was a question that asked the clubs to fill in the club that they were representing. Obviously, the ticket managers could have put in the names of the clubs they were not representing, but since this survey was sent through a respectable figure in Norwegian football and not me directly the chance of this happening is quite small and will not be worth discussing further. As mentioned in the methodology part of the thesis the questions asked in the thesis were in Norwegian. For this thesis to be consistent these questions have been translated to English in the results section, for the full original survey see the appendix number 3.

The first question relevant to the subject was:

"Which guidelines (policy) do you take into account when you determine the prices of the match tickets?"

This was an open question where the clubs could fill in their own answers. There were three main points taken from the clubs' answers.

1. *Competitive prices compared to other arenas. Mainly other football clubs but also other entertainment industries.*

The clubs argue that comparing themselves with other markets and clubs makes them competitive. The clubs find a benchmark price that they see is competitive in the market and price themselves accordingly. This is a strategy that could work well but is also risky considering that supporters/customers behave differently in other parts of the country. The importance of knowing your crowd and fans is undervalued here. Parris, Drayer and Shapiro (2012) mention this exact problem when creating a pricing model for the Dodgers. "Given the fact that each team is unique, it is vital that the Dodgers evaluate their specific situation to determine which factors that influence demand are the most relevant to them."

2. *Pricing themselves according to the total experience of a match. Meaning seats where you have a worse viewing angle of the match are cheaper priced. This makes it so tickets are more accessible*

This is a classic example of segmentation. Dividing the customers into groups, where customers' demand for better seating is set up against their willingness to pay. The pricing strategy closely resembles price discrimination. The prices are fixed and the factor that argues for the differences in prices is seating selection. Clubs can apply dynamic pricing in addition to price discrimination if they want. That can be done by keeping the different segments, but by adjusting the prices of the segments according to demand by dynamic pricing. The MLB club San Diego Parades has implemented such a pricing strategy. The VP of strategy and Business Analysis for the Parades said in an interview: "If I look at a game and I have two neighboring sections, which are priced five dollars apart, and the cheaper section is sold out, whereas the more expensive section is not very well sold, the market is telling me to lower the price on the more expensive section."

3. *Prices are made in comparison to prices of tickets in earlier seasons.*

Another classic way of pricing. Looking at the prices of former years and comparing the output for different prices is a great way to start the process of deciding ticket prices, however if you put too much into former years, the club can get exceeded by clubs with more innovative pricing strategies.

The second and third questions were yes and no questions regarding newer pricing techniques. Looking back at what we said during the introduction, there were three teams that answered twice. Some teams answered the same the two times they answered, but others answered differently. The only correct way of solving this would be to not count the clubs that answered differently since the information could not be trusted.

Question 2 asked the following:

"Does your club look at the price sensitivity of supporters when your club chooses ticket prices for the season? (Price sensitivity means how sensitive the demand is, facing changes in price)"

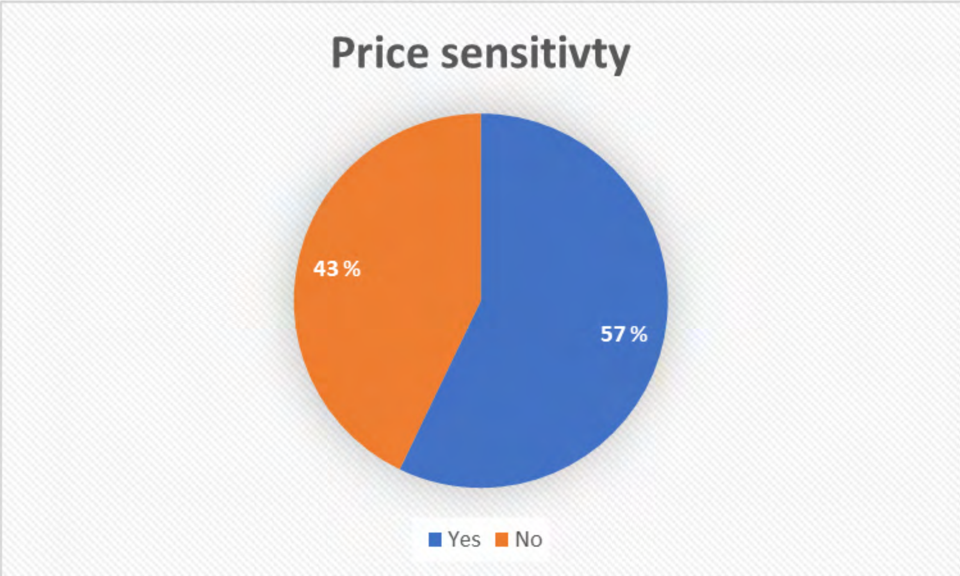

Figure 6: Price sensitivity

As we see in figure 6, a majority of the clubs answered that they look at the price sensitivity of the supporters when choosing how to price their tickets. However, not a single club mentioned that they use this information when setting their price in the first open question about ticket pricing guidelines. The clubs might have this data, but from the answers collected it does not look like they give it much weight. One club, Lillestrøm Sportsklubb, mentions CPI (the consumer price index), though that is more a measure of the purchasing power of individuals in the nation. It describes how prices of everyday goods and services have changed compared to a base year and do not really focus on their own club and fans (Store Norske Leksikon, 2019).

The third question of the survey asks a question directly linked to the thesis:

“Has your club considered a type of dynamic pricing? For example, that the price of a ticket varies according to the opponent, time in the week or time of purchase.”

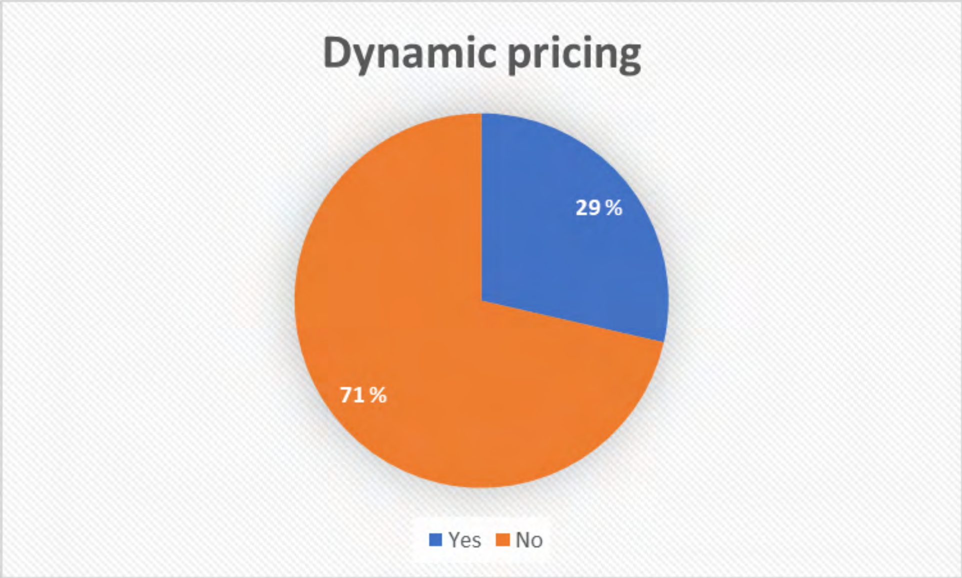

Figure 7: Dynamic pricing

There were two clubs that answered yes on this question while the five others answered no. Fewer clubs answered yes to this question than the question about price sensitivity, as expected. Price sensitivity can help us understand the benefits of dynamic pricing but can also help with adjusting fixed pricing. Dynamic pricing on the other hand is a bigger step in the direction of changing the whole club’s pricing strategy. One of the clubs that answered yes to this question was Strømsgodset, which we talked about earlier in the thesis, they had a year where prices changed in line with what opponents they were playing.

The last question was another open question and questioned the clubs about the trends in the Eliteserien division. It was written like this:

“What has your club done price wise to turn the trend of sinking attendance rates in Eliteserien?”

Like the first open question, we can group the answers into a few main points. These were:

1. *Straight up reducing the price.*

Some clubs have just reduced the prices of the tickets, suggesting that this will make the fans come back and increase demands. Reducing the price straight up can cause the perceived value of the product to decrease, resulting in a downward spiral of lowering ticket prices (Parris, Drayer, & Shapiro, 2012)

However, there are variations between the clubs when it comes to reducing the price. For example, Bodø/Glimt started looking at what they could do to increase the value of each ticket. To create a better experience, they looked at pregame fireworks and other activities in addition to the football game. Furthermore, the club looked at price points to find opportunities where they could reduce their price while increasing the total revenue. By increasing the number of fans in certain sectors, their price reduction became nullified for the total result.

2. *Price bundling or group tickets. Bundle a whole family together or have a 2 for 1 offer, creating a lower price per ticket*

Bundling tickets together makes a lot of sense. You sell multiple tickets by acquiring one customer. Bundling tickets or grouping tickets makes the individual prices in the package lower than when they are sold separately. With this pricing strategy the clubs are trying to appeal to customers or families that would reject the price when all of them would have to pay individually, for example at 400 kr. With price bundling the group would now only pay 300 kr instead, resulting in them accepting the offer. Price bundling also makes it easier for new people to experience a match for the first time. The barrier to entry is lower than usual. Fans that usually go to matches alone now also have an extra incentive to bring a friend or their family, because of the decrease in the individual price (Güler, Öztop, & Şen, 2009).

