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Revenue Management applicability on Coworking space

Operator perspective

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Master of Science thesis

Title: Application of Revenue Management System on Coworking space

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Abstract

This thesis explores the potential use and implementation of a revenue management model for coworking operators. With a critical realism philosophy and abductive approach, a quantitative study using primary data from a coworking operator has been conducted. Based on a comprehensive literature review, we have found that much research is done on revenue management in the airline and hotel industries. However, we found no research on revenue management models that intend to optimize revenue for coworking operations. Hence, this thesis aims to fill this gap in existing academic research. Features from revenue management models used in the hotel and airline industries are identified and analyzed with the objective of implementing these in the coworking industry to efficiently maximize revenue. The paper proposes the use of multinomial logit (MNL) model in the process of market segmentation; this method allows one to determine which factors influence the different segments. Moreover, the MNL model is used to define the demand function from which a probability (probable?) distribution of total demand can be separated into demands representing each product class. Furthermore, the demand is used to calculate protection limits according to the Expected Marginal Seat Revenue (EMSR) model, with the objective of allocating capacity to the highest-yielding customers.

Results indicate that the MNL regression is an effective tool to analyze the market segmentation and demand allocation for coworking operators. After our successful analysis, we are prepared to argue with confidence that revenue management models are applicable to coworking operations.

Masteruppsats

Titel: Tillämpning av intäktsoptimeringssystem på coworking verksamheter.

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Nyckelord: Intäktsoptimeringsmodeller, RM-modell, Coworking verksamhet, Co-working kontorsmarknad, resultatindikationer, benchmark, marknadssegementering, efterfrågan prognos.

Sammanfattning

I denna uppsats undersöker vi den potentiella användningen och genomförandet av intäktsoptimeringsmodeller för coworking operatörer. En kvantitativ studie med primär data från en coworking operatör har genomförts med en kritisk realismfilosofi och ett abduktivt tillvägagångssätt. Det finns mycket forskning kring intäktsoptimering, framför allt inom flyg- och hotellbranschen, men ingen som behandlar intäktsoptimeringsmodeller med avseende på coworking operatörer. Denna masteruppsats syftar till att bidra med kunskap för att fylla gapet kring revenue management för coworkingkontor, som saknas i befintlig, svensk akademisk forskning idag.

Vitala funktioner som utgör intäktoptimeringsmodeller ämnade för hotell- och flygindustrin har identifierats och analyserats med målet att utforska möjlig implementering för coworkingoperatörer. I uppsatsen genomförs en marknadssegmentering med hjälp av en multinomial regressionsanalys. Vidare görs en multinomial regressionsanalys med samtliga produktklasser som beroende variabler, för att få ut sannolikhetsfördelningen för vilka produkter som efterfrågas av den totala efterfrågan. Resultatet kan användas för att optimera totala intäkterna genom att beräkna hur många platser som bör reserveras åt högt avkastande kunder, och hur många som kan hyras ut i tidigt skede. För ändamålet har vi tillämpat den så kallade Expected Marginal Seat Revenue metoden, EMSR.

Resultatet indikerar att multinomial logistisk regression är ett effektivt sätt att analysera marknadssegment och styra efterfrågan till önskad produktklass. Samt att användandet av rekommenderad revenue management modell är applicerbar på coworking verksamheter. Alternativt: Resultatet indikerar att: i. multinomial logistisk regression är ett effektivt sätt att analysera marknadssegment och styra efterfrågan till önskad produktklass. ii. användandet av rekommenderad revenue management modell är applicerbar på coworking verksamheter.

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Content

1 Introduction

This chapter will provide the reader with the background of the chosen subject. It gives a brief overview of the macro parameters affecting the commercial office market in Stockholm, as well as a short introduction to coworking space and the revenue management model.

1.1 Background

The Swedish real estate market has attracted both domestic and foreign investors due to strong economic growth, low interest rates, high demand, and historically low levels of vacancies. In response, real estate development has boomed to meet the growing demand (JLL, 2018). Growth in the rental market is sensitive to movements in the business cycle and overall trends in the economy. Depending on the characteristics of the investment, macro-economic factors can influence vacancy rates differently depending on the volatility of supply. Cyclical behavior has a larger impact on elastic supply markets than on inelastic supply markets. In the short run, inelastic markets may be more sensitive to macro-economic influences; however, in the long run, elastic markets could be more sensitive (Fraser, 1986). Nonetheless, the outlook for the Stockholm office market is optimistic, with an expected prime rental growth of 4.7 percent until 2022 – the highest expected increase in Europe for the given time period (JLL, 2019).

Low vacancy rates are not only favorable for the national and regional economy. Due to limited vacant office space, companies are restricted in their expansion in terms of space for additional employees. Potential consequences if preferences are not met include that employers may relocate to a comparable city where supply is not limited to the same extent (Stockholm Chamber of Commerce, 2018). Employees' preference for having centrally located offices has led to more competition among companies looking for new labor. High demand for central office space and increasing rent has driven companies to seek space-efficient and creative solutions in order to meet staff preferences (Drury, 2016). A corporate solution for space efficiency is the phenomenon of coworking.

1.1.1 Coworking space

The global economy is moving toward a more collaborative and sharing economy that includes housing communities, car pools, and office hotels (RICS, 2017). Innovative solutions are being developed to accommodate the changes in the office market. This is one of the reasons why flexible offices create new structures to support changes in organizations (Danielsson, 2016). Coworking offices offer shorter leasing agreements compared to traditional offices – normally three months compared to three, five, or seven years. The payment is often agreed on per desk or working space, and moving in or out can be done on short notice (City Office, 2018). Coworking offices are filling this gap for offices where small enterprises and new ventures can find reasonable rent and length of contracts. Medium and large enterprises can find available office space close to city centers and with a flexible amount of space, making possible organizational changes such as movement and growth (Danielsson, 2016). The present economic climate also has many freelancers, thus consultants are working on shorter projects and in need of offices in a community (Bergström, 2018). An environment for workers who share the same values can inspire and encourage one another (Foertsch, 2013). A positive atmosphere for the users of premises forms a community that coworking offices enable (Cabral and Van Winden, 2016).

A common interpretation of the term coworking is a service that includes a work space where independent coworkers can network by engaging in peer-to-peer interactions (Spinuzzi, 2012). Amenities and levels of service differ according to the monthly fee and vary between different coworking operators. The administrative and operative services could include a representative reception, IT with technical support service, postal service, cleaning, furniture, kitchen, photocopy machine, and repair service. The monthly fee also includes property tax, insurance, electrical and heat (City Office, 2018).

Today, several kinds of office types are identified in the office market, and coworking is one of them. The different types are cell office; shared-room office; small, medium, or large open-plan office, flex office, and combi-office (Danielsson, 2016). Different businesses require different kinds of office space. For example, the cell office could consist of individual rooms or rooms for two to three people. The office layout with individual rooms is suitable for more independent businesses that do not necessarily require contact with colleagues (Toivanen, 2016). The shared cell-office rooms have desks that are normally separated by screens. The open-plan solution is favorable during organizational changes, since no larger space adoptions are needed. The office layout could vary from small to large open-plan solutions with four to more than 25 people. As with cell offices, the desks are separated using screens to minimize noise. The employees are normally working on individual duties with little need for communication. An activity-based office layout is suitable for businesses where the employees take a lot of responsibility for how and where they are working within the office. The space is distributed across different environments – i.e., individual meetings, telephone calls, desks, or lounges (Danielsson, 2016 see Toivanen, 2016).

Depending on the indoor climate and social relations in the workspace, the architectural design could have a significant impact on the employees' well being. The open-plan office space normally has more unwanted noise in the environment and lacks privacy, which could lead to decreased job satisfaction (Toivanen, 2016). At the same time, flexible offices could improve the communication, efficiency, and teamwork among the employees (Danielsson, 2016). Space efficiency can measured as square meter per member, which could contribute to higher revenue. In real estate economic terms, higher net operating income could increase the value of the real estate asset as discussed further in following chapter.

1.1.2 Real Estate valuation

The demand for office space is continuously growing in the Stockholm city. And the supply has still not caught up with demand (JLL, 2018). A growing office market leads to rent growth, since landlords have more opportunities to increase the yields of their property portfolio (Eriksson and Krumlander, 2018). Depending on the aspects included in a valuation process, different approaches for estimating the value can be used. The market approach, income approach, and cost approach are most commonly used by appraisers (RICS, 2017). There are constantly changes occurring in traditional valuation approaches in order to meet future customer expectations (RICS, 2017). The traditional appraisal method is based on the income approach which implies calculating future expected cash flow in the operation. These calculations include vacancy loss, operating expenses, debt service, rental revenue, and reversible cash flow (Slade, 2006).

Investment in office space often ends with a scenario analysis where the best-case, most-likely case, and worst-case scenarios are evaluated. The net operating income from the tenants is calculated as the gross effective revenue minus the total operating expenses for each year, in order to calculate the present value and the profitability of the investment (Slade, 2006). The valuation process is also seen as a risk assessment – i.e., it is a process where the possible profitability and the risks are taken into consideration (RICS, 2017). There are biases in the traditional valuation method. The method is based on present value in the Discounted Cash Flow method and is not affected by uncertainties in the future. The valuation is made by an individual valuer whose responsibility is to express the possible changes in the outcome, depending on changes in the market performance (Joslin, 2006). Scenario or sensitivity analysis can be used to investigate the uncertainties of in-going variables in the valuation appraisal (Ekelid *et al.*, 1998). According to Joslin (2005), the biggest uncertainties in the valuation process are the market conditions, the property's uniqueness, compatibles, and the individual valuer's view. According to the discounted cash flow method, increasing revenue will positively affect the value of the property (Born and Pyhrr, 1994). Consequently, property owners who run their own coworking operation have the possibility to increase the property's value if the revenue is optimized. Hence, adapting a strategical method of revenue management is important.

1.1.3 Revenue management

Either if the coworking operator is a property owner or an own operator, the revenue could increase with a reliable tool. The first evidence of a successful revenue management tool was presented by Professor Littlewood in 1972 (Talluri and van Ryzin, 2005). The "Littlewood rule" introduced a passenger bookings and cancellation model for airline industry, that could forecast load factors based upon bookings from one to 13 weeks for the British Overseas Airways

Corporation. Littlewood's rule was expanded further to include protection limits such as booking limits for different fare classes. Revenue management was further developed when the deregulation of the US air industry occurred. Dismantling government controls led to increased numbers of new, low-fare competitors. This became the starting point of the dynamic inventory allocation modeling optimizer, which was the world's first yield management system. As the industry matured, enabling more people to travel by air, new products were sold to attract new segment groups, such as family fares, and not only business travelers. Consequently, products and new routes were bundled to fit into the revenue management model, which resulted in more advanced and efficient models. According to Yeoman and McMahon-Beatte (2017), as the technology advanced, companies came to rely on computer processing power that runs complex algorithms to simulate airline network optimization. The technology advancement allowed a larger reach for customers, as companies were able to present customer-specific, real-time offerings. Being able to execute time-based pricing which responds to current market conditions extended traditional revenue management systems to include dynamic pricing. Online retailing also emerged from the airline and hotel industries and allowed the adjustment of the prices of products according to competitors, time, traffic, conversation rates, and sales goals. The aim of this type of retail was to increase revenue and profit. Enormous amounts of data can now be analyzed to understand consumer behavior, which boosts operational research and mathematical algorithms (Yeoman and McMahon-Beatte, 2017).

1.1.4 Application of revenue management

Today, the revenue management model is used in the airline, hotel, and e-commerce industries. The model is used to determine the best price, as adjusted to meet the demand. It is an efficient and constructive way of optimizing the revenue of a business. Common characteristics are found in revenue management models in the different industries. These common characteristics include: limited resources (such as rooms, passenger seats, rented cars, or entertainment tickets), products or services with a limited period of sale, value which deteriorates over time, the ability to accept orders to be fulfilled in the future, low per-product or service costs and high fixed costs, fluctuating demand, and the ability to segment the market or customers (Cortés *et al.,* 2011). Many service companies possess these characteristics. That is why, in the recent past, such companies – for example, those that offer renting of convention centers, golf courses, cars, travel on cruise liners, as well as restaurants, shopping centers, and so forth – have begun to use revenue management in their operations (Maddah *et al.,* 2010). An example of the traditional scheme of revenue management is visualized in figure one.

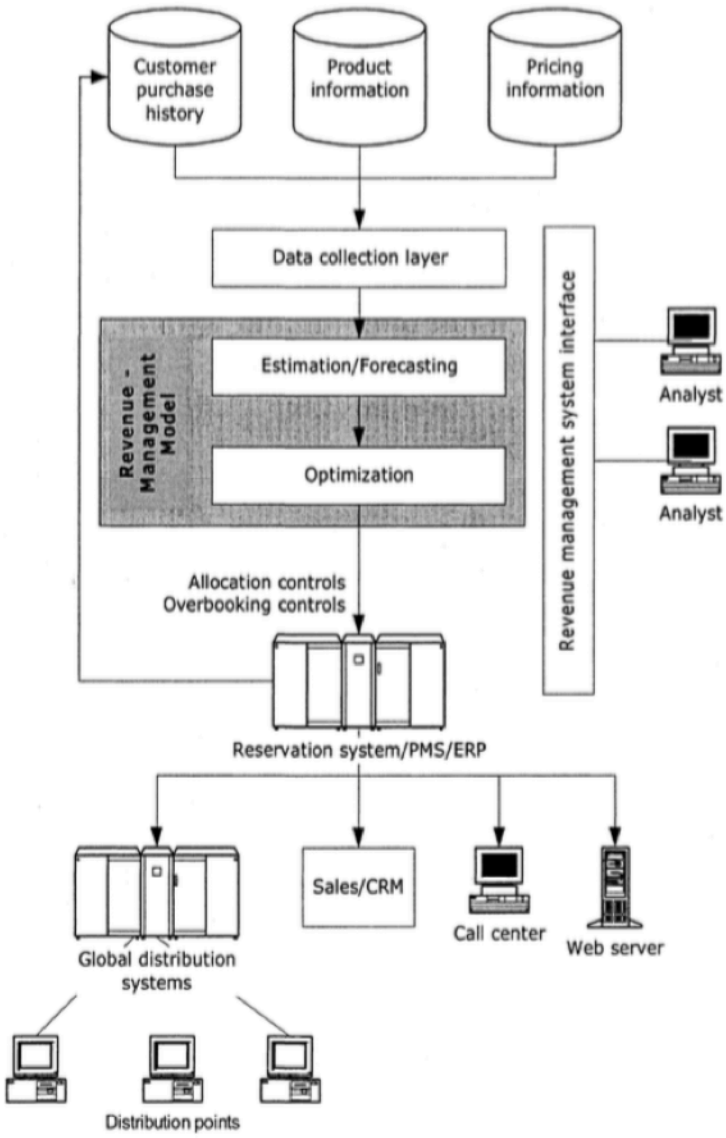

Figure 1: Talluri and van Ryzin (2005) schedule of the revenue management process.

