KADİR HAS UNIVERSITY
SCHOOL OF GRADUATE STUDIES
PROGRAM OF INDUSTRIAL ENGINEERING

A BEHAVIORAL STUDY FOR EXAMINING THE COMPLIANCE OF PRICING MODELS IN REVENUE MANAGEMENT THEORY WITH THE DECISIONS OF HUMAN DECISION MAKERS

CÜNEYT ERKOL

MASTER OF SCIENCE THESIS

ISTANBUL, AUGUST, 2020

Cüneyt Erkol Master of Science Thesis 2020

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MASTER OF SCIENCE THESIS

Submitted to the School of Graduate Studies of
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Master of Science in Industrial Engineering.

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ABSTRACT

This study involves four computer-based experiments based on different assumptions which are performed in a laboratory-setting. The behavior patterns of the subjects and the degree of deviation of these behaviors from optimal strategies are analyzed by various statistical methods. The common aim of the experiments examined in this thesis is to understand how successful Revenue Management theoretical models are in explaining real human behavior. In various cases, it has been possible to determine in which direction deviations from theoretical models occur and causes can be understood. In static competitor price treatment (in experiments 1 and 2), subjects exhibit a higher tendency to underprice. The "gambler's fallacy" bias is the dominant behavioral pattern observed in dynamic price setting. Humans consistently make pricing decisions below theoretical optimum, and only a small minority of the subjects are able to make optimum pricing decisions, supporting the presence of bounded rationality. Higher cognitive reflection skills help perform decisions closer to optimal, although not significantly better. Maximizing tendency does not show significance in meeting neither the optimum price, nor the potential revenue. Higher risk appetite makes better decisions in a dynamic competitor price setting. Neither the impact of learning effect, nor the demand-chasing bias is prevalent in the findings. Anchoring on the competitor price is observable in dynamic price setting. The study is useful in revealing the human factor issues that companies aiming to increase their profitability should pay attention to. Furthermore, the study can also be helpful in determining information to be provided to decision makers by an effective decision support system, and it proposes recommendations regarding the measures companies can take to improve human decision makers' decisions.

Keywords: Revenue Management, Behavioral Operations Management, Cognitive Reflection, Maximizing Tendency, Risk Appetite, Pricing

GELİR YÖNETİMİ TEORİSİNDEKİ FİYATLANDIRMA MODELLERİNİN İNSAN KARAR VERİCİLERİN KARARLARIYLA UYUMUNU İNCELEMEK İÇİN BİR DAVRANIŞSAL ÇALIŞMA

ÖZET

Bu çalışma, laboratuvar ortamında yapılan ve farklı varsayımlara dayanan dört bilgisayar tabanlı deney gerçekleştirmektedir. Deneklerin davranış kalıpları ve bu davranışların optimal stratejilerden sapma derecesi çeşitli istatistiksel yöntemlerle analiz edilmektedir. Bu tezde incelenen deneylerin ortak amacı, Gelir Yönetimi teorik modellerinin gerçek insan davranışlarını açıklamada ne kadar başarılı olduğunu anlamaktır. Teorik modellerden hangi yönde sapmaların meydana geldiğini ve nedenlerinin anlaşılabileceğini belirlemek mümkün olmuştur. Rakip fiyatının sabit olduğu düzenekte (deney 1 ve 2'de), denekler düşük fiyatlandırma eğilimi göstermişlerdir. "Kumarbazın yanılgısı", dinamik rakip fiyatı düzeneğinde gözlemlenen baskın davranış kalıbıdır. İnsan karar vericiler ısrarla teorik optimumun altında fiyatlandırma kararları almakta olup, deneklerin yalnızca küçük bir azınlığının optimum fiyatlandırma kararları verebilmesi, sınırlı rasyonalitenin varlığını desteklemektedir. Daha yüksek bilişsel yansıtma becerileri, önemli ölçüde daha iyi olmasa da, optimal olana yakın kararlar almaya yardımcı olmuştur. Ençoklama eğilimi yüksek karar vericiler, ne optimum fiyatı bulmakta ne de potansiyel gelire ulaşmakta yetkindir. Daha yüksek risk iştahı olan karar vericiler, dinamik rakip fiyatı düzeneğinde daha iyi kararlar verir. Bulgularda ne öğrenme etkisi, ne de talep peşinde koşma önyargısı yaygın görülmüştür. Dinamik fiyatlandırma düzeneğinde rakip fiyat üzerine çıpa etkisi gözlemlenmiştir. Çalışma, kârlılıklarını artırmayı hedefleyen firmaların dikkat etmesi gereken insan faktörü konularının ortaya çıkarılması açısından faydalıdır. Ayrıca çalışma, etkili bir karar destek sistemi tarafından karar vericilere sağlanacak bilgilerin belirlenmesinde yardımcı olabilir ve şirketlerin insan karar vericilerin kararlarını iyileştirmek için alabilecekleri önlemlere ilişkin öneriler sunar.