3. *Changed pricing structure. Segmenting the areas to make the differences in price more clear.*

Confusing ticket prices can make buying a ticket an unpleasant experience for a fan. It can also lead to fans thinking that prices are higher than they actually are. When clubs have a complicated pricing structure, it can be hard for people to understand and achieve the best prices. It could end up leaving a distaste in the fans of the clubs. For example, tickets for Disneyland in the US have been heavily criticized since the normal visitor gets exploited compared to the “know it all” super fan (Defunctland, 2021). Making the pricing structure easier, and segmenting parts of the stadium so customers easier can tell which parts of the stadium are for cheaper tickets and which are more premium usually ends with higher customer satisfaction (Kaura, Chalasani, & Sharma, 2015)

A few clubs suggested that their reduced attendance had nothing to do with the price, but that they were justified by weak performances on the field. While this makes sense for a few clubs, it does not answer for the reduced attendance for the whole league, which has been steadily decreasing for the last ten years (Hjelseth, 2019). There will always be clubs that underperform and overperform in a season. The answers provided in the survey make a good starting point and help us to argue for some of the points discussed while making the dynamic pricing model. First, we start with structuring our data.

6.2 Data set

To get an overview of our data, we can create a plot diagram with each of the two priced ticket categories, where the horizontal axis is the price, and the vertical axis is the attendance. The plot consists of blue and orange data points, where the blue points are numbers from 2017 and the orange points are numbers from 2018. Firstly, when looking at the cheap tickets we see that prices range from 50 kr to 250 kr. There is also little consistency in the graph, meaning there is not clearly a trend for the data points. To make it easier visually we can plot a trendline into the diagram. Trendlines are made by a calculation called ordinary least squares (OLS). OLS is a technique used for estimating coefficients of linear regression equations. It describes the relationship between one or more independent quantitative variables and a dependent variable. Least squares stands for the minimum squares error (SSE). This means that the trendline is made by minimizing the sum of squared residuals implying that the best fitted trendline has the shortest way to each point (Wooldridge, 2014). By using OLS, we find a trend that higher prices increase attendance slightly for the cheaper tickets, for both 2017 and 2018. We can see that by the trendline having a slight upwards slope.

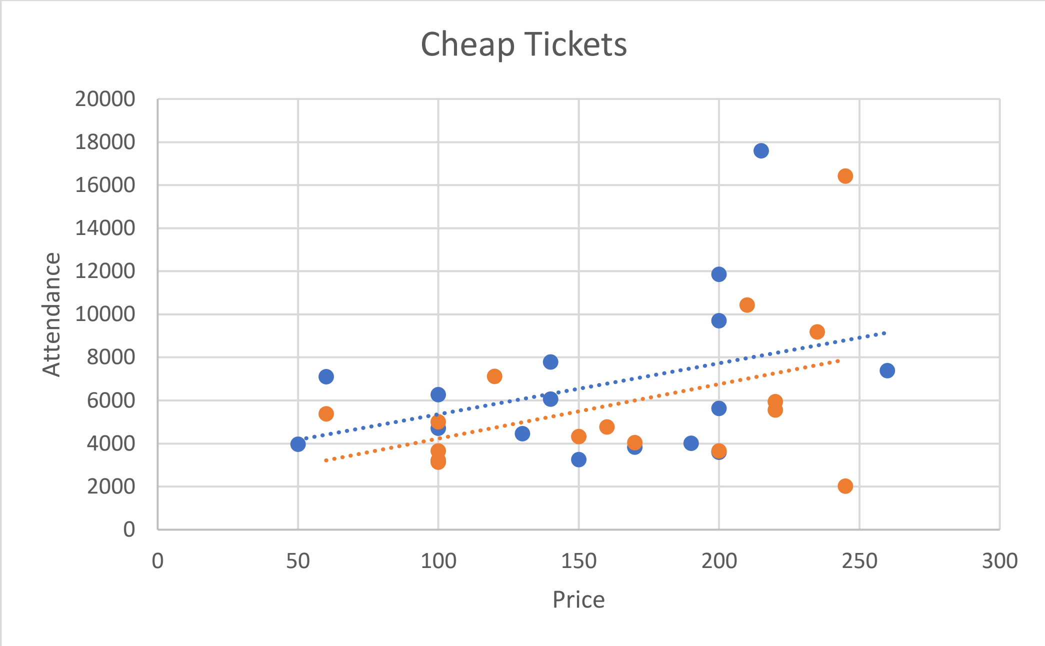

Figure 8: Cheap tickets

The expensive tickets show a much steeper trend line than the cheaper one. Here, increases in price show even more demand. The prices are also less spread, for example there are a lot of clubs in 2018 that price their expensive seats at 300 kr. The data also suggests that the trendline for 2017 is steeper than for 2018.

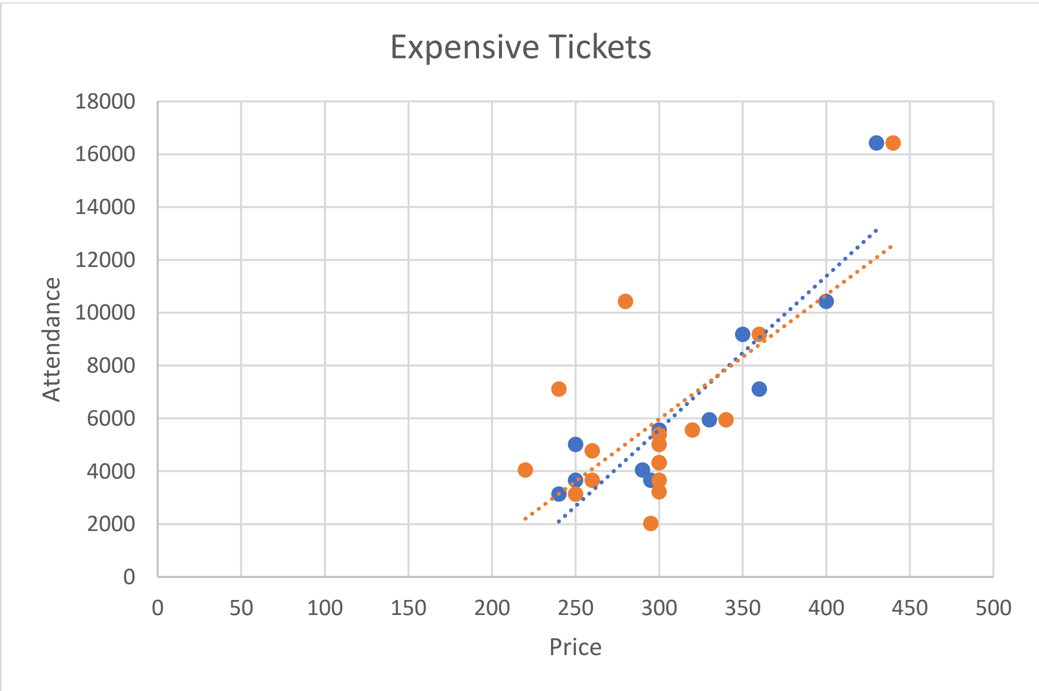

Figure 9: Expensive tickets

From the collection of data, we can calculate measurements that tell us the significance of the values. When looking at our data on the ticket pricing compared to attendance rates, we figure out that there are some problems with our trendlines and the fit.

Year	Type of ticket	R^2	Standard Error
2017	Average	0,533338	33,43198
2017	Cheap	0,136341	56,27532
2017	Expensive	0,711961	31,24444
2018	Average	0,399203	40,1091
2018	Cheap	0,190824	57,51013
2018	Expensive	0,476305	39,28067

Table 2: Regression Statistics

To determine the goodness-of-fit of the data and the regression line we use R-squared or standard error. The R-squared is interpreted as the fraction of sample variation in y that is explained in x (Wooldridge, 2014). The R^2 value when regressing prices on attendance is shown in table 2. When calculating R^2 we want to achieve a number as close to 1 as possible. Since a number of 1 tells us all the y values are accounted for by the x values. While achieving a 0 tells us the opposite. A result of 1 is near impossible to achieve in the real world, but the higher number the better. In our data we can clearly see that the R^2 values are fairly low. That is because there are other factors than price that determines demand. The highest R^2 number is of the expensive tickets in 2017 on the attendance in 2017. But the correlation is that higher prices give higher attendance. The reason for this is that the larger clubs like Rosenborg, Brann, Molde, Vålerenga and Viking are the ones with the highest prices on the expensive tickets. Therefore, the attendance and the prices correlate more.

The standard errors in the regression statistics are quite high, which means that the fit is not great. When it comes to standard errors there is no universal acceptable threshold, but the lower the value the better the fit. The standard deviation gives us the absolute distance that the data points deteriorate from the regression line, not just a percentage number like the R^2 (Frost, 2017). The conclusion of the regression statistics is that price alone can't explain the factor of attendance. So how do we determine that price changes will affect demand?

6.3 Price elasticity

To get a better understanding about the consumer and their price preferences we can look at the price elasticity. Price elasticity is defined as the ratio of percentage change in price to the percentage change in demand (Phillips, 2021). Finding the demand of the customers or the willingness to pay for a ticket across the whole league is hard. Because each club sets one price at the start of the season and then holds it constant, it is hard to know how many more people would show up if there were tickets for 50 kr or 100 kr less. There are also major differences between the different clubs. How the fans of Rosenborg and Stabæk would react to a change in price would most likely not be the same, however they most likely would go in the same direction. Bigger clubs with more fans might have a bigger reaction than smaller clubs with a smaller pool of fans to take from.