At present, theoretical knowledge, practical experience, and application software for the revenue management of airlines are well developed (McGill and van Ryzin, 1999). Less attention has been paid to the hospitality business, with research in this area being rather fragmentary. There is a gap between the revenue management theory and its practice in hotels.

1.2 Purpose

The purpose of this thesis is to identify areas within coworking spaces where revenue management is applicable. Furthermore, the aim is to suggest a revenue management model customized for coworking operators with objective to optimize revenue.

1.3 Research questions

The research questions that aim to fulfill the purpose of the thesis are as follows:

- Is it possible to implement a revenue management system for coworking spaces?
- Which parts of the revenue management system can be implemented in coworking spaces?
- Does the model provide a reliable forecast of future demand?

1.4 Contribution

The thesis contributes with knowledge within the field of revenue management and its usage in coworking space. There is no existing academic research, to our knowledge, that comprehends the subject area. Furthermore, methods to optimize revenue are suggested. The empirical testing proves the usage and functionality of implemented revenue management models. Interpretation of result may bring a larger understanding to the industry in aspect of understanding the importance of collecting and analyzing data according to suggested methods. Hence, understanding customers choice behaviour, willingness to pay and product specific demand with objective to maximize revenue. Quantity control is used to optimize revenue, however, recommendations to explore various methods using other controls are encouraged.

2 Literature review

2.1 Coworking space

The concept of coworking has developed from the phenomenon of a shared economy. Due to the slow shift in the industrial economy, this phenomenon has developed from being based on monetary capital to be more dependent on intellectual capital (Leclercq-Vandelannoitte and Isaac, 2016). It is the outcome of the information age, where increased communication and advanced technology led to a change in the traditional work models. In offices fewer people need fixed working spaces surrounded by colleagues and customers. More people tend to work in flexible working spaces with more flexible working hours (Akhavan *et al.,* 2019). The concept of coworking is also defined as office spaces where the users – unaffiliated professionals – are working next to one another for a fee (Spinuzzi 2012; Cabral and Van Winden, 2016).

The interior design of a coworking space should be beneficial for the users' interaction. The normal setup for a coworking space is to have it structured as an office area with one or more floors. Hallways function as informal meeting points. There is a reception area for all members and non-members where, for example, questions regarding the facility can be answered. Many coworking offices offer food, beverages, and a lounge area. The lounge is often used as a social area connected to the restaurant where both internal and external users can network or have meetings. The fixed capacity is often divided into a set of products – that is, flexible seats, semi-fixed seats, fixed rooms, and meeting rooms (Spreitzer *et al.,* 2018).

Traditional working spaces often have a more repetitive and concentrated work environment with tenants with hierarchical business models, while the coworking space is focusing on creativity, networking, and industrial diversity (Leclercq-Vandelannoitte and Isaac, 2016). Research has been done on the positive effects of coworking on the members of such networks. One interesting aspect mentioned is that, when working in a business surrounded by other businesses, each unique business idea is often explained to other members in that network. Thus, this gives a sense of the uniqueness and importance of the business (Spreitzer *et al.,* 2018). Furthermore, the flexibility that coworking spaces offer – unconstrained location and flexible working hours – is a way to attract new employees. This appeal makes coworking spaces an interesting option not only for small- or medium-sized enterprises, but also for large enterprises (Cabral and Van Winden, 2016).

Another attraction coworking offers is the community of members within the coworking space. Being surrounded by people in such a community facilitates networking, social events, and training events, which can have a positive effect on motivation within and effectiveness of the business (Spreitzer *et al.,* 2018). Since community is deeply embedded in a coworking operator's business model, it is of importance that management plan their operation so that members can interact with one another (Jakonen *et al.,* 2017). Office managers who use different strategies – such as social networking tools – to achieve high levels of networking can help management to increase interaction between coworkers. The selection process and selection criteria of new users of a coworking space could have a significant impact on the growth rate (Cabral and Van Winden, 2016). A similar concept is used in clustered areas where knowledge spillover, labor matching, and labor force are reasons for companies to move to clustered areas areas. According to O'Sullivan (2009), profits increase when more companies enter the cluster.

User preferences is of focus in order to meet future demand. In a research made by Danielsson (2016) analyzed workers' opinions regarding the aesthetic and functional dimensions of work places. Three types of workspace were analyzed with a focus on these two fundamental dimensions. The results showed that the different impacts that office types have on the employees depend on the office environment. An environment with focus on physical mind setting, creates larger focus from the employees on the aesthetic architecture rather than function in the office space (Danielsson, 2016). Geradts and coauthors (2017) claim that vacant space does not only affect the business itself, they show in their research that vacant space has a negative effect on neighborhood quality. The quantitative results indicate that an increase of 1,000 square meters structural vacancy can lead to up to 1.6 percent decrease in rent for surrounding office buildings within a radius of 500 meters. The research problem was to identify the gap between vacant offices and demand in the creative industry. Using an empirical and theoretical method, preferences of users from the creative industry formed the basis for a framework, which was divided into three levels: property, facility, and community. This enabled the authors to identify tenants who required space significantly smaller in size than today's standard – 13 to 20 square meters per employee rather than the standard 22 to 28 square meters. They argue that the negative effects can be explained both qualitatively and quantitatively. Vacant properties are too old and do not meet the criteria of tenants requiring smaller spaces. Oversupply can also explain the vacant spaces to some extent (Geraedts *el at.,* 2017).

2.2 Revenue management in other industries

2.2.1 Airline industry

In order to explore the usefulness of revenue management in coworking, it is important to have an overview of how revenue management is used in other industries. Revenue management is used in the airline industry as a way to find the optimal mix of customers for every single flight. Different discount systems are used with dynamic pricing to succeed in this endeavor.

When forecasting demand, Cramer *et al.* (2012) use stochastic demand in their revenue management model for the airline industry. They also suggest that approaching group demand is treated as a multivariate normal distribution. Instruments used to reject or accept a customer with the intention to optimize revenue could be protection level, bid price control, and booking limit (Cramer *et al.,* 2012). The segmentation process is similar to other industries. Previously, middle-aged males dominated business travel, since they were the high-yield segment. However, airlines have increasingly targeted female business travelers, who represent 60 percent of US wealth and influence 85 percent of purchasing decisions. In order to understand the demands of different consumer groups, they get clustered into different segments which represent either a demographic, geographic, psychographic, behavioral, or product-related segmentation variable.

Effective segmentation requires measurability, sustainability, accessibility, and actionability. Segmentation helps the operator understand which customer demands which feature or product (Camilleri, 2018a).

Business travelers tend to be over-represented in no-show figures and cancellation rates (Cramer, Boyd and Walczak, 2012). According to Sireag et al. (2014), an efficient heuristic solution method to optimize revenue has been developed. Their model takes into account cancellations and customer choice behavior. They approach the problem using a Markov decision process. The research tests different settings and analyzes if the cancellations and overbookings can be solved by a tractable solution method – either exactly or heuristically. The empirical results show that the heuristics performed very well (Sireag *et al.,* 2014). Revenue management can be applied in the decision-making process of upgrading a customer (Steinhardt and Gönsch, 2012). If too many people show up, then the term used is ”oversold”. For the opposite scenario – if there are still empty seats – the industry term is ”spoil”, which represents an opportunity cost for the airline (Smith *et al.,* 1992).

No-show rates averaged approximately 10 to 15 percent, with peaks as high as 20 percent in 1980s and 1990s (Belobaba, 2009 see Toh and Raven, 2003). Nowadays, no-show rates have declined to a more moderate seven to 10 percent (Lawrence, Hong and Cherrier, 2003). Lufthansa alone had 4.9 million no-shows – the equivalent of 12,500 full Boeing 747s – during 2005. To minimize the number of empty seats, Lufthansa allowed overbooking, which enabled them to carry more than 570,000 additional passengers and, hence, to increase their revenue by 105 million euro (denied boarding costs already deducted) during the same year. This proves what a powerful tool the concept of overbooking is and why it has become essential for airlines (Klophaus and Pölt, 2006).

Klophaus and Pölt (2006) suggest that revenue stream increases even further when taking willingness to pay into consideration in deciding the ”breaking point” for overbooking. The forecasting of overbooking is made under the assumption of a Gaussian no-show distribution, where the probability of each combination of overbooking level and survivals, together with the associated expected denied boarding and spoilage costs, are minimized. Airlines have to pay penalty fees to customers who get overbooked. The penalty cost varies depending on which laws are applied in that country. However, it is usually a minimum of 125 percent of the initial ticket cost. There are alliances formed within the airline industry (e.g., star alliance) that help overbooked flights to find replacement flights within the alliance network (Klophaus and Pölt, 2006).

Dynamic pricing is a technique in which the price of a particular product changes over time according to the level of demand, the time length between purchase and consumption, season of purchase, remaining available capacity, and product life cycle. For example, in airline industries, the price of a seat gradually increases as the time of departure is approaching – also called mark-up pricing (Davis, 1994). The mark-up pricing technique is suitable for companies with fixed capacity for which bookings should be made in advance. With this technique, the price of the service or product rises at the end of the booking period. In other words, as the last day of the booking period is getting closer and the available capacity is decreasing, firms can assign the free capacity to customers at a higher reservation price and lower price sensitivity (Christ, 2009). Donovan (2005) estimated that American Airlines made 500 million USD per year due to its yield management techniques.

According to Demydyuk (2011), when evaluating performance, commonly used Key Performance Index (KPI) in the airline industry are:

1. Available seat kilometers (ASK). ASK is obtained by multiplying the number of seats available for sale on each flight by the distance flown. A similar metric is revenue passenger kilometers (RPK), which is expressed as the number of fare-paying passengers on each flight multiplied by the flight distance. RPK is a measure of airline passenger traffic.

2. Passenger load factor (PLF) is considered one of the most important indicators for airline operations, as it is a measurement of capacity utilization. PLF can be obtained by dividing RPK by ASK and is expressed as a percentage.

3. PAX is the number of passengers who have boarded an aircraft and can be expressed for each flight or over a certain period of time. Passenger yield (PY) is a weighted average of fare paid and can be explained as the average

revenue collected per RPK. It can be calculated by dividing the total passenger revenue on a flight by the passenger kilometers generated by that flight. Costs per ASK measures the operating costs (excluding interest payments, taxes, and extraordinary items) and can be calculated by dividing total operating costs by total ASKs (Demydyuk, 2011).

2.2.2 Hotel industry

The process of defining demand for hotel businesses is slightly different from businesses in other industries. This is because customers have the option to extend their reservation and stay longer. Another factor that needs to be included when estimating demand is the walk-ins – the customers who have not made any reservation. A common way to display forecast demand is through a demand calendar (Aydin and Birbil, 2018). Xotels (2018) emphasizes the importance of market segmentation for the determination of the demand. Market segmentation could be widely used and has few limitations; however, with excessively narrow segmentation the results might be useless.

It is important to determine the profit from different groups, which represents the aggregate demand. Segments could be directly related to the hotel industry – e.g., purpose of the visit, whether it is a private or business visit, or through which travel agency the customer made the booking (Xotels, 2018). Controls are used to support the decision of whom to reject or accept, in order to locate high- and low-yield segments. Bid price is a widely used control in the hotel industry. A stochastic approximation can be done where bid price is a function to determine profit; taking into consideration market factors when rejecting a customer to successfully sell the product to a higher-yielding customer is considered to be dynamic pricing (Aydin and Birbil, 2018).

A recent study by Aydin and Birbil (2018) adjust a revenue management method adjusted for hotels with dynamic room allocation. The method takes into consideration day-based and period-based revenue management problems, with day-based revenue management being a dynamic model for advanced bookings and formulating a linear program for the problem. The resulting model is then solved with the constraint generation method. An alternative approximate model is being proposed to provide upper and lower bounds for optimal expected revenue. Aydin and Birbil's researched problem is approached as a dynamic programming formulation for single-day revenue management problems, allowing them to capture the temporal dynamics of the reservation requests more efficiently and accurately than comparable static models (Aydin and Birbil, 2018).

Furthermore, Aydin and Birbil's study explains the use of stochastic programming in terms of scenario optimization – how the deviation risk can be measured using the absolute mean value of the multi-day stay problem which is of relevance in the hotel industry (Aydin and Birbil, 2018). Both the single-night stay and multiple-night stay examples have been developed by the authors Bitran and Mondschein (1993). Their research resulted in two different policies that are optimal for the specific case. For the single-night, say: "Given a period of time, if a request is accepted for a certain capacity, then it is also accepted for any larger capacity. Furthermore, for every class of customer and every capacity vector, there exists an instant in time beyond which it is optimal to satisfy the customer's request" (Bitran and Mondschein, 1993, p. 440). In the case of the multiple-stay problem, the authors created an ad hoc heuristic calculation to empirically test the data, which resulted in a variation of simplified scenarios (Bitran and Mondschein, 1993).

Another commonly used feature of revenue management to boost hotel revenue is overbooking – simply selling more than their total available capacity. Overbooking is implemented because it is difficult to charge customers for being a no-show (unless a credit card has been registered) and because there are moderate numbers of cancellations; therefore, hotel managers apply this strategy to make sure the facility is used as much as possible. When utilizing overbooking, it is important to include the trade-offs between the cost of rejecting a customer and the potential gain in accepting one. Bitran and Mondschein (1993) present a case where customers are assumed to arrive at the same time and all customers are staying more than two nights. The case demonstrates that, with a high occupancy rate, it is optimal to reject low-fare customers (Bitran and Mondschein, 1993). If rooms are overbooked, upgrading guests to a premium room can many times solve it. Furthermore, Chathotha and Olsen discuss in their article ”Strategic alliances: a hospitality industry perspective”, sharing recourses between allying partners within the alliance help incumbent firms to build relationships with partners (Chathota and Olsen, 2003).