Anahtar Sözcükler: Gelir Yönetimi, Davranışsal İşlemler Yönetimi, Bilişsel Yansıma, Ençoklama Eğilimi, Risk İştahı, Fiyatlandırma

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To my mother and father

for encouraging me to pursue my academic goals further

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1. INTRODUCTION

Despite the popularity of Revenue Management, some behavioral assumptions underlying the models have not been studied so far. The extent to which the decision support systems (DSS) developed on the basis of theoretical models are taken into consideration by the decision maker for the optimal value proposals has not been tested extensively. However, few behavioral studies in this area indicate that real human decisions can be quite different from the decisions predicted by theoretical models, and therefore profitability rates can vary greatly. Practical applications of pricing models within the scope of Revenue Management are almost never studied. Nevertheless, considering that one percent more accurate pricing can increase operational profitability up to an average of seven percent, it is clear that this issue should receive more attention (Jacobson et al., 2012).

This thesis aimed to test the extent to which real human behavior fits within the theoretical pricing models in the field of Revenue Management and to develop behavioral models to explain various deviations. In this sense, the study aims to measure the differences between theory and practice in the field of pricing and to detect systematic errors in the decision-making behavior of human decision makers.

The method used is a set of computer-based experiments that are carried out in a laboratory environment. Within the scope of the study, four experiments based on different assumptions were defined. The data obtained from these experiments are analyzed and the behavior patterns of the subjects and the extent to which these behaviors deviate from the optimal strategies are analyzed by various statistical methods. Similar studies have been carried out in other areas of operations management (e.g., supply chain management, inventory management, etc.), but pricing has been studied very little in the literature and this study aims to eliminate a significant deficiency in the literature in this respect.

The common purpose of the experiments studied in this thesis is to understand how successful Revenue Management theoretical models are in explaining real human behavior. In various cases, it was possible to determine the direction of deviations and the type of information an efficient DSS to be developed should provide decision makers. In addition, firms are able to have more accurate information on issues such as how to limit the decisions left to decision-makers, how to determine different price ranges offered to customers more accurately, or how to have more realistic income expectations. The thesis is related to many research fields such as behavioral operations management, income management and pricing models, and even psychology and, in that sense, has an interdisciplinary nature.

2. LITERATURE REVIEW

The literature that is related to this thesis is highly widespread. The related papers will be discussed in four subsections.

2.1. Revenue Management

The history of revenue management (RM) literature can be traced back to Airline Deregulation Act of United States in 1978 which led to less controlled airline pricing and motivated innovative research in optimum pricing strategies (Chiang et al., 2007). Airline revenue management systems have been developed and multi-criteria pricing strategies have flourished ever since. The methods that can be used for revenue management in various businesses are extensively discussed in the book called *Revenue Management: Hard-core Tactics for Market Domination* written by Robert G. Cross (1997). Although revenue managements systems (RMS) have initially started in the airline industry, they are now widely used for hospitality sector as well as car rentals and many others. Revenue maximization and cost savings are realized thanks to revenue management systems: Marriott Hotel acquired an additional US$100 million per year (Cross, 1997). Boyd (1998) states that revenue management resulted in an increased revenue of US$300 million and US$500 million for Delta Airlines and US Airlines, respectively.

According to Chiang et al. (2007), there are three traditional industries where revenue management has been widely applied: airlines, hospitality, and car rentals. The common characteristics of these industries are large fixed costs, significant variations in demand, and time-sensitive product life. However, these industries have not been the only ones where RM research has been applied in various sectors with similar characteristics have been subject to revenue management theories and applications. Berman (2005) states that RM is an effective mechanism to allocate limited capacity of a service provider and to apply discounts on a larger scale.