Other research papers like the one that created a model for Bayern Munich, used a secondary market to see what the customers were willing to pay for a ticket. (Kemper & Breuer, 2016) However, in Norway there are no big secondary markets like eBay or SeatGeek that sells tickets second-hand. Therefore, this method cannot be used. There are clubs however that did in fact change their prices for one game or more, by doing what one could call price experiments. The reason for such price experiments could be because they wanted a surge of supporters in the stands, there was a sponsored event or they had an important match going forward. One of the clubs that did in fact do such an experiment was IK Start. In the end of 2018, in round 22 IK Start sold tickets for 1 kr and managed to achieve over 10 000 attendees. To calculate price elasticity for the supporters of IK Start we can compare the season averages in price and attendance against the results of the price experiments. Using the price elasticity formula, we achieve a price elasticity of

$$\frac{[p_1 * (d(p_2) - d(p_1))]}{[(p_2 - p_1) * d(p_1)]} = \frac{[210 * (10419 - 4368)]}{[(1 - 210) * 4368]} \text{ - } 1{,}39 \approx -1{,}4$$

An elasticity of -1,4 means that an increase in price with 10% will result in a 14% decrease in demand. The direction of change makes sense theoretically since demand would increase when there is a drop in price. The elasticity of $\varepsilon = -1{,}4$ is a rather elastic demand. Meaning that the consumers, in this case the supporters, are price aware and the price of the ticket has a big effect if they go to the game or not.

In 2013 IK Start did a similar price experiment like they did in 2018. They sold tickets for 50 kr each, which was a lot lower than the 235 kr average price they had during the season. The price experiment resulted in 10 345 tickets sold. In 2013 the average attendance was also quite a lot higher than in 2018. The price elasticity in 2013 was:

$$\frac{[235 * (10345 - 5586)]}{[(50 - 235) * 5586]} = -1{,}08$$

An elasticity 1,08 is lower than the 1,4 from 2018, meaning supporters of IK Start were more price elastic in 2018 than in 2013. The results can suggest that people are more price aware than before, meaning people are more price elastic in all parts of their life. For example, Norwegian sites like Prisjakt or Prisguiden have flourished in recent years making it easier for customers to find the lowest prices on products. According to the former CEO of Prisjakt, Are Vittsø, “more and more of us (Norwegians) have a conscious relationship to what things costs and what we want to pay for the goods we buy.” A survey that was done by Opinion for Prisjakt to chart the price awareness of the Norwegian people gave the result that the age group between 30 and 44 was more price conscious than other groups (Øksnes, 2019). When customers are more price aware they compare products against each other in the lookout for the best deal. With the competition of the football clubs growing, customers have more options that can outvalue the experience of going to a match. A representative of Rosenborg women’s team said “We are competing against a lot more than other sports events. We compete with social media, Netflix and all sorts of things. We have to borrow people’s free time.” (Øvstetun, 2021)

The price elasticities found above are based on the one game with the price experiment versus the whole season with fixed prices. However, during an entire season there are effects that might skew the result. The first games of the season might have a higher demand because of the wait and anticipation that has built up. There could also be higher demand for games during the summer because of the nice weather than in a winter game at the end of the season. We can also expect that the game on the 16th of may always has a higher number of supporters since this day is considered the “football holiday” in Norway. To remove these possibilities, we can look at the attendance rates of the games around the experiment.

The relevant game weeks to look at are rounds 18, 20, 22 and 25 for 2018 and round 18, 20, 22 and 24 for 2013. In 2018 the price experiment happened on round 22. As we know the experiment had an attendance of 10419, whereas the average of the other rounds was 3682. Since the price experiments in 2018 and 2013 happened during the same time of the year, we can easily compare the two. The price elasticity of 2018 is now:

$$\frac{[210 * (10419 - 3682)]}{[(210 - 1) * 3682]} = -1{,}83$$

The result of -1,83 is higher than when we took the average for the whole season. Suggesting that people respond more to price changes than before.

We can do the same for the 2013 season, here the price experiment happened in round 24 with an attendance of 10345 and the average around the experiment was 5155. This resulted in a price elasticity of:

$$\frac{[235 * (10345 - 5155)]}{[(50 - 235) * 5155]} = -1{,}27 \approx -1{,}3$$

Which again is higher than when we were using the whole season but is still quite a bit lower than 2018. The results suggest that people have been more price sensitive in recent years regarding tickets to games. When supporters are more price sensitive there is larger room for a dynamic pricing scheme, meaning supporters would react more to dynamic pricing. By using rounds around the price experiment, we can adjust for factors like seasonality. In the case of IK Start the average attendance was lower when we took the average attendance around the price event instead of the average of the whole season. Our new findings suggest that the supporters are even more price elastic than before, meaning the price has a bigger impact on demand than when we took the average of the whole season.

6.4 Price response function

The price elasticities have shown that there is room for a dynamic ticket pricing model in the Norwegian league. To create a dynamic pricing model, we first create a price response function. A price response function tells us what price creates what attendance. There are several different price response functions, we will look into two of them. The reason behind this is because we only have two points to make the graph, the one of the price experiment and the average of the whole season.

The first price-response function is the linear price response function. The linear price response function shows us the attendance and prices when the slope of the curve is constant over all ranges. In our example we get the following curve:

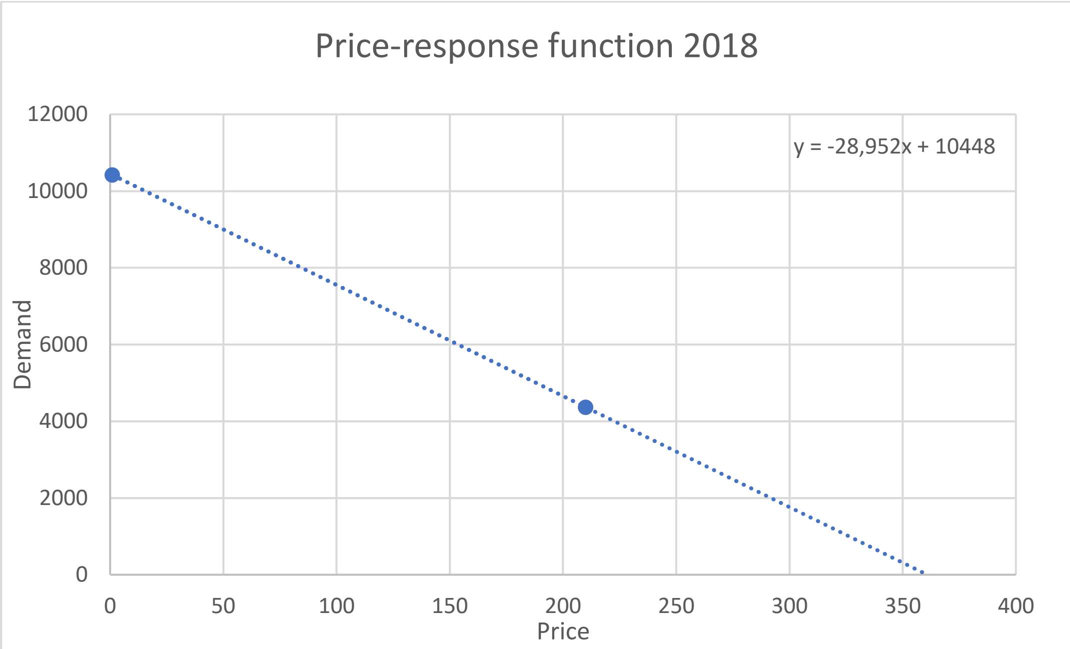

Figure 10: Linear Price-response function

The price-response function shows us that demand decreases by 29 with a 1 kr price increase. We can also make a price response curve with the average attendance of the rounds 18, 20 and 25, meaning around the price experiment, this would result in a steeper curve (see Appendix 2). The problem with doing this is that the price the club has set is fixed for the whole season. They would have taken into account the lower demand of these rounds, since the other rounds achieve higher demand. By making a price response function with only the lower demand rounds, even though they are at the same time of the price experiment, one would count out the better attended games that are accounted for with the price.

The second price response function to look at will be the constant elasticity price-response function. The function has a point elasticity that is the same for all prices. It is based on an exponential willingness-to-pay distribution. It can be written as $d(p) = C * p^{\varepsilon}$, where $C > 0$ and $\varepsilon < 0$ that are fitted values estimated by the price/demand data (Phillips, 2021).