Evaluating performance in the hotel industry requires certain performance indicators, Harris and Mongiello (2001) mentioned three major KPIs used to measure the economic success of a hotel: average daily rate, revenue per available room, and gross operating profit per available room.

1) *Average daily rate* is the average rate paid per room for a specific day.

2) *Revenue per available room* measures hotel utilization or the average daily room revenue generated per available room. However, this does not take into consideration other factors such as cost per occupied room or additional revenue per room for each individual room that is sold. Revenue per available room can be converted into total revenue per available room by summing up all revenue factors and dividing this by the number of rooms. Revenue per available room provides insights into total revenue; however, it does not take expenses into consideration.

3) *Gross operating profit per available room* offers more insight into the actual performance of a hotel than revenue per available room, because it considers all revenue factors generated by a hotel and its related operational costs (Harris and Mongiello, 2001).

2.3 Result from literature review

Based on the literature review it can be concluded that there has been no academic research about revenue management systems that are adjusted for the coworking industry. This area has not yet been academically explored; therefore, we intend to contribute insights and knowledge to fill the research gap. The areas from revenue management that will be investigated to determine if they are applicable in the coworking industry are described hereafter.

Demand. Although the demand triggers are not similar among reference industries and the coworking industry, we want to highlight the importance to continuously forecasting demand, as it is vital for any business's success. There are various methods used to forecast demand. In the theoretical framework, we consider demand from coworking operators perspective; therefore, further in-depth analysis of market segmentation will be done.

Characteristics of product classes. Similarities can be found between airline fare classes, different hotel rooms, and coworking space products. As price increases in reference industries, the customer receives more space – e.g., more leg space, more square meters in a bedroom, or a larger bed – when purchasing a more premium product. In many cases, customers are entitled to use more of the amenities free of charge. The same hierarchy can be seen in coworking spaces, where the lowest product class is shared office space in shared coworking areas and the highest product class is a private office in the coworking space.

Length of stay is a common control and feature to have in mind for a hotel revenue management team. In the airline industry, there's only one departure time to consider per flight, – meaning, the single-day problem is not an issue with the same magnitude as the hotel industry. Members of coworking spaces tend to stay longer than one day and, therefore, a multi-day stay problem will be taken into consideration when evaluating all features included in the coworking adjusted revenue management model.

Controls. Bid control is the most frequently used control for both reference industries. It refers to accepting the highest-yielding customer and rejecting lower-yielding customers if the circumstances require it. Another control used in both industries is booking limit – also called protection control – which reserves a predetermined amount of spots for moderate-yielding customers and low-yielding customers. Thus, the booking limit for high-yielding customers equals total capacity.

Market segmentation is highly necessary and well used in both reference industries, with clear understanding of demand and which customers can be reached and analyzed in groups. Segmentation is also relevant for coworking operators; therefore, further in-depth analysis of market segmentation will be done.

Overbooking. Findings from the literature review indicate that overbooking is a method used to increase revenue for an operation with fixed capacity. Coworking operators have the same prerequisites as the reference industries, with fixed capacity and products that are occasionally used; this justifies the usage of overbooking. However, dissimilarities can be identified between reference industries and coworking offices – namely, that the flexible contracts include a multi-day problem. We believe the criteria are met to further analyze this strategy in next chapter.

Dynamic pricing is a method used in the reference industries to optimize revenue based on demand forecast, expected occupancy rate, as well as external factors affecting demand and pricing. It is clear that differential pricing is acceptable in the reference industries due to different factors such as lead source and spread of customers' willingness to pay. Included in the concept of dynamic pricing, mark-up pricing is commonly used in the reference industries – meaning, the price get higher closer to the realization date. We will further investigate dynamic pricing to find a strategic use for it in the coworking industry.

Table 2 is a summary of Sections 2.2 and 2.3 demonstrating the implementation of revenue management tools in the airline and hotel businesses. The last column is our hypothesis – what occurs when the revenue management tool is implemented in coworking spaces. Table 3 presents underlying industries used for distribution of business strategies and functions in proposed revenue management model.

Table 2: Businesses using different RM tools.

Implementation in other businesses			
Function	Airline Business	Hotel Business	Coworking Business
Market segmentation	Yes	Yes	Yes
Overbooking	Yes	Yes	-
Control	Yes	Yes	Yes
Product Classes	Yes	Yes	Yes
Dynamic Pricing	Yes	Yes	Yes
Length of stay	Yes	Yes	Yes
Upgrade	Yes	Yes	-
Alliances	Yes	Yes	-

Table 3: underlying industries used for distribution of business strategies and functions in proposed revenue management model.

Relation of business strategy	
Function	Business
Market seg.	Hotel
Overbooking	Hotel
Control	Hotel
Dyn. Pricing	Airline
Length of stay	Hotel

3 Theoretical Framework

Revenue management is of particular relevance in cases where the fixed costs are relatively high compared to the variable costs (Kimes *et al.*, 1998). In the literature review, features from the airline and hotel industries related to the importance of revenue management have been identified and interpreted. In this chapter, we explain the mechanics of these features and our interpretation of how those can be applied in a revenue system as analysis and optimization tools theoretically suitable for the coworking industry.

3.1 Demand

The demand is normally described as a function with a deterministic component, explanatory variables, and an error term. Different functions can be used to determine the demand. The linear demand function is often used since it is easy to apply and can be done with simple regression analysis. The weakness in the linear function is the problem with optimization since the price needs to be constant. A log-linear demand function could also be used; the advantage of this function is that price can be more freely treated since the demand is non-negative. The disadvantage is that demand values that equal zero will not be defined due to the logarithms (Talluri and Van Ryzin, 2005). The demand function is based on the multinomial logit (MNL) method. Demand is the deterministic variable due to the demand implications of a unique choice of price. To find the optimized demand, similar methods are used to maximize the revenue function. The assumption of maximize the revenue function requires that the point is within the area Ω_p.

The MNL model does have some issues because it could have a negative effect on groups of products that have effect on one another. Talluri and Van Ryzin (2005) present an alternative demand function – a stochastic demand function. Poisson's and Bernoulli's models could help to manage the uncertainties – e.g., probabilities of demand and arrival over a specified time interval. Using the models from Poisson and Bernoulli, the demand function in the model is determined without estimating other attributes (Talluri and Van Ryzin, 2005).

Equation 1, shows the probability that an alternative j is given for a set associated to Multinominal Logit model:

$$F(x) = P(\xi_j \leq x) = e^{-e^{-(\frac{x}{\mu+\lambda})}} \quad (1)$$

$$E(\xi_j) = 0, Var(\xi_j) = \frac{\mu^2\pi^2}{6} \quad (2)$$

3.1.1 Demand optimization

The original model used in revenue management is Littlewood's model (Equation 3). It is used to calculate the protection level between two fare classes in order to maximize the revenue (Tullari and van Ryzin, 2005):

$$F_L \geq F_H Pr[X_H > \theta_H] \quad (3)$$

where F_L is the low-fare class, the F_H is the high fare class, and Pr is the probability that the high fare class, X_H, is higher than the protection level θ_H. The protection level is the minimum amount of seats that should not be sold at the low-class rate and instead be held for the higher-class rate.

An extension of Littlewood's model is the Expected Marginal Seat Revenue (EMSR) model (Tullari and van Ryzin, 2005). The difference between Littlewood's model and the EMSR model is the multiple fare classes included in the extension. The EMSR is also calculating the protection level needed to estimate maximized revenue for the operation but allows more than two compared protection levels in the calculation.

$$\theta_j = \sum_{k=1}^{j} y_k^{j+1} \quad (4)$$

where θ_j is the protection level of stage j, and the EMSR model is explained by equation 5.

$$Pr[X_k > \theta_k^{j+1}] = \frac{F_j + 1}{F_k} \tag{5}$$

EMSR is replacing the right-hand side on the Littlewood's rule (Tullari and van Ryzin, 2005). The demand in the EMSR model is based on the inverse normal distribution curve where the mean and variance of the demand is used in the calculation. The demand is calculated in order to find the protection level used to accept or reject customers. Based on the demand distribution, the protection level is calculated with a marginal estimator, meaning that the probability of future demand gives an indication of the minimum fare class that the next seat should be sold for. This is a quantitative decision related to allocation of capacity between the fare classes. Resources are withheld in the belief that the seats will be sold at a higher price, at a later time (Tullari and van Ryzin, 2005).

The demand optimization eventually leads to the probability density function and the cumulative distribution curve, where the mean and the standard deviation are needed to calculate the inverse probability function – crucial in the revenue management model. It is an integral part of the probability density function:

$$F(x) = \int_a^b f(x)dx = Pr[x \leq a] \tag{6}$$

The survivor function – inverse of the cumulative distribution function – is done in order to fit with Littlewood's rule.

$$1 - F(x) = Pr[x > a] \tag{7}$$

The Littlewood's rule adopts a normal distribution for the demand. Here, a survival function is used since a positive distribution of negative demand is not possible (Talluri and van Ryzin, 2005).

The first-order condition holds in order to find the necessary condition for the demand maximum:

$$J(p^0) = 0 \tag{8}$$

which leads to

$$d^0 = d(p^0) \tag{9}$$

If the demand is a function of the price, it could be defined based on the market size, N, and the probability that customers buy at price: p $(1-F(p) = \frac{e^{-bp}}{1+e^{-bp}})$.

$$d(p) = N\frac{e^{-bp}}{1+e^{-bp}} \tag{10}$$

where b is a coefficient of the sensitivity of price (Talluri and van Ryzin, 2005).

3.2 Pick-up analysis

The pick-up forecast is a tool used to understand how close to an arrival consumers make reservations, based on historical data. It contributes to a holistic overview of the operation, thereby making it possible to analyze the actual and expected outcome. This analysis is common and relevant for use in quantity-based revenue management. (Talluri and Van Ryzin, 2005). Pick-up analysis is used in the hotel industry as a schedule where the number of reservations is reported in relation to the number of days before arrival (Xotels, 2018). In the airline industry, the method is used in a similar way, where the booking for a specific flight is realized in relation to days before departure (Talluri and Van Ryzin, 2005). We have noted the potential benefits of having a tool to understand when new members sign their membership before the membership starts. According to Talluri and Van Ryzin, (2005), an additive pick-up method could be used:

$$\widehat{Z}(t+k) = \sum_{i=0}^{k} Z_{(i)}(t+k) \tag{11}$$

where k is days before the forecast of demand and $\widehat{Z}(t+k)$ is i days before the set date. We chose to interpret the pick-up analysis as the lead-time between when a new customer's account was created and when the customer actually moved in. Most of the transactions had their account created on the same day as they moved in. Due to the lack of frequent transactions in the coworking industry, the pick-up analysis has not been tested.

3.3 The concept of overbooking

Overbooking is a potential revenue stream and has been shown to add significant value in the airline and hotel industries. In quantity-based revenue management, the same product is sold multiple times to accommodate a certain number of cancellations; thus, the revenue is boosted without increasing supply (Talluri and Van Ryzin, 2005).

3.3.1 Potential revenue stream

In the airline industry, it is estimated that around 7 to 10 percent of bookings are canceled or no-shows (Talluri and Van Ryzin, 2005). There are significant differences between traditional overbooking used in the airline and hotel industries when compared to coworking offices. Traditionally, the overbooking system conducts reservations, including a right for future service, and includes an option to cancel before the maturity date (Talluri and Van Ryzin, 2005). Some adjustments need to be done to the traditional overbooking limit calculations, including some assumptions about customers' activity distribution, in order to make the feature applicable to the coworking industry. The intention is to statistically calculate the optimal number of times coworking operators can sell the same space and, thus, to find the appropriate trade-off between revenue and cost of denying a customer a desk. In the empirical analysis, we determine which assumptions and adjustments are included based on historical data. The following equation explains how overbooking can be calculated:

$$V_{T+1}(y) = \begin{cases} 0 \\ -c(y-C) \end{cases} \tag{12}$$

where C is the fixed capacity and c is the cost for the service.

Overage probability:

$$F(X^*) = Pr(Y \leq X^*) = C_u/(C_o + C_u) \tag{13}$$

Underage probability:

$$1 - F(X^*) = Pr(Y \geq X^*) = C_o/(C_o + C_u) \tag{14}$$

$$F(X^*) = Pr(Y \leq X^*) = \Phi(X^* - \mu)/\sigma \tag{15}$$

where $F(X^*)$ can be solved by entering the probability value (calculated from the overage probability equation) into the inverse cumulative function, Z, in Excel. By doing so, the value of X^* can be calculated:

$$(X^* - \mu)/\sigma = Z \tag{16}$$

$$X^* = Z * \sigma + \mu \tag{17}$$

where X^* represents the number of desks that should be sold in order to maximize revenue (Winston, 2003).

3.3.2 Key performance indicator and benchmarks

The usage of KPIs is a certainty for many industries, including our reference industries – airline and hotel. These can function as benchmarks within industries. KPIs are used to measure, for example, market, sales, and marketing efforts. These indicators help managers to effectively communicate information to stakeholders which facilitates assessment of risk and uncertainty and, thereby, manage risks and rewards. Benchmarks can be somewhat complex for project managers due to the uniqueness of the subject project or due to short life span of the project. However, there are usually some industry standards where KPI application fits. If the KPI target is met or exceeded, we are simply adding value to the business (Kerzner, 2013).

In order to successfully identify which KPIs to use, we need to identify the fundamental orientation and industry context of the industry and organization. Furthermore, we need to make sure these are measurable, quantifiable, and monitored (Fitzerald *et al.,* 1991a; Harris and Mongiello, 2001).

Based on the literature review, we can identify three main performance areas: operational, business, and community performance. The operational performance indicators refer to measuring how well the everyday operation runs. Business performance typically measures how well the business is doing, as expressed in revenue or profit. Community performance is how strong the community of members is and includes indicators such as high attendance of events or number of projects by members that have synergy among one another. For the revenue management model, we want to focus on displaying directly linked revenue KPIs; therefore, for this thesis, the main focus will be on locating KPIs that are associated with the business performance. When determining the relevance and number of KPIs, Kezner (2013) listed 14 characteristics of successful KPIs, together with the Pareto principle, which states that 20 percent of the all indicators shall have an impact on 80 percent of the project (Kerzner, 2013). In the results and analysis, we will describe how different actions proposed in the revenue management system can be evaluated using suggested KPIs.