2.2. Pricing Models

Revenue management (RM) problems can be categorized into various (but also highly inter-related) subsections, such as pricing, auctioning, forecasting, overbooking, capacity control, etc. Pricing models are the fundamental areas of research that constitute a big portion of RM problems, regarding determining the correct price to correct customer, and varying price in order to maximize revenue over time.

The effect of pricing models for revenue management is discussed broadly by Bitran and Caldentey (2003). Dynamic pricing strategy results in neutral or positive effect in revenue increase, but it decreases the cost of transactions and process complexity (Burger and Fuchs, 2005). Baker and Collier (1999) state that pricing setting method (PSM) performs much better than bid price method (BPM) in 27 out of 32 cases investigated. They also conclude that PSM causes a 34% increase in revenues on average.

2.3. Behavioral Operations Management

The main concern of Operations Management (OM) is designing and managing transformation processes in manufacturing and service organizations, establishing the mathematical theory of the interested phenomena, and testing the theory with data collected from the field. Behavioral Operations Management ("Behavioral OM" shortly) is a multidisciplinary OM branch evaluating human behavior's effects on process performance that is affected by cognitive biases, social preferences, and cultural norms (Loch and Wu, 2005).

Bearden et al. (2008) delivered the first study related to behavioral models in RM. The authors examined the problem of a decision maker selling a set of identical products under uncertain demand. In its context, customers differ in their willingness to pay for the product, and each incoming customer offers a price quote for purchasing one unit of the product. The seller must decide whether he will accept each offer. The authors point to three experiments with difference in parameters and investigate the vendor's decision-making framework. The experiment results highlight the importance of bounded rationality of decision makers in complex settings.

Bendoly (2011) uses a resembling setup to study the effect of feedback on the responses of decision makers involved in RM tasks by measuring their physiological responses. The author argues that the framework for the feedback is crucial in determining the subjects' decisions and the revenue levels achieved.

Kocabıyıkoğlu et al. (2015) explore decision-making behaviors and two-class revenue management models using the newsvendor problem. The authors find that decision-makers in both problems behave very differently from the normative theory. They state that RM allocation decisions are consistently larger than orders received from the newsvendor and argue this is due to the overage cost. The authors indicate that increased fluctuations in demand trigger increase in allocations and this behavior is in parallel with normative schemes where the sales price ratio of the two customer segments is less than half. In case this ratio is greater than 0.5, the opposite behavior is observed. On the other hand, the behavior of newsvendors in relation to changes in demand volatility is in line with the normative trends.

Kocabıyıkoğlu et al. (2016) present a study where decision makers are required to make two decisions, determining the selling price as well as the order quantity of a product. This joint decision-making setup is benchmarked against two conditions where subjects decide single-handedly on either price or quantity. The anchoring effect is observed on the expected demand when subjects decide on quantity, and also on the initial inventory level when subjects decide on price.

Akbay and Ayvaz Çavdaroğlu (2020) present another joint decision-making study in a two-class airline setting where subjects decide on the business class price and the protection level (the economy class price is fixed). This setup is benchmarked against a single decision treatment where subjects decide on the business class price while the protection level is calculated automatically. The authors conclude that pricing decisions, even for joint decisions treatment, do not differ significantly from the optimal. In case of determining the protection level, decisions significantly deviate from the optimal. The authors detect a “too low-too high” pattern by considering two levels for the economy class price and concluding that, low and high price conditions result in protection levels below and above the optimal, respectively. Detected behavioral biases include anchoring effect for not only pricing, but also protection level decisions. The authors discuss the importance of personality traits of subjects and reveal that higher cognitive reflection skills significantly affect experiment performance.

Cesaret and Katok (2018) examine the problem of capacity allocation with ordered and unordered arrivals, as well as a simplified version in which the decision maker has already made a single capacity allocation decision. The authors conclude that subjects generally accept too many low-type clients, leave too few unused capacity, and thus, serve very few high-type clients. The authors also state that up-front decision-making cause a significant performance improvement in ordered arrivals and does not degrade performance in unordered arrivals. Their study develops a behavioral choice model taking the regret element into account. Cesaret and Katok's study covers only static price treatment; whereas, this study covers both static and dynamic price treatments.

2.4. Cognitive Biases

Frequently-encountered biases in behavioral operations management literature are summarized in the following sub-sections.