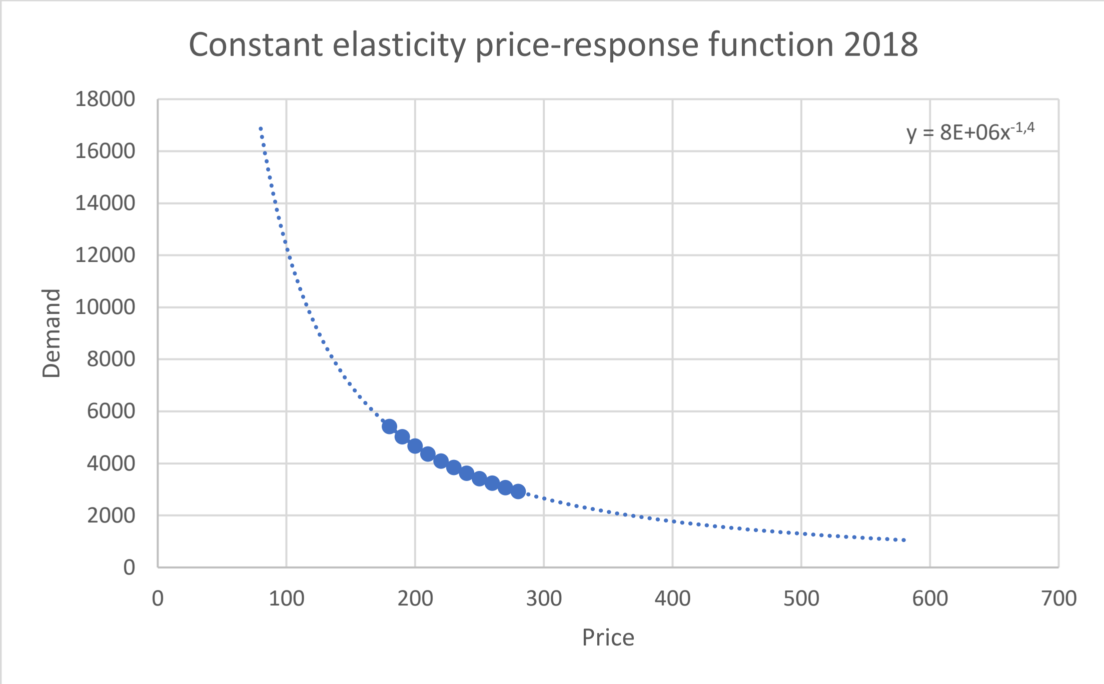

Figure 11: Constant elasticity price-response function

This price-response function has a constant elasticity of 1,4 that came from the results of the elasticity calculations. The constant elasticity price-response function can fit during low changes in prices or demand, but over larger changes we can see visually and mathematically that the results are unreasonable (Phillips, 2021). For example, take a ticket price of 50 kr, that would result in an attendance of 33460, three times as large as the stadium. Because of the exponential nature of the constant elasticity price-response function it is not applicable to large changes. Therefore, the fit for our dynamic pricing model is better with the linear price response function.

A third price-response function that could be interesting to examine is the logit price-response function. The function describes a state where price elasticity is high near the market price but is lower for very high or low prices (Phillips, 2021). The logit price-response function is often referred to as being more applicable to real life, however having only two points, there is no possibility to make such a price-response function. Therefore, we conclude that the linear price-response function is the best available function for the dynamic pricing model.

6.5 Creating the dynamic price model

After selecting the correct price-response function, we can look at the possibilities of making a dynamic pricing model. The model will focus on time as a determining factor along with the attendance and price. To be able to add time to one of the variables we make a graph showing the relationship between time and quantity.

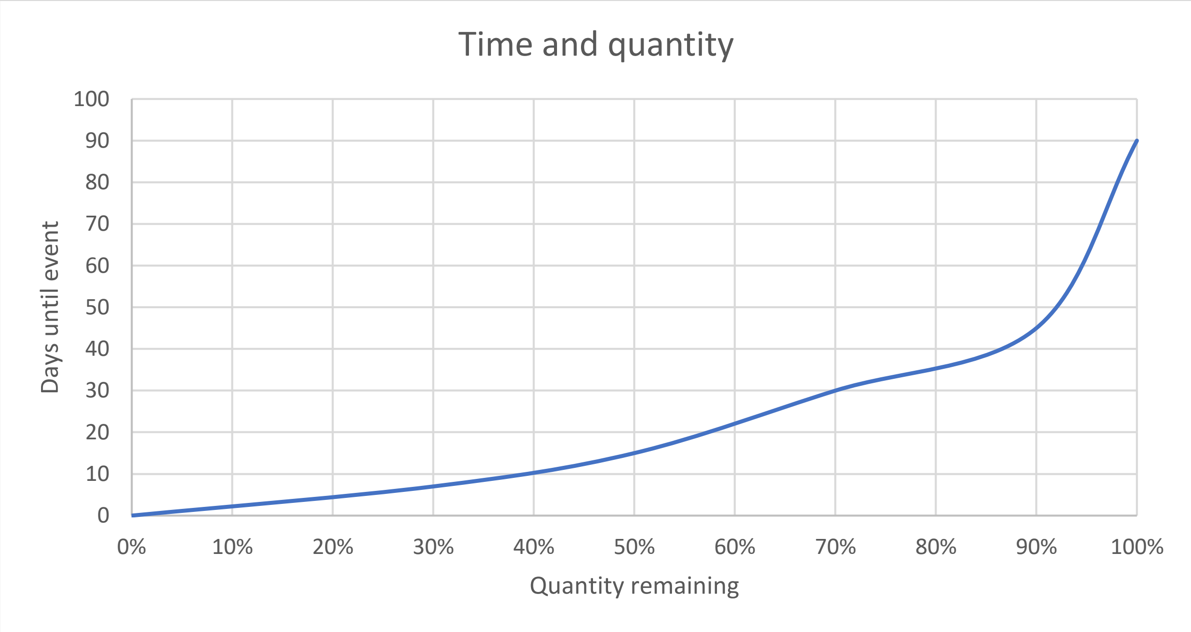

Figure 12: Relationship between time and quantity

To understand figure 12 properly we need to read it from right to left. In the figure we see that quantity decreases as time decreases with a downward sloping line. At day 90 there are no tickets sold for the specified match, and even 45 days beforehand there is still 90% of tickets left. We see that around 50% of the tickets get bought within the last 15 days.

After having successfully made a graph between time and quantity we can now merge the graphs to make our final graph showing the relationship between price and time. The following figure (figure 13) shows how it is done.

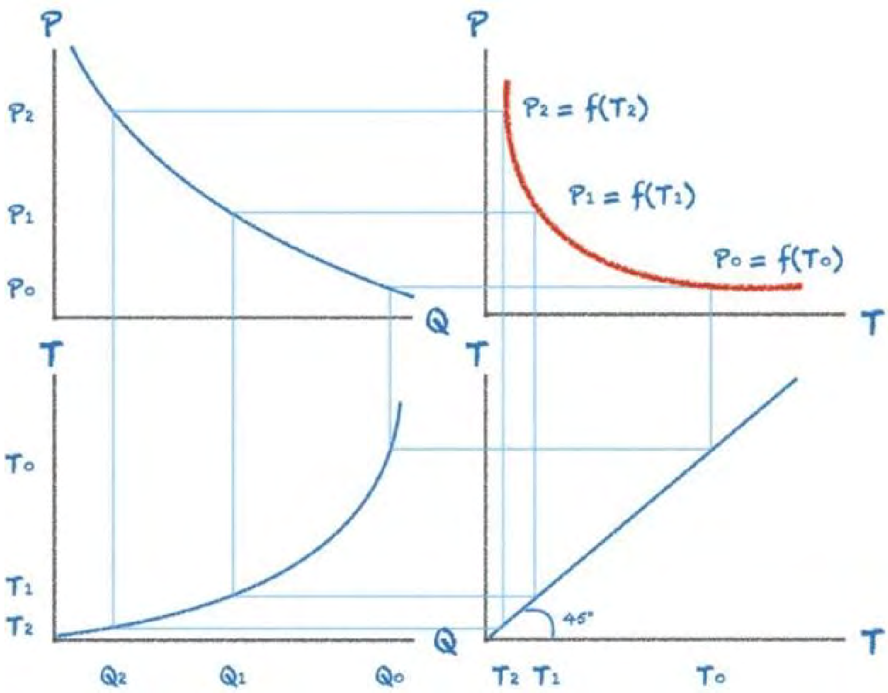

Figure 13: Finding the relationship between price and time (Yuan, 2020)

By creating a price and time graph like in figure 13, we can adjust our price according to time while quantity is also accounted for. We see in the figure that a place on the price and time graph corresponds with a place on the other graphs we made. The price time function for the dynamic model is the following.

Figure 14: The relationship between Price and Time

This graph shows us that the closer to match time it is, the price increases, just like you can see in other sectors like aviation and hotels. But what happens when people do not act like their normal selves or there is a change in consumer purchasing power, can we still follow the curve?

When we sell more or less tickets than expected it creates shifts in the current curves. Lower demand for tickets than normal makes the curve shift towards the left, while higher demand makes the curve shift to the right. By not adjusting the price when there is a higher demand than usual, tickets will sell out before the clubs are able to reach the higher prices that happen in the periods closer to the match. Therefore, by increasing the prices early the demand stays stable, and tickets will go out at the normal pace again. Similarly, when there is a smaller number of tickets sold than usual it means that at the given time and price there is less quantity sold than what is expected, if we go further with the same price, there will be much lower attendance than normal. The correct way to adjust this would then be to shift the curve down by making the tickets cheaper.