3.4 Market segmentation

The market segmentation is a fundamental part of the revenue management model. This is a process of defining the segment of customers, and a common way to do this is to divide customers into groups with similar payment preferences. Successfully doing so means defining groups that are neither too broad nor too narrow in their price response (Aydin and Birbil, 2018).

3.4.1 Defining a segment

Market segmentation can be defined as ”the process of splitting customers, or potential customers in a market into different groups, or segments” (McDonald, 2012, p. 9). In other words, market segmentation allows one to analyze different customers in groups. Collecting customer-specific data by using data-driven technologies – such as sensor analytic, geolocation, and social data-capture business managers – allows one to track and analyze customer movements and consumption patterns. This method allows business managers to adopt a more systematic approach when planning and making strategical decisions for the future. The tourism business has achieved a high level of customer-centric endeavors with the help of disruptive technologies (Schegg and Stangl, 2017 see Camilleri, 2018a). Market segmentation can also explain customers' differing willingness to pay. In the hotel industry, segmentation related to willingness to pay plays an important role since it is used to target the highest-paying customer for each product (Xotels, 2018).

3.4.2 Different approaches in market segmentation

A cluster analysis could be used to define the market segmentation – an approach frequently used in the market segmentation in different industries. To define the optimal number of clusters in the chosen subject, k-means clustering could be used, where $n = 10,001$ in larger samples sizes; although, k-means can be used in an exploratory form of reasoning. As a way to determine the fit of the cluster in relation to the whole data set, the F-value can be used (Müeller and Hamm 2014) as a way to minimize the easier the comparisons of the result. The factor analysis is used to minimize the correlation between the variables to a reasonable level. Müeller and Hamm (2014) uses a confirmatory factor analysis and an exploratory factor analysis to do this. According to Müeller and Hamm (2014), market segmentation should be made through individual strategies. The use of cluster analysis in market segmentation has its flaws due to consumer patterns continuously changing.

In revenue management, choice modeling is commonly used to predict the probability of individuals or groups making particular choices given the different features of the available options. Choice modeling is often used to determine willingness to pay for goods and services and to make important pricing and marketing decisions. Choice modeling attempts to model the decision process of an individual or segment via revealed preferences or stated preferences made in a particular context or contexts. Typically, it attempts to use discrete choices in order to infer positions of the items on some relevant latent scale (Talluri and van Ryzin, 2005).

Christ (2009) defined five stages that are significant in understanding the decision-making process. The stages are as follows:

1. the definition of the problem where the choice is initiated,
2. staging the alternative choices,
3. evaluating the different alternatives,
4. identifying the outcome of the alternatives,
5. finally, the implementation of the chosen alternative.

The set of choices is defined as mutually exclusive and collectively exhaustive, meaning that the set excludes all the other alternatives at the specified time and also that the set has to be all the possible alternatives during the specific time period. This model is part of the behavior theory used in many industries. To implement the behavior theory with unbiased results, decision rules are used. The decision rules ensure consistency and transitivity (Christ, 2009).

In many cases, it is not possible to observe if a new customer belongs to a certain segment since there's no data for that specific customer available yet. However, an MNL model can be used to determine the probability that a new customer belongs to a certain segment. An extension of the MNL model is a finite-mixture logit model:

$$q_l = \frac{e^{v_l}}{\sum_{i=1}^{L} e^{v_i}}, l = 1, ..., L \tag{18}$$

$$P_j(S) = \sum_{l=1}^{L} q_l \frac{e^{\beta_l^j}}{\sum_{i \in S}^{L} e^1}, j \in S \tag{19}$$

where the probability, P, of choosing a specific alternative, j, chosen from a set, S, depends on the number of segments – I. β is the identical vector of coefficient β, which determines all the customers in segment L. The market segmentation is tested to define the explanatory variables of the determinant industry. However, the probability function (Equation 18) has not been tested due to its complexity and lack of data to find an accurate result.

3.5 Price optimization

Differential pricing is a key feature that enables optimization of revenue with fixed capacity – simply meaning that customers can purchase the same product, at the same time, for different prices (Camilleri, 2018b). For quantity-based revenue management, economic principles are applied to control inventory in which the optimal price, given the inventory, is calculated. Demand-management decisions are generally addressed and categorized according to three different decisions: structural, pricing and quantity decisions (Ingold *el at.,* 2000). Structural decisions include the process of segmentation with the objective of identifying which term to offer each segment, thereby maximizing revenue. Quantity decisions are used to decide whether to accept or reject demand based on capacity – that is, withholding quantity from the market and selling later to high-yielding ones. Pricing decisions involve pricing products over time based on demand while considering market segment and capacity at a given time.

A classical deterministic model uses capacity control to seek an optimal number of units to be reserved. Demand is treated as if it were deterministic and equal to its expectation. This model is explained by following formula (Goldman *et al.*, 2002):

$$f = \sum_{\alpha,L,k} P_k * L * X_{\alpha,L,K} \tag{20}$$

subject to

$$\sum_{\alpha,L,k,\in,N_l} X_{\alpha,L,k} \leq C_l \forall l \tag{21}$$

$$X_{\alpha,l,k} \leq d_{\alpha,L,k} \forall \alpha, L, k \tag{22}$$

$$X_{\alpha,L,k} \geq 0 \forall \alpha, L, k \tag{23}$$

A transaction, observation, or demand is presented as (a, L, k), where a represented the arrival day L, is the length of stay, and k equals the product class. The set of stays that make use of day I is denoted by $N_l = [(\alpha, L, K) : I = A : a + L - 1]$. Furthermore, the parameters are explained as follows:

P_k: The price for product class k
$d_{\alpha,L,k}$: The expected demand of a stay of type (a,L,k)
C_l: The available capacity for day I.
$X_{\alpha,L,k}$: The Optimal allocation to a stay of type (a,L,k)

A remodeled version of the classical deterministic model mentioned above integrates a price control tactic. This means that the decision variables will be the prices that are set every day. Moreover, the price elasticity is also included into the suggested model. The model allows managers to change prices from day to day depending on demand and capacity for each product class (Klein, 2007):

$$\sum_{\alpha,L,k\in,N_t} X_{\alpha,L,k} \leq C_l \forall l \tag{24}$$

$$\sum_{I=1}^{MaxI} P_I O_I \tag{25}$$

$$O_I \leq C_I \forall I \tag{26}$$

$$P_I \leq 0 \forall I \tag{27}$$

The decision variables are as follows: P_I: Price for night I

Computed auxiliary variables are: P_I: The number of units allocated to type a and L

$$X_{\alpha,L} = d_{\alpha,L}(\frac{\sum_{I=\alpha}^{\alpha+L-1}}{L * P_{nominal}})^{e} \tag{28}$$

O_I: Refers to the number of units reserved in a given day, which equals:

$$O_I = \sum_{\alpha,L,\in,N_l} X_{\alpha,L} \tag{29}$$

For the given model, the input parameters are: $P_{nominal}$: Historical average price or "standard price" e: Elasticity between price and demand $d_{\alpha,L}$ and N_l : Same definition as for classic model, stated above. C_I: Total amount of vacant units

The output of the model will display the optimal price for each day given the input parameters. To identify optimal rates associated for each product, a parametric analysis can be made with the objective of inducing a dynamic change in rates as occupancy and demand change over time (Aziz *el at.,* 2011). The models mentioned above (Equations 18 to 27) have not been tested empirically. Instead, we used quantity control by applying the EMSR model in order to optimize revenue. The reason of explaining price optimization model, is to give the reader a understanding of the different ways to maximize revenue.

4 Methodology

Quantitative methods were applied in this study. The model was built on findings from literature on revenue management from reference industries – namely, the airline and hotel industries. Factors necessary for revenue management were identified in order to be transferred into the suggested revenue management model for coworking operators. In the quantitative study, data were gathered from a coworking operator and the significance between included variables was tested.

4.1 Research design

For this thesis, the critical realism philosophy was adopted and an abductive approach utilized. The comprehensive literature review complemented the quantitative method and resulted in a better understanding of the nature of the problem. Developing the theory through an abductive approach enabled the researchers to go back and forth between theoretical study and analyzing data in order to adjust models during the work process (Saunders *et al.,* 2016).

The quantitative analysis was primarily conducted using a data set provided by a coworking operator. It is used to see historical patterns of costumer spending, activity, trends, and length of stay in order to create viable optimization. By testing different explanatory variables, both significant and insignificant correlations have been shown between product price and explanatory variables. Moreover, same analysis has been done for the market segmentation. Secondary data has been used so as to take into consideration the effect of historical rental rates of office spaces.

4.2 Data selection

We contacted five coworking offices in Stockholm in order to find stakeholders to participate in our study. We attached a thesis proposal with a summarized presentation describing our chosen subject. We received answers from two of the companies and decided to continue with one of them. The company we chose – an established coworking operator in Stockholm – fit our requirements and provided a large sample data set.

4.3 Data processing

4.3.1 Data sample

The sample was downloaded from the company's customer relationship management system. For accurate examination, the data sectioning was made in Excel to calculate the variables needed in the newly developed system. The regressions were made in Stata, a statistical program often used in econometric studies. The secondary data was collected from Datscha and was used to correct the rent levels for previous years due to rent growth and inflation for the specific location.

The data set consisted following variables:

- Industry of the company
- The accounts monthly fee
- Date of first contact
- Date of signed contract
- The arrival date
- The exit date
- Product type
- Lead source
- Location
- Seller.

We estimated following variables from the consisted data:

- Estimated number of employees
- Estimated length of stay
- Estimated lead time.

The data set was not complete in many aspects, since the company had to enter data manually. Dates and comments are delayed and mistaken; therefore, we could not give any accuracy with the data set that has been given. To increase accuracy of the model, correction of data set and errors has been done manually.

The data set was manually cleaned of obvious biased observations. Since the models are based on historical data, current customers were excluded from the study. The data was retrieved on 9 April; observations including contracts ending later that 9 April were removed from the study. Customers with a length of stay less than 20 days were removed in order to use observations with a length closer to one month – the same time factor as the amount. Lead time less than zero between the lead time and lead source was excluded from the regression. This meant that 5 percent of the observations were removed from the sample to receive a more reliable result. The study did not consider the occupancy rate. We have also removed observations where the data set was not complete of explanatory variables, as this might create bias in the regression. Information such as industry and age of members was manually corrected and completed by the researchers. After specifying the model, the data was corrected to meet requirements of running the regression analysis. We ran an MNL regression to search for significance of the correlation between the deterministic variable and the explanatory variables.

4.3.2 Explanatory variables

The explanatory variables will be placed in the exponent as a linear equation. The MNL regression is shown in Equation 28:

$$P(Y_n = j|x_n) = \frac{e^{\beta_{j'x_n}}}{\sum_l e^{\beta_{j'x_{nl}}}} \tag{30}$$

We chose to segment customers according to their industry. This was done to investigate whether the explanatory variables – e.g., the length of stay and the fee – are impacted by the customer's industry. The data we received initially consisted of a very large number of industries in relation to the total sample available.

In the process of dividing demand into separate demand functions representing demand for each product class, our deterministic variables were the different product classes – namely, lounge, flexible desk, fixed desk, and private room. The explanatory variables were price, start date, end date, length of stay, and industries (one dummy variable for each industry).

Length of stay is of importance to analyze how long time the different segmentation groups stay within that product class or as members, and it was calculated by subtracting customer arrival date from estimated end date.

In the process of finding the model for market segmentation, the industries were used as the deterministic variables.

4.3.3 Multinomial logit regression

An MNL regression is a predictive analysis and was conducted to analyze the probability of future customers' demands – i.e., the demand function for each product class. It allows us to predict outcomes for more than two deterministic variables, which separates MNL regressions from binomial models that can only predict outcomes for one deterministic variable (Tallury and van Ryzin, 2005). There are many similarities between MNL and standard multilinear regression;

however, MNL regression assumes that the dependent variable is a stochastic event, while in standard multilinear regression the dependent variable needs to be measured on a continuous scale. The MNL analysis method is attractive because it does not assume normality, linearity, or homoscedasticity.

The reason to run an MNL regression analysis was that it allowed us to predict the outcomes for more than two deterministic variables, as mentioned above. This feature enabled us to statistically separate total demand into demand representing each product class. The results of each product-specific demand were used to calculate protection levels in Littlewood's model.

Using Stata, we converted the multinomial models into separate binomial models; each model tested the probability of the chosen deterministic variable used in that binomial model. For the demand function our deterministic variables were the four different product classes: lounge, flexible desk, fixed desk, and private room. Whereas for the market segmentation model, the industries described in market segmentation were used as deterministic variables. It is possible to run the MNL regression as one model; however, due to the small number of dependent variables and the simplicity of dividing them into separate binomial logit regressions, we chose to conduct the regressions using that approach.

4.3.4 Diagnostics and model fit

Initial data analysis should be thorough and include careful univariate, bivariate, and multivariate assessment. In particular, multicollinearity should be evaluated with simple correlations among the independent variables. Furthermore, sample size guidelines for multinomial logistic regression indicate a minimum of 10 cases per explanatory variable (Schwab, 2002). The number of observations in our case exceeded the minimum number of 10 observations, which satisfied the variable assumption mentioned above. Using Stata, a model fit function for multinomial logistic regressions can be obtained by typing the command "fitstat" in Stata. This function could be used to detect outliers or influential data points. Moreover, another that facilitates, among others, the Hausman test. This command is called

”mlogtest” and is a post-estimation command. Three non-standard problems are important in the revenue management system. Those are endogeneity, heterogeneity, and competition (Talluri and Van Ryzin, 2005). The endogeneity problem occurs if one of the explanatory variables is correlated with the random-error term. This can be corrected with instrumental variable techniques. Which is an exogenous variable that can edit the correlation between the error term and the independent variable. Another common problem in revenue management models is heterogeneity in the market segments. As explained in the theoretical framework, the finite-mixture logit model is an extension of the MNL model which can be used to find the heterogeneity in the market segmentation analysis. The last of the three commonly appearing problems is competition. The airline and hotel industries are more established and transparent compared to the coworking industry, leading to more information about competitor price setting. This is thus something that cannot be applied in this master thesis.