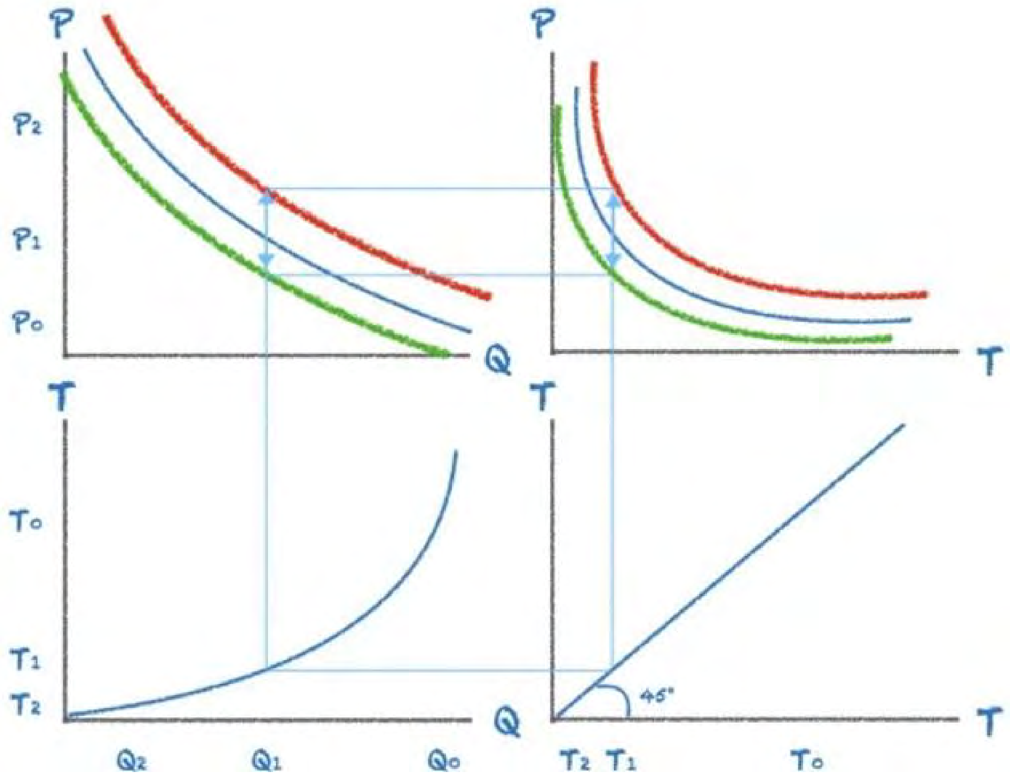

Figure 15: Shift in curves (Yuan, 2020)

There are several reasons why the price curve must shift. It could be because of what opponent the team is facing or the home team is behaving better or worse than normal in the current season. We can then make a price matrix to make it easier to adjust for such changes in customer behavior.

6.5.1 The price matrix

In a price matrix we can show the output of price, quantity and time in a single table, where both the normal situation is accounted for, but also when the demand is lower or higher at any possible time. The price matrix looks like this:

	T10	T9	T8	T7	T6	T5	T4	T3	T2	T1	T0
Q10	P10	P	P	P	P	P	P	P	P	P	P
Q9	P	P9	P	P	P	P	P	P	P	P	P
Q8	P	P	P8	P	P	P	P	P	P	P	P
Q7	P	P	P	P7	P	P	P	P	P	P	P
Q6	P	P	P	P	P6	P	P	P	P	P	P
Q5	P	P	P	P	P	P5	P	P	P	P	P
Q4	P	P	P	P	P	P	P4	P	P	P	P
Q3	P	P	P	P	P	P	P	P3	P	P	P
Q2	P	P	P	P	P	P	P	P	P2	P	P
Q1	P	P	P	P	P	P	P	P	P	P1	P
Q0	P	P	P	P	P	P	P	P	P	P	P0

Table 3: Price matrix

From the matrix we see that vertically we have the quantities, Q0-Q10 while horizontally we have different values of time, T0-T10. The diagonal of the matrix is the normal state of prices, this is when the current situation is following the curve in figure 14. However, when the situation is not in the usual state, we end up in either the green or red squares. When we are in the red squares the price of a ticket would be higher than before at the same point in time, and for the green squares the tickets would be cheaper. Say for example that we are at the time T4, but the quantity is already at Q7, then we need to increase the prices to be able to maximize the potential profit.

Making our own matrix

After understanding how the price matrix works, we can make our own matrix with the numbers of the football club IK Start. When making the matrix there were actions taken to make the pricing less complex for the attendee. For example, one could have different segments where prices were different at different times, like short sides and far sides of the football pitch. However, when first implementing a dynamic structure, we wanted to make the results easier to analyze, so we didn't split up the stadium. There is also a possibility that a part of the stadium has a dynamic price scheme while another has a fixed price, this makes it easier to try out a new pricing scheme while not fully abandoning the old one. This is how the

San Francisco Giants started with dynamic pricing in America. It was first when they saw increased results, they implemented the scheme to the whole stadium (Shapiro & Drayer, 2012).

Another important subject when discussing the dynamic pricing model is the price roof and floor. While statistics and data are interesting, how it is implemented is important. When implementing a new pricing scheme, it is important not to irritate the fans of the club. Similarly, to the example of dynamic pricing in the championship division that was mentioned earlier in the thesis, the rule of the price floor should be that the price for the ticket should not be lower than what the season ticket holder pays for the game, that would annoy the loyal fan. For this particular model the lowest possible price of a ticket was set to 20% of the highest price. The roof of the price for a match ticket would be the price for the most expensive ticket at the moment. Even though the most loyal fan might pay more for a ticket, the goal of this thesis is to have higher attendance at games, and by increasing the prices this will likely not happen. In addition, it will also piss off fans making them think that the new pricing methods are only made for the clubs to earn more money. The roof could however be increased at some point if the dynamic pricing strategy is a success. Having made these assumptions, we can now plot the numbers.

	1	3	5	7	14	21	30	45	70	90
0 %	260	260	260	260	260	260	260	260	260	260
10 %	250	260	260	260	260	260	260	260	260	260
20 %	231	244	260	260	260	260	260	260	260	260
30 %	211	221	234	260	260	260	260	260	260	260
40 %	153	159	172	179	191	198	208	213	221	231
50 %	91	101	112	117	125	135	148	161	169	177
60 %	52	52	52	60	68	78	86	94	104	122
70 %	52	52	52	52	52	52	52	52	65	78
80 %	52	52	52	52	52	52	52	52	52	60
90 %	52	52	52	52	52	52	52	52	52	52

Table 4: Price matrix made for IK Start

From the matrix in table 4 we see that the dynamic model suggests prices under the floor of the pricing until we reach 30 days before match start. Then from days 30 to 7 days before the match we see increases in the prices until we hit the roof at 260 kr. Here the prices normally would have gone higher than 260, but because we want to increase attendance, we do not go higher than this price.

With a logit price-response function instead of a linear price-response function, the middle part of the matrix would have been more stretched out, meaning that we would have had a larger spread in prices shown by the matrix. With the current price-response curve, we reach the cap of 100% fairly early and have a longer time with the bottom cap early on. The quantity and time curve that this matrix was based on was taken from the train industry, while it has some similarities like that the tickets start getting bought around 90 days before the happening, we cannot guarantee the same graphs for both industries. There were attempts made to get such data by reaching out to different clubs, this information was obtained at a late stage in the thesis. The following results came from the data obtained.

6.5.2 Dynamic pricing model with Bodø/Glimt's time and quantity data

In a late stage of the thesis, I obtained information about the number of tickets sold at each time of the selling period. Joe Foster is the ticket coordinator at Bodø/Glimt. He answered the following to my question about when match tickets get bought:

"Anecdotally, during last season we would see roughly 50% of tickets sold during the first 2 days of the event being posted, then sales would drop off until 2-3 days before the event and then they would pick up again." (J. Foster, personal communication, January 11, 2022)

Based on Forster's response the following quantity and time function was made

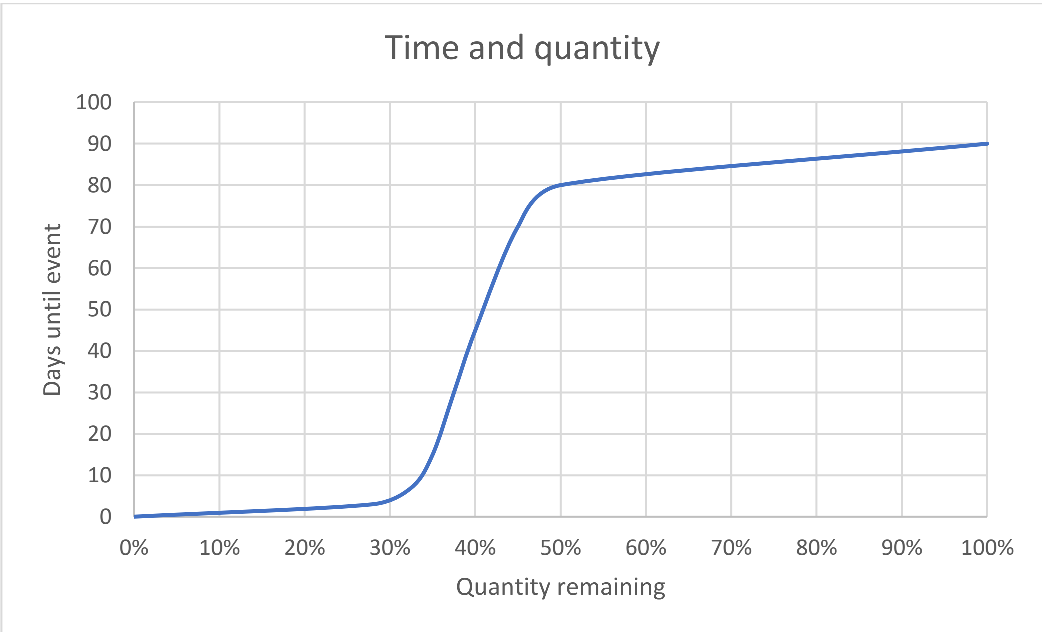

Figure 16: Time and quantity curve based on Bodø/Glimt's numbers

From figure 16, we see that large parts of the tickets are being sold early on when the tickets have just been released. The first 50% of the tickets are being sold in the first days and afterward there is a break in the sales.