4.4 Method critique

4.4.1 Ethics

The empirical testing of our revenue management model is based on data from a coworking operator that has chosen to remain anonymous.

Aside from the discussion of the results, where articles from property magazines have been used, the majority of the literature that has been used consists of peer-reviewed articles.

The participants have been informed of the purpose of the thesis and that the goal is to contribute to in-depth knowledge about the coworking market through a literature review and a model to maximize revenue of the coworking operation.

4.4.2 Limitations

We have limited our thesis and revenue management model by utilizing single-use resource models where members will be the only resource that is able to undertake a flexible value. This, due to the significant characteristics of that resource, it is the operator's main revenue stream and includes a floating contract time, which makes it suitable to adjusting price based on demand and willingness to pay. In the case of a multiple-resource model (network model), we can model a total revenue management model that seeks to maximize total revenue per customer, taking into consideration all consumption patterns. While the potential benefit may be high, a network revenue model presents significant implementation and methodological challenges – especially the increase in complexity and volume of data that must be collected, stored, and managed.

The complexity of revenue management models and the number of sub-problems used in the models, have led to many limitations in this study. The research focus has been demand and market segmentation. The concept of overbooking will not be empirically tested due to lack of data related to member activity on site, which is essential for calculation of overbooking limit according to Equations 10 to 15. The calculation of price optimization according to Equation 17 to 26 will not be empirically tested due to its complexity and the requirement of a large and accurate data set. Consequently, we have chosen to optimize revenue according to the EMSR method. No fixed or variable costs have been taken into consideration in this thesis; for usage of any optimization function, costs for each product ought to be included. This paper is also limited to testing the marginals of the market segmentation and the revenue optimization based on demand. The benchmarking is also a large contribution to the revenue stream, according to Tullury and van Ryzin (2005). However, given the low transparency in the coworking industry, there are limited possibilities for investigating competitor demand and market segment to create more accurate models.

4.5 Hypothesis

The hypotheses are based on the theoretical framework and the presumptions from the provided data set. Since this study applies two sub-problems of the revenue management system, two regressions are made to test the significance of relationships among exploratory variables in both the demand optimization and the market segmentation.

4.5.1 Demand

The different products – in this case called product classes, determine the demand. The estimated probability, based on the demand distribution curve, is used to calculate the demand for a higher product class using the EMSR model – an extension of Littlewood's rule (Tullary and van Ryzin, 2005) – presented in Section 3.1.1 Demand Optimization.

Figure 2 presents the graphic distribution of the products and Table 4 presents the frequency and the percentage distribution among the four products.

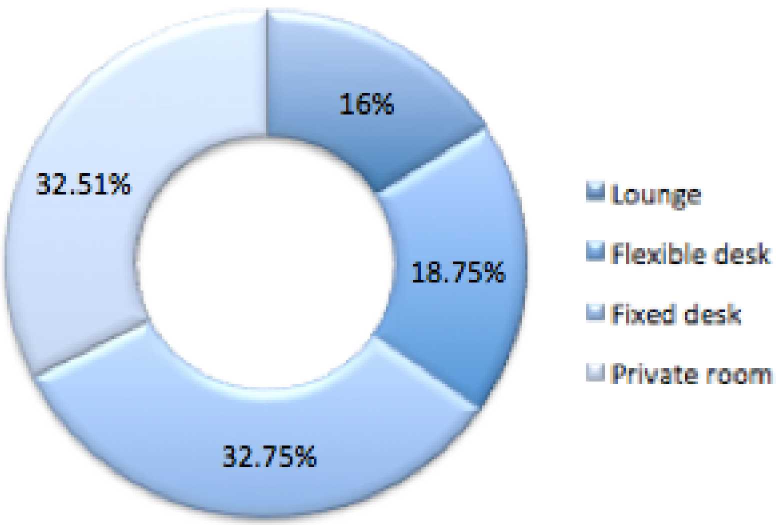

Figure 2: Distribution of the four different products

Table 4: Summary and distribution of the product classes

Product	VAR	Freq.	Percent
Private room	R_P	449	32.51
Fixed desk	R_{Fix}	452	32.73
Flexible desk	R_{Flex}	259	18.75
Lounge	R_L	221	16.00
Total		1381	100

We are assuming that coworking space has an elastic price. The price has a strong negative impact on the demand.

Hypothesis A:

$H_{DA,0}$: *There is a significant relation between the price and the demand.*

We are testing if the arrival date, the exit date, and the length of stay have a significant impact on the determined variable, since one of the advantages of coworking space is the shorter contracts with flexible arrival and exit dates (City Office, 2018). Also, since we determined the demand depending on the transaction for the specific product class, when the end date or the length of stay extends, the occupancy rate increases and the demand decreases.

Hypothesis B:

$H_{DB,0}$: *There is a significant relation between the start date and the demand.*

Hypothesis C:

$H_{DC,0}$: *There is a significant relation between the end date and the demand.*

Hypothesis D:

$H_{DD,0}$: *There is a significant relation between the length-of-stay and the demand.*

Different industries could have different significant impacts on the demand.

Hypothesis E:

$H_{DE,0}$: *There is a significant relation between the industry and the demand.*

4.5.2 Market segmentation

The market segmentation can be determined by a choice decision method. In order to get an accurate result from the choice modeling, the data set needs to include all the choices available on the market and where the choices are initiated (Christ, 2009). The available data set lacks this information. In order to implement the market segmentation model with our data set, the industry will define the customers segment. As mentioned in the theoretical framework, seven industries have been defined in the data set. The largest industries regarding to Newsec (2019), has been identified as the largest sources. The other minor industries have been clustered to one of the larger groups.

Figure 3 presents the graphic distribution of the largest industries and Table 5 presents the distribution among the industries.

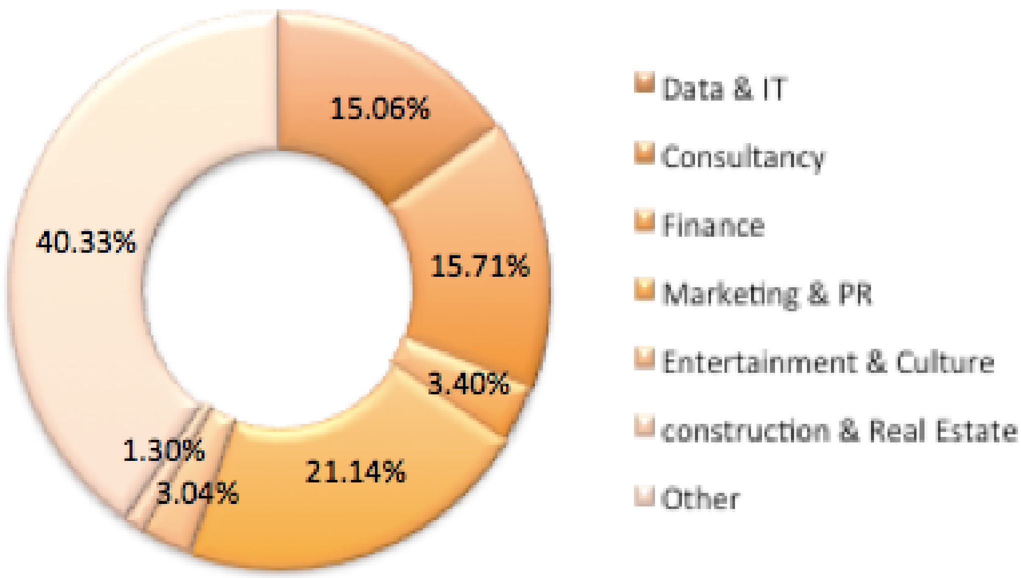

Figure 3: Distribution of the seven different industries

Table 5: Summary and distribution of the industries

Industry	VAR	Freq.	Percent (%)	Rank	Pareto
Other	I_O	557	40.33	1	40.33 %
Construction/Real Estate	I_{RE}	18	1.30		
Data/IT	I_D	208	15.06		
Finance	I_F	47	3.40		
Consultancy	I_C	217	15.71	3	15.71 %
Marketing/PR	I_{PR}	292	21.14	2	21.14 %
Entertainment/Culture	I_E	42	3.04		
Total		1381	100		77.18 < 80

The price determination of the market segmentation can reflect a customer's willingness to pay and can, therefore, have a negative impact on the market segment (Bitran and Leong, 1989; Aydin and Birbil, 2018).

Hypothesis A:

$H_{MA,0}$: *There is significant relation between the price and the industry.*

The arrival date, exit date, and the length of stay could have a significant impact on the determined variable. The flexible contract is often a relevant reason for customers to start their membership with a coworking operator (City Office, 2018). The increased length of stay could have a negative impact on the industries since the occupancy increases, leading to less vacant space.

Hypothesis B:

$H_{MB,0}$: *There is a significant relation between the start date and the industry.*

Hypothesis C:

$H_{MC,0}$: *There is a significant relation between the end date and the industry.*

Hypothesis D:

$H_{MD,0}$: *There is significant relation between the length-of-stay and the industry.*

The customer's choice of type of room could also have a significant impact on the market segment. The relationship can explain the demand for a specific type of product, depending on the market segment.

Hypothesis E:

$H_{ME,0}$: *There is significant relation between the type of product and the industry.*

5 Empirical result

This chapter presents the result from the empirical testing of two of the four chosen applications- market segmentation and demand optimization. Maximizing revenue by using quantity as control according to the EMSR model. Empirical result presents the number of desks to be protected to less price sensitive customers, i.e. higher yielding customers, in order to maximize the revenue. Market segmentation aligns with the process of identifying willingness to pay for each segment. Empirically testing market segment by using the MNL method we can estimate the change of odds a customer belonging to a market segment, explained in chapter 5.2.

5.1 Demand optimization

This chapter presents the result from the hypothesis testing and the protection-level calculation.

5.1.1 Hypotheses tests

The MNL method has been used to calculate the probability distribution of demand for the different determinants, where the fare classes are the determinants of the demand in the coworking operation. The MNL are checked by the pseudo R^2, which is between 0 and 1, and should be as high as possible. The model assumes normal distribution with a significance lower than 5 percent. The confidence interval gives a illustrative range of where the parametric quantity lies. The confident interval should include zero if the null hypothesis is accepted, otherwise is the null hypothesis rejected. Similarly to a binary regression, the z, should be higher than 1.96 and since the MNL-model assumes normal distribution, the significance, $P > |z|$, should be lower than 5%, according to UCLA (2019). The model is an extension of equation 15, from chapter 3.4 Market segmentation.

$$P(Y_n = j|x_n) = \frac{e^{\beta_{j'x_n}}}{\sum_l e^{\beta_{j'x_{nl}}}}$$

where the Y is the probability of choosing a specific alternative j, chosen from the significant variables x. The estimated exponents for each fare class are presented later in this chapter (eq. Dem_2, Dem_3 and Dem_4) and explain the logistic coefficients for each explanatory variable. The significant values indicate that the explanatory variable had an expected change relative to the base outcome that influences if a unit change in the determined variable. This is held if the other explanatory variables are constant. Table 6 is an excerpt of the full regression (see Appendix A) where the determined variable is the product class Private room and the base outcome is the product class "Lounge".

Table 6: An excerpt from the full regression shown in Appendix A, the determinant variable is Private room, * implicates the significance

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Longe Base outcome						
Dependent variable: Private room						
Interception	1381	57.08779	10.27	0.000	46.19643	67.97915
Price*	1381	0.0133323	18.79	0.000	0.0119414	0.0147232
Start date*	1381	0.0302708	3.31	0.001	0.0123513	0.0481903
End date*	1381	-0.03454	-3.78	0.000	-0.05246	-0.016618
Length of stay*	1381	0.0340873	3.73	0.000	0.0161561	0.0520184
Industry I_O	1381	-	-	-	-	-
Industry I_{RE}*	1381	2.361415	3.12	0.002	0.8797029	3.843128
Industry I_D*	1381	1.598576	2.41	0.016	0.2967567	2.900396
Industry I_F	1381	2.09604	1.40	0.160	-0.82928	5.021362
Industry I_C*	1381	6.473193	7.36	0.000	4.748516	8.19787
Industry I_{PR}	1381	-8.359104	-0.02	0.983	-795.3617	778.6435
Industry I_E	1381	-28.3394	-0.00	1.000	-1828541	1828484

The explanatory variables for the demand of private room, are the price, the start date, end date, length of stay, industry real estate, industry data and the industry consultancy. It implies that one more unit in price, increase the probability that the customer demand a desk in a private office than a lounge seat. It also implies that one day increase in the variable start date, increase the probability that the customers demand desk in a private office compared to a lounge seat. If the end date increase with one day, leading to decreased probability that the customers demand a desk in a private office compared to a lounge seat. If the customer comes from the market segment consultancy, there is a larger probability that the customer demands a desk in a private office than a lounge seat, compared to customers that comes from data.The same theory holds for customers containing the industry real estate, the probability is higher that the customer demand a desk in a private office than to a lounge seat, compared to a customer that comes from the market segment data. This is explained by the coefficients, since the MNL-model is comparing the probability with the base case, the included dummies are comparing the result with the omitted variable and the lowest valued coefficent (UCLA, 2019).

If there is one unit increase of the product lounge, the probability decrease that the customers contains the industry Marketing PR compared to the base outcome industry other. The same theory holds to the product flexible desk, if the variable increase with one unit, decrease the probability that the customer contains the market segment marketing and PR, compared to the market segment other. If the product fixed desk increases with one unit, the probability increase that the customer contains the market segment marketing and PR compared to the base outcome industry other.

The full regression, including all determinant variables, has a Pseudo R^2 of 57.9%, meaning that almost 58% of the variation in demand can be explained by the explanatory variables in this model. Still, many of the variables have no significant impact on the determinants. Table 7 summarizes the significant variables with the true sign of the coefficients.

The data conducts 1,381 observations. The minimum case was 221 times, which represents the number of members signing up for the Lounge product class. Hence, the variable assumption of amount of cases is satisfied. The model was tested to collate with the growth of rent in Stockholm city.

Table 7: Significant explanatory variables of the demand and the expected and true signs.