The flow of tickets is then continued by further sales right before the match takes place. The changes in our time and quantity graph makes changes to our price and time graph as well. The following graph is the result of the changed time and quantity graph.

Figure 17: New price and time function

The price changes a lot during the initial buying phase, then stays stable until the late buyers buy a ticket at the end. If we want to make a matrix similar to the one made earlier in the thesis we have to make a small change to it. If we want to keep the same time instances (top row) as before we need to make changes to the left vertical that shows the quantity remaining.

	1	3	5	7	14	21	30	45	70	90
0 %	260	260	260	260	260	260	260	260	260	260
28 %	250	260	260	260	260	260	260	260	260	260
30 %	231	244	260	260	260	260	260	260	260	260
33 %	218	226	234	243	250	257	260	260	260	260
35 %	179	190	198	205	217	226	239	247	255	260
37 %	187	200	205	213	221	225	237	242	247	255
38 %	179	190	198	203	213	221	237	244	252	260
40 %	164	169	174	185	192	198	205	214	221	234
45 %	153	161	166	174	182	187	195	203	207	216
90 %	52	52	52	52	52	52	52	52	52	52

Table 5: New price matrix

With the time instances equal we can clearly see that the quantity on the left side of the matrix goes down from 90% to 45% in the first instance, this is because half of the tickets already gets sold during the first days, as Foster said. The jump is very high, to time period 2 at 70 days, and stays quite stable until the right before the match occurs. We do not see the jump in price right before the match starts like figure 17 shows, since we made a price cap at 260 that was discussed earlier. The dynamic pricing process of the first days has to be frequently updated for the dynamic pricing to work. If not done correctly, a large amount of the supporters might get cheaper tickets than the scheme suggests. Though, with modern programming tools this should not be too hard.

The price matrixes show how a dynamic pricing strategy would work in practice. The two suggested models also give us an insight in how important the different inputs are since the models are quite different. However, when the clubs use their own historical data and incorporate that with the data they have on the supporters of the club they have a better foundation for creating a model than a third party. For further research the two models made in this thesis can be simulated with Monte Carlo simulation or a similar simulation method to compare results against a fixed model the clubs are using currently.

7. Discussion

7.1 Room for varaible pricing

According to what was found in the results of the survey with the different clubs and the making of the dynamic pricing model there are clear signs that there is a possibility for the clubs to employ dynamic pricing on tickets.

How each of the clubs employs it and how many factors they account for is something each club must decide. They could employ it with regard to the size the of the opponent's fan base, or according to the position the opposing club has in the league. If a club has a good season there is a higher chance that they would have increased away supporters in the stands. However, with the experiment of Strømsgodset in the Norwegian league, we have seen that only implementing one of these factors offer little to no improvement. Therefore, implementing it directly based on demand would be the best way, even if it requires more work to implement.

The empirical findings of our study back up and enhances the idea of what has already been emphasized in previous literature. The study of Bayern Munich by Kemper and Breuer (2016) and similar studies done in the United States suggest that dynamic pricing can increase revenues both when the club already has a high attendance rate and when the club is struggling to attract fans. The perspective of this thesis is to increase the population or the number of supporters in the stands. To further discuss the research question of the thesis I look back at the hypothesis we proposed earlier in the thesis and utilize them to deliver a clear and strong conclusion to the research question.

7.1.1 The interest in Norwegian football

The first hypothesis was the following:

Hypothesis 1: *"Interest in the Norwegian league has decreased the last 10 years."*

The number of supporters in the stands has been decreasing in Norwegian football. Meaning that less and less people go to the games. Even though fewer people attend matches, it does not directly imply that interest has sunk. The supporters could consume the product in a different way. In the survey conducted for the thesis Bodø/Glimt mentions that "a lot of supporters have used their money on TV subscriptions because of the limited capacity of the stadium in this and the previous season.”

In addition to wrong pricing there are other effects that can amplify the reduction in attendance. Eliteserien has a lot more competition nowadays, that was not appearing in years 2007-2009 when the attendance numbers were very high. In Norway, Premier League has always been popular, but in recent years the matches have been more available to the Norwegian viewer. One of Norway’s biggest channels, Tv2, which had the coverage of the Norwegian Eliteserien, lost their tv-deal in an auction against C more in 2012. On this lesser-known channel, the league lost a lot of its viewers, and the league got less popular. Besides a short tenure in 2015-2016, the Norwegian league has not been shown on a major tv-channel (Stormoen & Henriksen, 2016).

Tv2 still had a lot of famous football commentators on their paycheck after the loss of the Norwegian league tv-rights and sent the majority of them to the Premier League, which they bought the tv rights to in 2010. Many casual football fans started following the Premier League, instead of the Norwegian one. The result of a study made by Gjestvang and Reinhardsen (2015) came to the conclusion that Premier League football impacted the attendance rates in Eliteserien negatively. If a top team in the Premier League played at the same time as IK Start it would cause less people to attend the matches. Another study done by Halberg (2015) supported this claim and stated the majority of young adults in Oslo, the capital of Norway, consumed more international football. The young adults found Norwegian football less interesting.

Eliteserien is also competing with other forms of entertainment like Netflix and HBO. When a good seat at a home game costs approximately the same as a monthly subscription to Netflix, HBO and Spotify, the decision for a younger adult might be an easy one. In the fall of 2021 after the corona-restart, clubs saw disappointing numbers of supporters after two years without going to the stands (Brandt & Gullachsen, 2021). It makes a lot of sense that people were cautious with the virus. However, in the first game back for the Norwegian national team against Montenegro the stadium was filled (Arntzen & Boge-Fredriksen, 2021).

Will the results say that the Norwegian league is just outnumbered by the competition? No, there are plenty of examples that the league still can be attractive. We have seen that price experiments have worked before. In 2013 the club IK Start had close to 10000 supporters at a match because of a ticket reduction to 50kr. Recently, in 2022 on what is considered the national football holiday in Norway, the 16th of May, a new record was set for attendance for Eliteserien and OBOS-ligaen combined. A total of 126 715 supporters were reported to be in the stands (Opphus, 2022). In addition, with Norway's national team gaining more traction, and the team consisting of former Eliteserie players that are now international stars, like Erling Braut Haaland and Martin Ødegaard, attracting fans back to the stands should be possible. Ticket campaigns and sales have shown that clubs can attract a large number of fans with a lower ticket price.

If we look at the results from our calculations of elasticity, we see that IK Start is very elastic when it comes to price. A high elasticity is a good indicator that dynamic pricing could work. If we assume that other clubs have similar elasticities, the clubs can fetch new supporters with a new pricing strategy.

7.1.2 Price elasticity

Hypothesis 2: *"Supporters are more price aware or more price elastic than in previous years"*

From the calculation made in the result section of the thesis, we see that the evolution in elasticity confirms the hypothesis that supporters have become more price elastic. For overall elasticity the differences between 2018 and 2013 were -1,4 and -1,1, and with elasticity calculated around the rounds the differences were higher, -1,8 and -1,3. There are several reasons that can explain the change in the elasticity.

First of all, there is greater competition from other types of entertainment as mentioned earlier in the thesis. Since the business world has changed to become more service based than before, a lot of consumers have recurring costs (Chung, 2021). Consumers have memberships on these services which means that a certain amount of their monthly wage is locked to keeping these upright. Recent studies suggest that the context of when customers use money is one of the most powerful drivers of price sensitivity. An example of that would be that consumers are more price sensitive when dining out with their kids, than when they dine out as a couple (Witschi, Bharadwaj, Izaret, & Taylor, 2021). If going to a match is done by only one part of the relationship, the experience might become undervalued or underappreciated compared to activities or services that can be shared by the two of them. It also decreases the time spent together, however if they watch the match on television they could still spend time together even though they are not watching the same program.

The normal supporter has also changed in recent years. In a recent study by Charlotte Pick and Alex Gillett (2019), they try to identify what they call the enthusiast. They mention in their report that a lot of the studies have been done on Premier League clubs which are so big they cannot really compare to other leagues. Therefore, their study is based around the 2nd to 4th division in England. They segment different supporters in different groups. For example, in one of the groups the supporters are totally loyal to their club, and they use the club as a form of their own identity. Some prefer remote types of consumption like through the television or the internet, while others attend the games live with different levels of frequency. The study suggests that the lower league clubs will have a higher percentage of hardcore fans than clubs in the Premier League since they are dedicated to supporting relatively unsuccessful clubs. (Pick & Gillett, 2019) However, in Norway there is still the possibility of attracting so-called glory hunters that only go to matches when their club is successful or close to winning the title, at the highest level. But since a lot of the casual supporters have started to watch English football, there is less to pick up on that front than earlier.

A surprise result in the study relates to the insignificance the family history with the club had on the amount of loyalty a fan perceived with the club. They assumed that if the family had a history with the club, for example their father was a fan of the club, the kids would follow (Pick & Gillett, 2019). That result can explain some of the evolution we see in the Norwegian league. In Norway a lot of the focus of the Norwegian league has been to create the best experience for kids. Kids were usually brought to matches by their parents and the clubs have focused on these families. This has been done by providing family tickets and other events for kids around the games like the concept Fanzone. Their mindset would suggest that if they get the family over and the kids start going to the games, they will continue to go when they are older. However, the result in the report suggests otherwise. In a recent podcast about the topic of how to attract fans to the stadiums in the Norwegian League. CEO of the 2nd division club Ull/Kisa, Andreas Aalbu, said “We (Norway) have focused an awful lot on children and young people for them to attend matches, but we must not forget our age group (20-50 years), we are the ones that needs to be attracted, we create the atmosphere during the matches, we are the ones who stand on field O (which is a standing tribune) or the people in “Klanen” (which is a hardcore supporter group in Norway for the club Vålerenga)” (Aalbu, 2022)

If consumers value the experience less than they did before, the consumer becomes more price elastic, meaning the price of the product has a bigger effect on if the consumer decides to go or not. As discussed earlier in the thesis the age group between 30-44 has been reported as being the most price conscious group in Norway (Øksnes, 2019). To attract more fans, the football clubs have to do more to increase the perceived value of a match. Another option would be to change the price itself, here is where dynamic pricing could come into the picture.

7.1.3 Challenges with dynamic pricing

Hypothesis 3: *"Norwegian clubs are faced with a lot of challenges when it comes to creating a dynamic pricing model"*

Considering this hypothesis, the first obvious challenge is that there is not a secondary ticket selling market in Norway where the clubs can measure the willingness to pay of fans. The lack of a secondary market makes it harder for the clubs to know at what price the consumers or fans value a ticket. Every consumer has a different willingness to pay, so one fan's number is different from another's. What most of the clubs do know however is the price sensitivity of the supporters of the club. In our survey done by the ticket managers of the clubs over 50% answered that they do take the price sensitivity of the supporters in mind when they are setting their prices for the season. From the sensitivity of the prices the clubs can extract the ideal prices of tickets because it helps with understanding the supporter's mindset and behavior.

In general, there is not a lot that is stopping the clubs from trying a dynamic pricing scheme, many fans are agree that changes have to be made. The fans are already used to paying for the tickets in advance and not on match day. A few clubs also mentioned that they have looked at possibilities of dynamic pricing in the survey. The fact that clubs are actively looking at it as an option makes me believe that there is a real possibility for it to happen

The individual clubs may fear the response from the supporters by implementing a dynamic ticket pricing model. If prices aren't consistent and prices fluctuate over time consumers might think of it as unfair and may choose not to purchase a ticket. However, studies have shown that the perception of unfairness declines over time as consumers become more familiar with regular price changes based on market factors (Wirtz & Kimes, 2007). Consumers are also familiar with this type of pricing from other industries like aviation and lodging

7.1.4 Countermeasures

Hypothesis 4: *"There are not enough countermeasures done by the clubs to stop the loss of attendees"*

Clubs are seeing their attendance rates go down year by year but what are they doing to counter this change? The last question of my survey was made especially for this hypothesis, but only in the form of pricing. The clubs' answers were: just straight up reducing the price, price bundling and better segmentation. Reducing the price could cause consumers to see the product as lesser than before but could also increase attendance. Price bundling could have an effect but would rule out the people who usually go to the matches alone. Better price segmentation and more defined lines between sections sounds good, but will it really make a change in attendance rates? The results of these countermeasures have been less than successful, since the attendance rates continue to sink. Another measure done by the league is setting up tents or areas called Fanzones that are meant to appeal to kids, pre-match. These tents include various activities that kids can participate in. Nevertheless, clubs have other countermeasures they want to implement, but some of them have politicians standing in their way.

First of all, the clubs want to increase the consumers' perception of what the value of a football match is. To do so they need to think about the experience beyond the two halves of 45 minutes. The first controversial topic of the Norwegian football league is pyro. There have been a lot of debates about what is considered allowed and not allowed with pyro. "Pyro really helps with the entertainment value and increases the atmosphere at the games... When posting a photo online it is usually of the pregame pyro, it helps attract fans to the stands." Says Kristoffer Løkberg, a current player in Eliteserien when asked about pyro (Løkberg, 2022). At the end of the day a football match is there for the entertainment value, having pyro would add to that.

Another controversial topic is alcohol at the games. This has been a hot topic in Norway for several years. Since the Norwegian way has been to allocate to kids and younger adults, beer or alcohol has been banned from matches, before matches, under and after. Some clubs try to counter this by having local bars right next to or incorporated in the stadium where they can sell beer. (However, these are not reachable from inside the stadium, you will have to go out of the stadium to enjoy a beer.) Countries like England, Germany, The Netherlands and many more sell beers at stadiums. Some countries only allow consumption during pre-match and in the breaks, while in other countries you can bring your beer to the stands. Politicians have clearly stated that alcohol and sports do not go together. What is ironic is that the politicians often watch the matches from the VIP-tribune where they are allowed to consume alcohol. From the same podcast that was referenced earlier a suggestion was made to “split up the stadium, let one of the long sides allow for alcohol while the other is alcohol-free” (Løkberg, 2022). A solution like that would solve the concern the politicians have for children’s safety. Alcohol could also contribute to more engaged supporters, supporters joining in on supporter songs and in general an increased atmosphere.

Another recent countermeasure done by some of the clubs in Eliteserien is implementing a subscription-based ticket. The ticket works as a season ticket, but you pay a monthly fee. The subscription-based ticket gives consumers a higher freedom of choice and they can select the monthly price that best suits them. The service has a 6-month binding time, with a one-month cancellation period. The subscription solution was made as a response to the increased number of membership-pricing models we discussed earlier in the thesis (Viking Fotball, 2021). Since the clubs implemented a new pricing strategy, they are in agreement that something has to be done price wise to attract more fans. The subscription-based model is another way of pricing the season ticket, it does not change the ticket prices of a single match like a dynamic pricing model. The impact of the subscription-based model is too early to determine since it has just been implemented, but it could create the increase in attendance we wanted from the dynamic pricing model suggested in the thesis.

8. Conclusion

This thesis aims to explore the possibilities of applying a dynamic pricing model scheme to the Norwegian Eliteserien in an attempt to increase attendance. Theoretical findings suggest that the implementation of a dynamic ticket can have positive impacts on both attendance and revenues. Christoph Breuer and the Munich example shows the possibilities of gaining revenue while keeping people in the stands. The Norwegian football league has several competitors in the sports industry but also in other forms of entertainment. To make the league more attractive they should implement dynamic prices, making matches more affordable.

Results from the survey answered by different clubs in Eliteserien suggest that they have the data necessary to implement such a strategy. Furthermore, the price elasticities found in the thesis indicate that the consumers are more price sensitive than in previous years. The implementation of a dynamic pricing scheme would make the barrier to entry smaller. If the willingness-to-pay of a supporter is low, they might want to go to a mid-week game with low demand instead of a weekend game where the prices are higher.

The variable pricing experiment of Strømgodset in 2017 might have had little effect on the attendance numbers, but it is a bad representation of dynamic pricing, since it was a variable pricing strategy that varied with one single variable and the price difference was 20 kr between the highest and lowest price. The dynamic pricing model proposed in this thesis is a better representation of what such a strategy should look like. Where the three factors of price, quantity remaining and time to the event are all accounted for. For the optimal benefit of dynamic pricing, prices should be automated by an algorithm and should vary for the same game, based on the demand at the time you bought the ticket. Some clubs might find this one step too far and fear backlash from fans, since they are paying different amounts for an identical ticket (same section). However, this is a model justified by other industries like the hotel industry and the travel industry. If you buy a ticket on match day, you will not get the same price as someone who bought a ticket six weeks in advance. Thus, this thesis has provided a proposed dynamic pricing model that seeks to increase the attendance in the Norwegian football league.

Limitations and further research

The following limitations were apparent in this study. First of all, there was little information in general about the willingness-to-pay of supporters in the Norwegian League. The lack of a secondary market made this limitation apparent. The price-response curve was therefore based on price experiments done by IK Start. The dynamic pricing model was then consequently built upon this data. An evaluation of the other football clubs could have revealed different demand functions. The data considering the prices of tickets from the different clubs were taken from two different web pages, while these had some of the same categories there is always a margin of error when you compare data from different sites. Lastly, we could also have split the dynamic prices into different seat sections that had their own dynamic price. However, this would make the models a lot more demanding than they currently are.

For further research the two proposed models that were created in the thesis should be simulated against a fixed price model that the clubs are using currently. This could be done by running a Monte Carlo simulation. Further, the results of the new subscription-based pricing model the clubs are now providing should be analyzed thoroughly and compared against other pricing strategies.