Variable	VAR	True relation
Dependent variable: Lounge Base outcome		
Dependent variable: Flexible desk		
Price	P	Positive
Construction/Real Estate	I_B	Positive
Data/IT	I_C	Positive
Consultancy	I_E	Positive
Dependent variable: Fixed desk		
Price	P	Positive
Start date	D_S	Positive
End date	D_E	Negative
Length of stay	L	Positive
Construction/Real Estate	I_{RE}	Positive
Data/IT	I_D	Positive
Consultancy	I_C	Positive
Marketing/PR	I_{PR}	Positive
Dependent variable: Private room		
Price	P	Positive
Start date	D_S	Positive
End date	D_E	Negative
Length of stay	L	Positive
Construction/Real Estate	I_{RE}	Positive
Data/IT	I_D	Positive
Consultancy	I_C	Positive

We have chosen the Lounge product class as the base outcome in the regression. Our motivation for this; it is the least expensive product class, whilst the increased revenue comes from the higher product classes and seats should be saved for the higher-paying customers in order to optimize the revenue.

The result from the hypothesis testing is presented in table 8. The test resulted in rejected null hypothesis between some of the cases for all the hypotheses $H_{DA,0}$-$H_{DD,0}$.

Table 8: The result from the hypothesis testing - Demand.

Dependent variable: Lounge Base outcome			
Hypothesis H_0	Flexible desk	Fixed desk	Private room
Hypothesis A	Fail to reject	Fail to reject	Fail to reject
Hypothesis B	Reject	Fail to reject	Fail to reject
Hypothesis C	Reject	Fail to reject	Fail to reject
Hypothesis D	Reject	Fail to reject	Fail to reject
Hypothesis E	Fail to reject	Fail to reject	Fail to reject

The developed exponents for the demand model are presented below.

Demand for Flexible desk,

$$Dem_2 = 18.042 + 0.005428(P) + 1.425(I_{RE}) + 1.348(I_D) + 5.815(I_C) + \varepsilon$$

Demand for Fixed desk,

$$Dem_3 = 30.143 + 0.0106(P) + 0.0119(D_S) - 0.0143(D_E) + 0.0138(L) + 2.618(I_{RE}) +$$

$$1.418(I_D) + 7.313(I_C) + 4.410(I_{PR}) + \varepsilon$$

and the demand for Private room,

$$Dem_4 = 57.088 + 0.0133(P) + 0.0303(D_S) - 0.0345(D_E) + 0.0341(L) + 2.361(I_{RE}) +$$

$$1,599(I_D) + 6.473(I_C) + \varepsilon$$

where ε is the error term for the equation and the shortening for the variables are presented in table 7.

5.2 Calculation of protection level

The EMSR model, explained in chapter 3.1.1, is being used in the determination of the protection level for our case; the resulting protection levels are shown in table 9.

The EMSR model, an extension of Littlewood's rule, was used to calculate the protection levels for each product class.

$$F_L \geq F_H \frac{F_j + 1}{F_k}$$

With the mean and the standard deviation for each product class calculates the probability, that a marginal amount of seats will be sold in the future. The results for the protection levels as presented in Table 9.

Table 9: The result from EMSRs protection level calculation.

Product class	Class	$\mu(j)$	$\sigma(j)$	Prot. level 4	Prot. level 3	Prot. level 2 and 1
1	Private room	3,78	10.62	10.5	1.5	0
2	Fixed desk	3.75	6.1	7	1.5	-
3	Flexible desk	2.15	4.19	2.5	-	-
4	Lounge	1.86	2.87	-	-	-
				20	3	0

The calculation resulted in the probability that higher paying customers will arrive in the demand of flexible seats, fixed seats and private room compared to lounge and flexible desk. Twenty one customers with a willingness to pay for a lounge seat, will be rejected to buy a higher product for lounge price. Since three customers will show up to pay full price for a flexible desk, seven customers willing to pay full price for a fixed desk and 11 customers willing to pay full price for a desk in a private room. The same theory is presented in the column for protection level 3. If four customers will show up with a willingness to pay for flexible desk, they should be rejected, since two customers are willing to pay full price for a fixed desk and two customers willing to pay full price for a desk in a private room, in the future.

This is an optimized revenue that the operator would have lost if the manager had accepted the customers when the lower paying customer entered and vacant space.

5.3 Market segmentation

This chapter presents the result from the hypothesis testing for the model of market segmentation. As with the demand model, the MNL method was used to determine the significant explanatory variables of the determinants. The model are checked by the pseudo R^2, which is between 0 and 1, and should be as high as possible. The model assumes normal distribution with a significance lower than 5 percent. The confidence interval gives a range of where the parametric quantity lies and should include zero if the null hypothesis is accepted, otherwise is the null hypothesis rejected. Similarly to a binary regression, the z, should be higher than 1.96 and since the MNL-model assumes normal distribution, the significance, $P > |z|$, should be lower than 5%, according to UCLA (2019).The same model is used in the demand determination, and is explained in chapter 3.4 Market segmentation.

$$P(Y_n = j|x_n) = \frac{e^{\beta_{j'} x_n}}{\sum_l e^{\beta_{j'} x_{nl}}}$$

The determinants in the market segmentation are the industries clustered into seven larger groups. We rearranged the industries into new categories matching Newsec's Outlook (2018). This resulted in the industries, Other, Data and IT, Finance Consultancy, Marketing and PR and Entertainment and Culture. The estimated models for the significant determinants are presented as Equations I_{RE},

I_D, I_F, and M_C, I_{PR} and I_E. The base outcome in this MNL model is industry "Other".

Table 10 is an excerpt from the full regression (see Appendix B). Where the base outcome is Other and the determinant is the industry Marketing and PR. The full regression's pseudo, R^2, is 15.22%, meaning that 15.22% of the model can be explained by the explanatory variables.

Table 10: An excerpt from the full regression shown in Appendix B, determinant variable = Industry Marketing and PR, * implicates the significance

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Industry Other Base outcome						
Dependent variable: Industry Marketing and PR						
Interception	1381	18.45987	8.23	0.000	14.06595	22.85378
Price*	1381	-.0012121	-5.42	0.000	-0.00165	-0.00077
Lounge*	1381	-3.297879	-5.29	0.000	-4.51894	-2.07682
Flexible desk*	1381	-0.87384	-2.18	0.029	-1.659322	-0.08837
Fixed desk*	1381	0.707544	3.21	0.001	0.2754483	1.13964
Private room	1381	-	-	-	-	-
Start date	1381	-0.00223	-0.32	0.751	-0.015954	0.011505
End date	1381	0.0013579	0.19	0.846	-0.01235	0.0150617
Length of stay	1381	-0.00106	-0.15	0.880	-0.01479	0.012671

The explanatory variables for the market segment marketing and PR, are the price, the product classes lounge, flexible desk and fixed desk. It implies that one more unit in price, decrease the probability that the customers contains the market segment marketing and PR compared to the base outcome industry other. If there is one unit increase of the product lounge, the probability decrease that the customers contains the industry Marketing PR compared to the base outcome industry other. The same theory holds to the product flexible desk, if the variable increase with one unit, decrease the probability that the customer contains the market segment marketing and PR, compared to the market segment other. If the product fixed desk increases with one unit, the probability increase that the customer contains the market segment marketing and PR compared to the base outcome industry other.

Table 11 presents the significant variables and the true sign of in the models for the market segmentation. industries, where the confidence interval excludes zero. The industries *Data and IT*, *Consultancy*, *Marketing and PR*, and *Entertainment and Culture,* can be explained by the explanatory variables.

Table 11: Significant explanatory variables of the market segmentation, the expected and the true signs.

Variable	VAR	True relation
Dependent variable: Industry Other Base outcome		
Dependent variable: Industry Data and IT		
Price	P	Negative
Lounge	FC_4	Negative
Flexible desk	FC_3	Negative
Dependent variable: Industry Consultancy		
Price	P	Negative
Lounge	FC_4	Negative
Dependent variable: Industry Marketing and PR		
Price	P	Negative
Lounge	FC_4	Negative
Flexible desk	FC_3	Negative
Fixed desk	FC_2	Positive
Dependent variable: Industry Entertainment and Culture		
Price	P	Negative
Lounge	FC_4	Positive
Start date	D_S	Positive
End date	D_E	Negative
Length of stay	L	Positive

The developed coefficient for the models in the market segmentation are presented below, the base outcome and compared determined variable is industry other.

Market segment of the industry Data and IT,

$$M_D = 8.648 - 0.00069(P) - 2.592(FC_4) - 1.075(FC_3) + \varepsilon$$

Market segment of the industry Consultancy,

$$M_C = -3.037 - 0.000548(P) - 1.838(FC_4) + \varepsilon$$

Market segment of the industry Marketing and PR,

$$M_{PR} = 18.460 - 0.00121(P) - 3.298(FC_4) - 0.874(FC_3) + 0.708(FC_2) + \varepsilon$$

Market segment of the industry Entertainment and Culture,

$$M_E = -38.7600 - 0.00155(P) + 11.931(FC_4) + 0.093(D_S) - 0.0918(D_E) +$$

$$+0.0912(L) + \varepsilon$$

where ε is the error term for the equation and the shortening for the variables are explained in table 11.

The hypotheses were tested and the results are presented in Table 13. In the market segmentation model, we have found that there is a significant relationship between some of the determinant variables price and the industry, meaning that when the price increase with one unit the probability that the customer contains this market segment increases, and vice verse. There is no significant relationship between the arrival or the exit date and the industry. But there is a significant relationship between the explanatory variable length of stay and the determinant variable industry in the case , market segment entertainment and culture. Which means increased length of stay decreases the possibility of belonging to this specific market segment compared to the base outcome, industry other. The last hypothesis, the significant relationship between the product class and the industry, is failed to reject. The result differs depending on the industry and the type of product. For example, for the industry Marketing and PR (presented in Table 11), there is a positive relationship between the market segment and fixed desk, but a negative relationship between the market segment and the flexible desk.

The result from the hypothesis testing is presented in table 12 and 13. The test resulted in rejected null hypothesis between some of the cases for all the hypotheses $H_{MA,0}$-$H_{MD,0}$.

Table 12: The result from the hypothesis - Market segmentation.

Hypothesis H_0	Real Estate	Data	Finance
Hypothesis A	Reject	Fail to reject	Reject
Hypothesis B	Reject	Reject	Reject
Hypothesis C	Reject	Reject	Reject
Hypothesis D	Reject	Reject	Reject
Hypothesis E	Reject	Fail to reject	Reject

Table 13: The result from the hypothesis - Market segmentation.

Hypothesis H_0	Consultancy	PR	Entertainm.
Hypothesis A	Fail to Reject	Fail to reject	Fail to reject
Hypothesis B	Reject	Reject	Reject
Hypothesis C	Reject	Reject	Reject
Hypothesis D	Reject	Reject	Fail to reject
Hypothesis E	Fail to reject	Fail to reject	Fail to reject

6 Analysis and discussion

The application of a Revenue Management system

Flexibility in pricing is necessary for quantity-based revenue management – i.e., being able to adjust prices based on demand, each segmentation group's willingness to pay, and estimated occupancy rate for the given time. Flexible pricing presents the opportunity for coworking operators to increase revenue without expanding their capacity. The largest part of the total revenue comes from the membership fees. The price could differ depending on the customer, time of purchase, what membership the customer purchased, what the agreement included, and length of stay. These factors are all negotiable and, therefore, there are few ”standard” transactions. Analyzing each product class and its characteristics separately allows us to find ways to increase revenue in each separate income stream. The product classes for the reference product are lounge, flexible desk, fixed desk, and private room.

We know from the literature review that market segmentation is used in the airline and hotel industries as a tool to define which customers are most relevant and most profitable. The hotel industry does specific marketing targeting customers with the highest willingness to pay contributing to total revenue per customer. The same concept can be applied to the coworking industry, where it is important to include length of stay in market segmentation. The concept is used in order to predict future occupancy rates and determine where to accept or reject new inquiries, based on profitability associated with length of stay.

Interpretation of the MNL regression can tell when the change of odds the independent variable affect the dependent. The results of market segmentation is which variable can affect the change of odds of future customers belonging to a certain industry. For example, results indicates that increasing the variable fixed seat, will increase the odds that future demand belongs to the industry PR and marketing relative to the industry Other. Another example of practical usage: management may want to increase the number of customers belonging to the industry Entertainment and Culture. To do so, they could increase the length of stay with one day, since the Entertainment and Culture industry seems to be positive in relation to the other industries. However, the results are marginal and would likely not produce a measurable result given the low quantity of signed members. It could be use to determine which actions to take to attract members from different market segmentation, in order to complement current skill sets within the coworking network.

When having demand of each product class as dependent variables, results can be interpreted as which independent variable affect the odds of either increase or decrease future demand relative the base case: Lounge. Results shows by increasing the start date with one day, will better the odds that future demand meets the product class: private room relative to the product class: fixed desk and the product class: lounge. Another example; if management increase marketing efforts toward the market segment marketing and PR, they would better the odds that future customers will demand a fixed desk relative product class: Lounge. We consider this as a useful tool, allowing management to target customers demanding chosen product. Integrating this method into a revenue management system could support decision makers with regards to which marketing efforts can be used to maximize occupancy for each product class.

Using quantity as control to allocate resources to highest yielding customer, is a common used method in quantity based revenue management models. Calculations according to the EMSR model, giving result of number of desks to be protected for each product, to higher yielding customers. As shown in table 9, 2.5 desks of product class flexible desk ought to be protected for higher yielding customers base on the probability that a higher yielding customer will show up in the future. The higher price from the saved seats optimize the revenue from the operator. Theoretically the method is found applicable for coworking operations.

To analyze the revenue optimization further, the protection level could be used together with the demand calendar. It could be used as a tool to display quantified estimated demand of new customers per year, week, and day. The demand calendar is applicable to the coworking industry and could facilitate functions such as booking limits with regards to customers' willingness to pay and estimated occupancy rate. These functions, in turn, support decisions whether to accept or reject a customer. Moreover, we would argue that the pick-up analysis is more relevant for the mentioned reference industries, since more frequent transactions are made, the length of stay is low, and they have larger capacities. This is not the case with the coworking industry. Therefore, we did not see the full potential of using the analysis method for the coworking industry.