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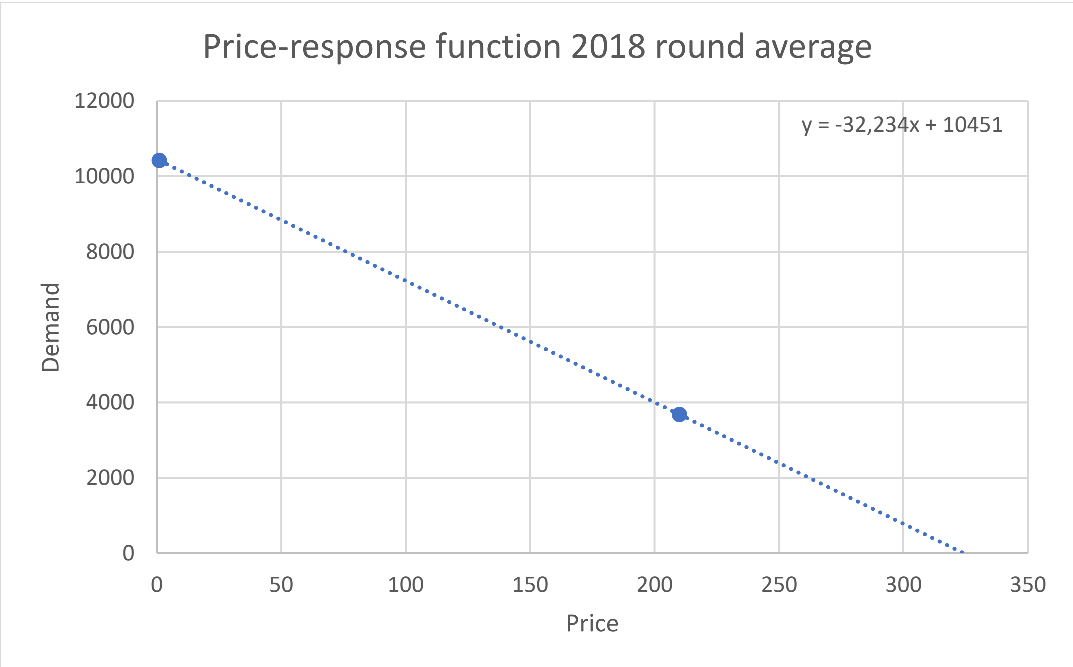
Appendix

Appendix 1: Data on prices and attendance for the individual clubs in Eliterserien for 2017 and 2018

	Price (expensive)		Price (cheap)		Average price (c and e)		Attendance	
Club	2017	2018	2017	2018	2017	2018	2017	2018
Brann	400	280	200	210	300	245	11859	10431
Haugesund	300	300	130	150	215	225	4455	4317
Kristiansund	290	220	170	170	230	195	3824	4042
Molde	360	240	140	120	250	180	7785	7111
Lillestrøm	300	320	200	220	250	270	5629	5560
Odd	300	300	60	60	180	180	7106	5383
Rosenborg	430	440	215	245	322,5	342,5	17593	16424
Sandefjord	240	250	190	100	215	175	4012	3136
Sarpsborg 08	250	300	100	100	175	200	4701	5005
Stabæk	295	300	50	200	172,5	250	3960	3656
Strømsgodset*	330	340	100	220	215	280	6272	5939
Tromsø	250	260	200	100	225	180	3596	3655
Vålerenga	350	360	200	235	275	297,5	9703	9180
Aalesund	240		140		190		6062	
Sogndal	300		150		225		3246	
Viking	360		260		310		7380	
Bodø-glimt		300		100		200		3219
Ranheim		295		245		270		2018
Start		260		160		210		4772
Average	312	298	157	165	234	231	6699	5866

Appendix 2: Price-response function made with round attendance average



Appendix 3: The whole survey in its original language.

Navn på fotballklubb?12 responses

Lillestrøm Sportsklubb
Brann
Stabæk fotball
FK Bodø/Glimt
Molde Fotballklubb
Strømsgodset Toppfotball
Vålerenga
Sarpsborg 08
Bodø/Glimt
Vålerenga Fotball Elite
Sandefjord Fotball
Stabæk Fotball

Hvilke retningslinjer (policy) tar dere hensyn til når dere fastsetter prisene på deres kampbilletter?12 responses

-Konkurransedyktige priser i forhold til andre arenaer (fotballlag, underholdningsaktører) -
Billigere for barn, studenter og honnør
- Konsumprisindeksen

De beste er dyrest (midt på), billigere for barn i svingen osv.

Usikker

Vi vurderer den relative verdien av seeropplevelsen sammenlignet med andre områder på stadion. For dårligere opplevelser (inkludert mangel på dekning fra elementene) tar vi lavere priser.

Vi ønsker at flest mulig skal få mulighet til å komme på kamp, og prøver så langt som mulig å sette prisnivået korrekt. Har ikke endret billettprisen de siste 5 årene. For 2022 går snittprisen litt ned

De beste plassene kan godt koste litt, for disse blir solgt uansett, men vi skal alltid ha et rimeligere tilbud på stadion. Spesielt mot barnefamilier.

Vår egen prisstrategi

Vi skal ha en bra bredde i prissetting så alle skal få mulighet.

Vi ser dette i sammenheng med den totalopplevelsen som vi gir publikum på arena, men i utgangspunktet ønsker vi å prise oss så lavt som mulig for en klubb i den tiden vi er i.

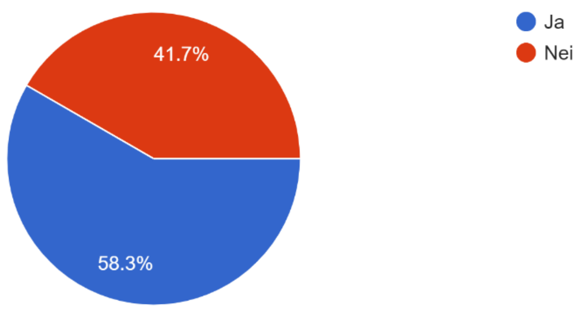
Vi sammenligner oss med resten av Eliteserien. Samt priser over siste sesongene. Vi inkluderer våre supportere for å fastesette priser.

Vi ser på hva andre klubber gjør, og hvordan vi har priset tidligere

Vi fastsetter ulike priser på ulike deler av stadion. De beste plassene har høyest pris feks. Vi har også tilpasset priser til barn og familier. Vi ønsker å ha et tilbud til alle i nærområdet, små og store.

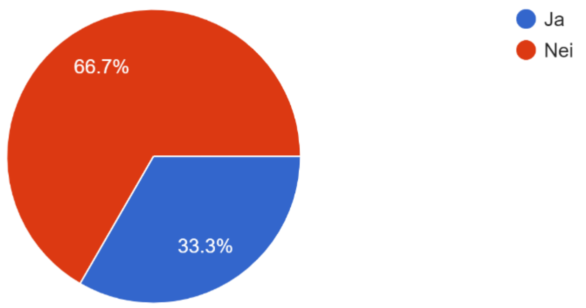
Ser dere på prisfølsomheten til supportere da dere setter priser på kampbilletter for sesongen? (Prisfølsomheten vil si hvor følsom etterspørselen etter billetter er overfor prisendringer)

12 responses



Har klubben deres vurdert en type dynamisk prising? Som for eksempel at prisen på en billett endres i forhold til motstander, tid i uka eller kjøpstidspunkt.

12 responses



Hva har klubben deres gjort prismessig for å snu trenden med synkende tilskuertall i eliteserien?12 responses

Ingen endringer i pris da det ikke er pris som er årsak til synkende tilskuertall

Forenklet sesongkortprisene og satt ned prisene på sesongkort. Flere kategorier og flere tilgjengelige felt. F.eks egen "supporterkategori" som er billigere og kalt de dyreste billettene for Premium osv.

Vi har 2 for 1, ta med en kompis kampanje, foreldrebilletten (2 barn + 1 foreldre)

Vi prøver forskjellige metoder, spesielt på grunn av mengden supportere som har brukt pengene på TV-abonnement, på grunn av den begrensede kapasiteten til stadioner gjennom denne sesongen og forrige sesong. Når det gjelder pris, har vi revurdert hva vi kan gjøre på stadion for å øke den relative verdien av en billett – for eksempel en forbedret opplevelse før kampen (for eksempel fyrverkeri og ikke-tradisjonelle partneraktiveringer på banen). Vi har også sett på prispunkter for å se hvor vi kan senke prisene for å øke den samlede inntekten – ved å øke gjennomsnittlig antall vifter i spesifikke sektorer til det punktet hvor prisreduksjonen er ugyldig.

Har forenklet prisstruktur foran 2022 (medfører noe lavere pris på nummererte seter)

Ungdomsbriser, familiepriser, studentrabatt og egne kamper hvor hele stadion er billigere

Vi har senket prisene 15-20%.

Nei, men vi har likevel (før i år) klart å ha vekst. Også i en tung 2019-sesong. Enkeltstunt kan gjøres med bedrifter som kjøper av oss og deler ut til lag osv. for å få grupper på kamp.

Vi har økt prisene våre, men samtidig tilrettelagt prismessig for noen grupper som barnefamilier og supportere.

Vi satte ned prisene foran 2020-sesongen. Vi gjør en vurdering foran 2022-sesongen.

Ingen tiltak i 2021, men vurderer å la barn få gratis inngang i 2022

Vi reduserer barn og familie prisene. Vi segmenterer tydeligere på feltene våre. Vi tydeliggjøre konseptet enda mer, hva du faktisk får av innhold i et junior support medlemsskap feks. Vi ser at det er en sammenheng mellom sportslige resultater og antall publikummere.