Additional revenue has been realized when implementing overbooking in reference industries. Product classes that are characterized by impersonal and infrequent usage is supported by the use of overbooking. For the case project, product classes: lounge and flexible desk possess these characteristics. However, to make accurate calculations of the optimal overbooking limit, data of customers activity pattern on site must be collected and analyzed. If suggested data is collected and being analyzed using the MNL regression, an optimal tenant mix could be identified, having activity (days and hours) as deterministic variables and data such as industry, age, profession, and so forth as explanatory variables.

Results could then be interpreted to determine which explanatory variable affect the probability of future demand to use the facility during low-activity hours and days, enabling a more efficient usage of the space. We recommend running simulations of the output frequently, since customer behavior is not always predictable – each member can have different characteristics which might result in different probability distributions. Consequently, adding a member may change the total probability distribution; hence, it is advisable to run the simulation after a change has occurred. A suitable KPI to evaluate the performance of overbooking could be number of members for a given product divided by total square meters or square meters assigned to that specific product. For benchmarking, we suggest square meters assigned per product, since the capacity allocation of different products may vary for each operator.

In the statistical approach of calculating the optimal overbooking limit, a penalty cost needs to be taken into consideration. Arguments for both high and low penalty costs should be considered. Arguing for a high penalty cost would include the long-term effect of a dissatisfied customer that may drop their membership and, in a worst-case scenario, negatively influence other members or non-members by speaking badly of the operation. Long-term negative effects could arise if there are many dissatisfied customers due to exceeding the overbooking limit. Negative comments could cause serious damage to the overall business image; therefore, we recommend running simulations often in attempt to find the optimal mix of segments to achieve the highest possible overbooking limit.

We would argue for having a less critical view of consequences when overbooking a lounge member. The lounge membership can be compared to sitting in a cafe or similar facility with common attributes and conditions. Taking into consideration the simplicity of finding similar places to work at little or no cost to the member, we argue that the penalty cost should not be too aggressively estimated. Compared to reference industries such as hotels, the cost would equal a compensation of booking another hotel room for the customer. Optional way to handle an overbooked customer could be to upgrade the customer to higher membership for the day or week, resulting in no additional cost and, hopefully, a satisfied customer. For the flexible desk option, we would argue a higher penalty cost due to the larger negative impact when a customer gets rejected from the desk that he or she paid more for. Furthermore, the difficulty in finding comparable working space at such short notice is significantly larger for this product class.

Alliances are formed to create competitiveness against competitors. These partnerships are common in reference industries, where resources are shared, availability and geographic boundary complements all included businesses. As workplaces are becoming more ”fluid” and impersonal, we see potential of forming alliances between coworking operations. Sharing resources such as desks, conference rooms, gym, podcast recording room, could potentially favour the operators by attracting wider range of customers. To our knowledge there are no such alliances between coworking operators in Stockholm.

From a theoretical standpoint, benchmarking and KPIs are not well utilized in the industry. The argument that operators are too different from one another and, therefore, are not suited to generalizations is partly true. We believe that, as the coworking industry matures, we will see more frequent use of KPIs in a collaborate way that uses benchmarks among rival operations. Revenue per available desk day (RPADD) could be used as an effective and reliable indicator of a coworking operator's performance. However, this metric may not provide the whole picture of the subject's performance. For coworking operators, margins and revenues from all products sold should be taken into consideration when evaluating the coworking operator's performance, with the goal of maximizing not just revenue but also the profit. Therefore, we suggest using profit per available desk day and profit per available square meter as metrics to measure overall effectiveness of a coworking operator's performance.

Sustainability

In contrast with the traditional office market, where new tenants require individual corporate solutions to fit with their business, the office layout of coworking spaces (as presented in Section 1.1.1 Coworking space) is often related to the leaser's business. A cell-office layout is a better fit for businesses with individual working tasks, and shared cell-office solutions are a better fit for project-based companies where colleagues are more interactive. The coworking office tenant has longer leasing agreements with less adaptable office layouts. The property owner has less participation in the corporate solutions, which leads to less refurnishing in the long run; this has a positive impact in an environmental sense. The overbooking strategy is a phenomenon with a positive ecological impact on the environment. Compared to traditional offices, coworking operators can create a more efficient usage of space, resulting in less energy consumption per employee, by incorporating a revenue management model into their business.

We also believe that coworking offices have a positive impact on the social environment in a city. This industry is a part of the collaborative economy in which space is shared among different identified groups – both internal and external users (as explained in Section 1.1.1 Coworking space). The physical barriers between private offices and public spaces decrease, meaning that coworking spaces contribute to a more transparent and accessible office market for all citizens. This feature aligns with global Sustainable Development Goal 11, ”Sustainable Cities and Communities”, which focuses on inclusiveness and accessible urban environments (Ministry for Foreign Affairs and Ministry of the Environment 2018). Since the location of coworking spaces is normally near the city center or in the city’s submarkets, consumers have a better chance of being placed closer to the central business district compared to if they were not sitting on a coworking office. This also creates a larger social, sustainable environment. Freelancers and small enterprises interact with one another and work in a community, which can have a positive effect on their mental health (Danielsson 2016). As described in Section 3.3.2 (Key performance indicators and benchmarks), the revenue management system is discussed as a tool to evaluate customer activity in the office space. This can increase knowledge about customers’ well-being, and support changes in the operation to improve the mental health of members.

Since coworking operations are associated with added value for the property owner, where longer lease agreements imply smaller risk in the property portfolio, a profitable business may motivate others to start and run their own operations. Potential outcomes could be more coworking spaces and increasing interaction between the city and its citizens as well as added social value of the neighborhood. The revenue management system aims to increase the revenue for the operator, which leads to economically sustainable development for the company. Since more property developers are opening their own coworking facilities, this also increases economically sustainable development for property developers and land owners.

Validity and reliability

The suggested revenue management model is based on our case study – i.e., suitable for their specific operation. By using their data, one can argue that the internal validity and reliability is high when applying the system to the case. However, due to different business structures, revenue streams, and the variety of customers among different coworking operators, we believe the validity and reliability are low when applying the revenue management model to other coworking operators. Therefore, we recommend running a thorough due diligence assessment of a specific operation before implementing the suggested model.

7 Conclusion and recommendations

We argue for the use of revenue management systems in order to increase the revenue of coworking operators. We have found that it is possible to apply parts of the revenue management system to coworking spaces. Features from revenue management models used in the hotel and airline industries were identified and analyzed with the objective of implementing them in the coworking industry to efficiently maximize revenue. The thesis proposes the use of multinomial regression analysis in the process of market segmentation; this method allows one to determine which factors influence the different segments. Moreover, the MNL method is used to define the demand function through which a probability distribution of total demand can be separated into demands representing each product class. The results obtained indicate that MNL is an effective tool to analyze market segmentation and demand allocation for coworking operators.

The market segmentation and demand optimization models have been tested in order to increase the revenue for the coworking operator. We have found that it is possible to apply the demand forecast in order to calculate the protection levels needed to optimize revenue. Market segmentation can also be applied, based on the provided data. Furthermore, in order to create reliable and accurate results, benchmarking and in-depth knowledge about customer behavior is advisable. We have found that a company collecting local benchmarking data in the coworking business has not yet been developed since the transparency in this industry is limited. Finally, price optimization based on demand can also be calculated. We believe revenue management will be more frequently used as the industry matures, including the development and application of key performance indicators used as benchmarks.

Future Research

Benchmarking is an important tool used in the revenue management systems of other industries. It would be interesting to investigate if it is possible to create a benchmarking system for the coworking industry – perhaps through evaluating the most suitable KPIs for different business models within the coworking industry.

Another interesting feature of revenue management is the tracking of activity on site. Applying overbooking calculations to real-life cases measures the potential revenue gains within the operation. Furthermore, by tracking consumer activity, more reliable market segmentation can be created. Activity tracking provides greater in-depth knowledge about the operation, which can lead to clearer vision and strategy.

It would be interesting to include additional case studies in order to apply the models on more than one operator. This could be implemented with a focus on evaluating the possible alliances within the coworking industry. The advantage of such alliances is for operators to complete and complement one another, as well as offer combined products; this approach would increase the overall revenue and avoid opportunity costs.

Further research could also investigate dynamic pricing in coworking spaces, including flexible membership with dynamic pricing based on movements in the demand curve. Time periods with less demand could present an opportunity to offer discounts (e.g., first month -+free) to attract new customers and reach the recommended breaking point. The closer the recommended breaking point, the smaller the discount a new customer will receive. To succeed in this approach, a lot of transaction data is required to create a reliable time-series regression analysis for the demand.

Finally, it would be interesting to understand how the revenue management system correlates with business cycles. This could be determined using a time-series analysis in order to understand how macro indicators affect the performance of the revenue management models. This could also contribute to the change in demand during the time of years. Since we have applied our research on 10 years. It would be interesting to divide the data in two parts in order to understand how the demand have shiftet with a five year perspective.

References

Akhavan, M., Mariotti, I., Astolfi, L. and Canevari, A.(2019). Coworking Spaces and Social Relations: A Focus on the Social Streets in Italy. *Urban Science*. Vol. 3, No. 1.

Aydin, N. and Birbil, S.I. (2018). Decomoposition methods for dynamic room allocation in hotel revenue management. *European Journal of Operational Research*. Vol. 27, No. 1, pp. 179-192.

Aziz H.A, Saleh M., Rasmy. M.H. and Elshishiny H. (2011). Dynamic room pricing model for hotel revenue management systems. *Egyptian Informatics Journal*. Vol. 12, No. 13,. 177-18.

Bergström, M. (2018). Coworking slukar allt mer yta. *Fastighetsvärlden* 29 May. Available at https://www.fastighetsvarlden.se/notiser/coworking-slukar-allt-mer-yta/ [Accessed 2019-05-31].

Bitran and Mondschein, S. V., (1993). An Application of Yield Management to the Hotel industry considering multiple day stays. *Operations Research*. Vol. 43, No. 3, pp. 427-443.

Born, W. and Pyhrr, S. (1994). Real Estate Valuation: The Effect of *Market and Property Cycles*. *Journal of Real Estate Research*. Vol. 9, No. 4, pp. 455-485.

Cabral, V. and Van Winden, W. (2016). Coworking, an analysis of coworking strategies for interaction and innovation. *International Journal of Knowledge-based Development*. Vol. 7, No. 4, pp. 357-377.

Camilleri, M. A. (2018a). *Market Segmentation, Targeting and Positioning*. In: Travel Marketing, Tourism Economics and the Airline Product: Springer, Cham. Chapter 4.

Camilleri, M. A., (2018b). Pricing and Revenue Management. *Travel and Marketing, Tourism Economics and the Airline Product.* Switzerland: Springer Nature

Chathotha, P.K., Olsen, M.D. 2003. *Strategic alliances: a hospitality industry perspective.* Hospitality Management, Vol. 22, No. 4, pp. 419-434.

Christ, S. (2009). *Operationalizing Dynamic Pricing Models.* Augustburg: University of Augustburg

City Office (2018). *Om kontorshotell.* Availible at https://www.cityoffice.se/om-kontorshotell/. [Accessed 2019-05-10].

Cortés, P., Guadix, J., Muñuzuri, J. and Onieva L. (2011) An overview of revenue management in service industries: application to car parks. *The Service Industries Journal,* Vol.31, No.1, pp. 91-105.

Cramer, R., Boyd, A., Walczak, D. (2012). *Revenue management.* In: C. Barnhart and B. Smith (eds.), Quantitative problem solving met: Boston Springer. pp.101-160

Danielsson, C. (2016). Office types association to employees' welfare: three studies. *Work.* Vol. 54, No. 4, pp. 799-790.

Davis, P. (1994). Airline Ties Profitability Yield to Management. *SIAM News.* Vol. 27, No. 5.

Demydyuk, G., (2011). Optimal Financial Key Performance Indicators: Evidence from the Airline Industry. *Accounting and Taxation.* Vol. 3, No. 2, pp. 39-51.

Donovan, A.W. (2005). Yield management in the Airline Industry. *Journal of Aviation/ Aerospace Education and research.* Vol. 14, No. 3, pp. 11-19.

Drury, P. (2016). Employer branding: Your not-so-secret weapon in the competition for young workers. *Human Resource Management International Digest*. Vol. 25 No. 3. pp 29-31.

Ekelid, M., Lind, H., Lundström, S. and Persson, E. (1998). Treatment of uncertainty in appraisals of commercial properties. *Journal of Property Valuation and Investment*. Vol. 16, No. 4, pp. 386-396.

Eriksson, M. and Krumlinde, M. (2018). Investeringsklimat på kontorsmarknaden. Fastighetsnytt, 25 Oct. https://fastighetsnytt.se/2018/10/investeringsklimat-och-uthyrningstrender-pa-kontorsmarknaden [Accessed 2019-05-10]

Fitzgerald, L., Johnston, R., Brignall, T.J., Silverstro, R. and Voss, C., (1991a). Performance Measurement in Service Businesses. *Management Accounting*. Vol. 69, No. 10, pp. 34-36.

Fitzgerald, L., Johnston, R., Brignall, T.J., Silvestro, R. and Voss, C., (1991b). Product costing in service organizations. *Management Accounting Research*. No. 2, pp. 227-248.

Foertsch, C. and Cagnol, R. (2013). The history of coworking spaces in a timeline. *Deskmag*, 2 September. Available at http://www.deskmag.com/en/the-history-of-coworking-spaces-in-a-timeline [Accessed 2019-04-08].

Fraser, W. (1986). Supply Elasticity and the Rental Value of investment property. *Journal of Valuation*. Vol. 4, No. 4, pp. 354-369.

Geraedts, R.P., Remøy, H., and Van Der Hoek, A. (2017). *Refitting Vacancy for the Creative Industry: A Strategy to Create and Maintain a Creative Community*. Conference of the European Real Estate Society. The Netherlands, 28 June to 1 July, 2017.

Goldman P, Freling R, Pak K, Piersma N. (2002). Models and techniques for hotel revenue management using a rolling horizon. *Journal of Revenue and Pricing management.* No. 1, vol. 3, pp. 207–19.

Harris, P. and Mongiello, M. (2001). Key performance indicators in European hotel properties: general manager's choices and company profiles. *International Journal of Contemporary Hospital Management.* Vol. 13, No. 3, pp. 120-127.

Ingold A., Yeoman I. and McMahon-Beattie, U. (2000). *Yield management: strategies for the service industries.* London: Cengage Learning.

Jakonen, M., Kivinen, N., Salovaara, P. and Hirkman, P. (2017). Towards an Economy of Encounters? A critical study of affectual assemblages in coworking. *Scandinavian Journal of Management.* Vol. 33, No. 4, pp. 235-242.

JLL (2018). JLL *Nordic Outlook Autumn 2018.* https://www.jllsweden.se/en/trends-and-insights/research/jll-nordic-outlook-autumn-2018 [2019-04-02]

JLL (2019). JLL *Nordic Outlook Spring 2019.* https://www.jllsweden.se/content/dam /jll-com/documents/pdf/research/emea/sweden/ /jll-nordic-outlook-spring-2019.pdf [2019-04-02]

Joslin, A. (2005). An investigation into the expression of uncertainty in property valuation. *Journal of Property Investment and Finance.* Vol. 23, No. 3, pp. 269-285.

Kerzner, H. (2013). *Project Management Metrics, KPIs, and Dashboards - A Guide to Measuring and Monitoring Project Performance.* (2^{th} edn) Hoboken: John Wiley and Sons, Inc.

Kimes, S.E, Chase, R.B., Choi, S., Lee, P.Y. and Ngozi, E.N., (1998). Restaurant revenue management: Applying yield management to restaurant industry. *Cornell Hotel and Restaurant Administration Quarterly*. Vol. 29, No. 3, pp. 32-39.

Klein R. (2007). Network capacity control using self-adjusting bid-prices. *OR Spectrum*. Vol. 29, No. 1, pp. 39–60.

Klophaus, R. and Pölt, S. (2006) Airline overbooking with dynamic spoiling over costs. *Journal of Revenue and Pricing Management*. Vol. 6, No. 1, pp. 9-18.

Lawrence, R.D., Hong, S. J and Cherrier, J. (2003). *Passenger-based predictive modeling of airline no-show rates*. International Conference on Knowledge Discovery and Data Mining. Washington D.C, 24-29 Aug. 2003.

Leclercq-Vandelannoitte, A. and Isaac, H. (2016). The new office: how coworking changes the work concept. *Journal of Business Strategy*. Vol. 37, No. 6, pp. 3-9.

Maddah, B., Moussawi-Haidar,L., El-Taha, M. and Rida, H. (2010). Dynamic cruise ship revenue management. *European Journal of Operational Research*. Vol. 207, No. 1, pp. 445-455.

McDonald, M. and Dunbar, I. (2012). Market segmentation: how to do it and how to profit from it. (Revised 4th edn). United Kingdom: John Wiley and Sons, Ltd.

McGill, J. I. and Van Ryzin G. J. (1999). Foreword to the Focuses Issue on Yield Management in Transportation. *Transportation Science*. Vol. 33, No. 2, p. 135.

Ministry for Foreign Affairs and Ministry of the Environment (2018). *The Global Goals and the 2030 Agenda for Sustainible Development.* Stockholm: Government Offices of Sweden. https://www.government.se/government-policy/the-global-goals-and-the-2030-Agenda-for-sustainable-development/ [Accessed 2019-05-21]

Müeller, H. and Hamm, U. (2014). Stability of market segmentation with cluster analysis - a methodological approach. *Food Quality and Preference.* Vol. 34, pp. 70-78.

Newsec (2019). *Newsec Property Otlook - Spring 2019.* Availible at http://www.e-magin.se/latestpaper/f5vn542f/paper/paper/zdm7ms4q/16. [Accessed 2019-05-27]

O'Sullivan, A. (2009). *Urban Economics.* (8^{th} edn) New York: McGraw-Hill Companies.

RICS (2017). *The Future of Valuations.* Available at https://www.rics.org/ssa/news-insight/research/insights/the-future-of-valuations/ [Accessed 2019-05-02]

Saunders, M.,Lewis, P. and Thornhill, A. (2016). *Research Methods for Business Students.* (7 edn) Essex: Pearson.

Sierag, D., Koole, G., van der Mei R., van der Rest, J and Zwart, B. (2014). Revenue Management under customer Choice Behaviour with cancellations and overbooking. *European Journal of Operational Research.* Vol. 246, No. 1, pp. 170-185.

Slade B. A. (2006). Property Risk Assessment: A Simulation Approach. *The Appraisal Journal.*

Smith, B. C., Leimkuhler, J. F. and Darrow, R. M. (1992). Yield management at American Airlines. *Informs Journal on Applied Analytics.* Vol. 22, No. 1, pp. 8-31.

Steinhardt, G. and Gönsch, J. (2012). Integrated revenue management approaches for capacity control with planned upgrades. *European Journal of Operational Research*. Vol. 223, No. 2, pp. 380-391.

Stockholm Chamber of commerce, (2018). *Företagen larmar om kontorbrist.* https://www.chamber.se/rapporter/foretagen-larmar-om-kontorsbrist.htm [Accessed 2019-04-28]

Spinuzzi, C. (2012). Working Alone Together: Coworking as Emergent Collaborative Activity. *Journal of Business and Technical Communication*. Vol. 26, No. 4, pp. 399-441.

Spreitzer, G., Bacewise, P. and Garett, L. (2015). Why People Thrive in Coworking Spaces. https://hbr.org/2015/05/why-people-thrive-in-coworking-spaces [Accessed 2019-04-25]

Schwab, J. A. (2002). Multinomial logistic regression: Basic relationships and complete problems. http://www.utexas.edu/courses/schwab/sw388r7/SolvingProblems/ [Accessed 2019-04-05]

Tallury, K.T., van Ryzin G. (2005). *The theory and practice of revenue management*. United States of America: Springer Science and Business Media.

Toh, R. S., Raven, P. (2003). Perishable asset revenue management: Integrated Internet Marketing Strategies for the airlines. *Transportation Journal*. Vol. 42, No. 2, pp. 30-43.

Toivanen, S. (2016). *Framtidens arbetsplatser*. Stockholm: Vitt Grafiska.

UCLA (2019). *Multinomial Logistic Regression - Stata Announced output*. Availible at: https://stats.idre.ucla.edu/stata/output/multinomial-logistic-regression-2/ [Accessed 2019-05-05]

Yeoman I. and McMahon-Beattie,U. (2017). The turning points of revenue management: a brief history of future evolution. *Journal of Tourism Futures* Vol. 3, No. 1, pp. 66-72.

Winston, W.L. (2003). Operations research: Applications and Algorithms. (4^{th} edn) Boston: Cengage Learning (1987)

Xotels (2018). *Leadership in Revenue Management.* Availible at https://www.xotels.com/images/Revenue-Management-Manual -Xotels.pdf [Accessed 2019-02-27]

Appendices

Appendix - Contents

A MNL regression - Demand Optimization

Demand optimization, Pseudo $R^2 = 0.5790$, * indicates significance

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Lounge Base outcome						
Dependent variable: Flexible desk						
Interception	1381	18.04919	4.66	0.000	10.4564	25.64198
Price*	1381	0.005428	10.69	0.000	0.0044332	0.006423
Start date	1381	0.0142178	1.70	0.089	-0.00217	0.030608
End date	1381	-0.01546	-1.84	0.066	-0.031927	0.001004
Length of stay	1381	0.0134208	1.60	0.110	-0.00303	0.029866
Industry I_O	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Industry I_{RE}*	1381	1.424605	2.38	0.017	0.2538127	2.595397
Industry I_D*	1381	1.348084	2.60	0.009	0.3308959	2.365271
Industry I_F	1381	0.9149715	0.89	0.371	-1.090148	2.920091
Industry I_C*	1381	5.815141	7.68	0.000	4.330669	7.299613
Industry I_{PR}	1381	0.1392935	0.18	0.860	-1.411599	1.690186
Industry I_E	1381	-0.39098	-0.33	0.743	-2.731973	1.950014
Dependent variable: Fixed desk						
Interception	1381	30.14273	6.01	0.000	20.30863	39.97683
Price*	1381	0.0105581	15.81	0.000	0.0092493	0.0118669
Start date*	1381	0.0118905	2.33	0.020	0.0018945	0.0218866
End date*	1381	-0.01434	-2.80	0.005	-0.02437	-0.00430
Length of stay*	1381	0.0137697	2.69	0.007	0.0037486	0.023791
Industry I_O	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Industry I_{RE}*	1381	2.617867	3.59	0.000	1.187035	4.048699
Industry I_D*	1381	1.41825	2.23	0.026	0.1719987	2.664501
Industry I_F	1381	1.747088	1.22	0.224	-1.06612	4.560293
Industry I_C*	1381	7.313429	8.51	0.000	5.628229	8.998629
Industry I_{PR}*	1381	4.410345	4.10	0.000	2.302094	6.518596
Industry I_E	1381	-0.46922	-0.15	0.883	-6.73392	5.795475

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Private room						
Interception	1381	57.08779	10.27	0.000	46.19643	67.97915
Price*	1381	0.0133323	18.79	0.000	0.0119414	0.0147232
Start date*	1381	0.0302708	3.31	0.001	0.0123513	0.0481903
End date*	1381	-0.03454	-3.78	0.000	-0.05246	-0.016618
Length of stay*	1381	0.0340873	3.73	0.000	0.0161561	0.0520184
Industry I_O	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Industry I_{RE}*	1381	2.361415	3.12	0.002	0.8797029	3.843128
Industry I_D*	1381	1.598576	2.41	0.016	0.2967567	2.900396
Industry I_F	1381	2.09604	1.40	0.160	-0.82928	5.021362
Industry I_C*	1381	6.473193	7.36	0.000	4.748516	8.19787
Industry I_{PR}	1381	-8.359104	-0.02	0.983	-795.3617	778.6435
Industry I_E	1381	-28.3394	-0.00	1.000	-18.28541	18.28484

Appendix A: Full regression - Demand

B MNL Regression - Market Segmentation

Market Segmentation, Pseudo$R^2 = 0.1522$, * indicates significance

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Industry - Other Base outcome						
Dependent variable: Industry - Construction and Real Estate						
Interception	1381	-25.8086	-0.03	0.979	-1961.646	1910.029
Price	1381	-0.00040	-0.57	0.570	-0.001776	0.000979
Lounge	1381	15.30438	0.02	0.988	-1920.5	1951.109
Flexible desk	1381	14.27307	0.01	0.988	-1921.053	1950.576
Fixed desk	1381	14.7443	0.01	0.988	-1921.057	1950.546
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date	1381	-0.00256	-0.26	0.796	-0.02199	0.0168652
End date	1381	0.0029983	-0.30	0.762	-0.01645	0.0224428
Length of stay	1381	-25.8086	-0.39	0.694	-0.02358	0.0156933
Dependent variable: Industry - Data and IT						
Interception	1381	8.648408	4.38	0.000	7.781661	12.51515
Price*	1381	-0.00069	-3.24	0.001	-0.001107	-0.00027
Lounge*	1381	-2.59203	-4.31	0.000	-1.770282	-1.413768
Flexible desk*	1381	-1.074502	-270	0.007	-1.855078	-0.29393
Fixed desk	1381	0.0294351	0.13	0.894	-0.40307	0.4619369
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date	1381	-0.00524	-1.03	0.303	-0.01522	0.0047397
End date	1381	0.0048549	0.95	0.340	-0.005118	0.0148279
Length of stay	1381	-0.00495	-0.97	0.331	-0.01494	0.0050342
Dependent variable: Industry - Finance						
Interception	1381	-22.97016	-4.76	0.000	-32.4230	-13.51734
Price	1381	0.0001877	0.56	0.578	-0.00047	0.000849
Lounge	1381	-0.29408	-0.28	0.781	-2.365295	1.777143
Flexible desk	1381	0.1874978	0.25	0.801	-1.267981	1.642977
Fixed desk	1381	-0.313651	-0.76	0.450	-1.127598	0.5002975
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date	1381	-0.00334	-0.62	0.533	-0.01384	0.0071544
End date	1381	0.0043333	0.81	0.418	-0.00616	0.0148242
Length of stay	1381	-0.00372	-0.69	0.487	-0.01423	0.0067809

Variable	n	β	z	P>|z|	Min	Max
Dependent variable: Industry - Consultancy						
Interception	1381	-3.03653	-1.69	0.091	-6.562154	0.4890932
Price*	1381	-.000548	-2.91	0.004	-0.00092	-0.00018
Lounge*	1381	-1.838369	-3.41	0.001	-2.89606	-0.78068
Flexible desk	1381	-.3421368	-0.95	0.345	-1.05165	0.3673761
Fixed desk	1381	-0195438	-0.88	0.380	-0.631344	0.2404675
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date	1381	-0003975	-0.78	0.437	-0.0140	0.0060449
End date	1381	0.0041657	0.82	0.415	-0.00585	0.0141801
Length of stay	1381	-0.00390	-0.76	0.446	-0.013921	0.0061267
Dependent variable: Industry - Marketing and PR						
Interception	1381	18.45987	8.23	0.000	14.06595	22.85378
Price*	1381	-.0012121	-5.42	0.000	-0.00165	-0.00077
Lounge*	1381	-3.297879	-5.29	0.000	-4.51894	-2.07682
Flexible desk*	1381	-0.87384	-2.18	0.029	-1.659322	-0.08837
Fixed desk*	1381	0.707544	3.21	0.001	0.2754483	1.13964
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date	1381	-0.00223	-0.32	0.751	-0.015954	0.011505
End date	1381	0.0013579	0.19	0.846	-0.01235	0.0150617
Length of stay	1381	-0.00106	-0.15	0.880	-0.01479	0.012671
Dependent variable: Industry - Entertainment and Culture						
Interception	1381	-38.7600	-0.08	0.936	-988.253	910.7328
Price*	1381	-0.00155	-4.68	0.000	-0.0022	-0.00090
Lounge*	1381	11.93133	0.02	0.980	-937.5075	961.3702
Flexible desk	1381	14.70758	0.03	0.976	-934.730	964.1455
Fixed desk	1381	654.0875	2.80	0.005	195.8656	1112.309
Room	1381	Omitted	Omitted	Omitted	Omitted	Omitted
Start date*	1381	0.0930021	3.99	0.000	0.0472793	0.1387248
End date*	1381	-0.091778	-3.94	0.000	-0.137395	-0.046161
Length of stay*	1381	0.0912029	3.90	0.000	0.04541	0.1369958

Appendix B: Full regression - Segmentation

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