2.4.1. Anchoring Effect

Teovanović (2019) defines "anchoring effect" as "a systematic influence of initially presented information on subsequent judgments, even when presented initial information is irrelevant, and arbitrary". Tversky and Kahneman (1974) introduced a two-step procedure to detect the presence of anchoring effect: First, people are asked to decide whether certain amounts are greater or less than a certain value that is generated randomly by spinning a wheel of fortune. Subjects were then asked to provide their own numerical estimates for the same amount. The results showed that the random values had a significant effect on the participants' estimates. This is called the "anchoring effect" and the term is frequently used in behavioral operations management literature.

2.4.2. Bounded Rationality

When humans make decisions, their rationality is limited by various factors such as the time available to come up with a decision, the cognitive limitations of their intellect, and the ability to understand the problem ("Bounded Rationality", 2020). Simon (1957) states that the majority of people are limitedly rational, and they are rather irrational during the remaining part of their actions. The term "bounded rationality" is widely used in behavioral operations and it is accepted that people make shortcuts in their reasoning, and these shortcuts carry the risk of leading to poor decision-making. Simon (1957) also argues that, when faced with a complex situation, economic agents refer to heuristics for making decisions instead of following a guideline for optimization.

2.4.3. Demand-Chasing Bias

“Chase Demand” is a strategy used in production operations management. Slack et al. (2016) define the term as “an approach to medium-term capacity management that attempts to adjust output and/or capacity to reflect fluctuations in demand”. This strategy gave rise to a new terminology in behavioral OM, “demand-chasing bias”.

Research on newsvendor behavior asserts that subjects tend to adopt a demand-following behavior, that is, they adjust order quantities by taking prior demand into consideration. Even though demand is stochastic in the newsvendor problem, subjects behave as if past demand values have some kind of an informative value with regards to future demand; as a consequence of which, their order quantities chase prior demand values.

2.4.4. Gambler’s Fallacy

Gambler’s Fallacy, also known as the Monte Carlo Fallacy, is a mistaken belief that if a certain event occurred less often than usual in the past, it is more likely to occur in the future (or vice versa).

Even though such events are purely coincidental and statistically independent from each other, the subject has an inaccurate understanding of probability. This erroneous judgement regarding the likelihood of upcoming events is a cognitive bias.

Gambler’s Fallacy is a frequently-used behavioral term in investing. For instance, the presence of a long-term increasing trend in a stock price creates such a belief that its position is more likely to decline very soon. Consequently, after a series of successive gains, investors choose to liquidate their position (Gambler’s Fallacy, 2019).

3. THEORETICAL MODEL

3.1. Theoretical Model of Experiments 1 and 2

In the first experiment there is only one customer class and there is a competitive linear pricing model. Customer demand varies depending on the price determined by the subject and the price (p_1) of another competitive firm that exists in the environment. Assuming that the subject knows the price of the other firm (and this price remains constant throughout the decision-making process), it is possible to determine the price that will maximize profit by solving an optimization problem to be modeled. The focus of Experiment 1 is how the subject will determine the price (p_2). In Experiment 1, the price chosen by the competitive firm was relatively low (p_1=30) and in Experiment 2, the price chosen by the competitive firm was relatively high (p_1=120). Thus, understanding the impact of the observed competitive price on pricing decisions becomes a newly-achieved outcome.

In scenarios of Experiments 1 and 2, there is a single customer class and there is a competitor company in the environment. The price applied by the competing firm, p_1, is predetermined and fixed. The price offered by the current firm, p_2, is determined by subjects. The average of the company's customer demand distribution, $\overline{D}$, depends on the price to be determined and is formulated as $\overline{D} = K - mp_2 + np_1$. The distribution gap width is fixed at w where w is lower in the first half of the experiment while it is doubled in the second half of the experiment to study the effect of demand variance on the decisions of the subjects. In these experiments, after the subject has made the pricing decision, the random customer demand takes place and the next season starts with the calculation of the profit obtained and the decision season is concluded. The subjects decide for 43 seasons in total, three warm up seasons and 40 actual seasons that are accounted for in computing the total revenue. In the first experiment, the competitive price is relatively low (p_1 = 30). In the second experiment, the competitive price is relatively high (p_1 = 120).

Parameters of this setting are as follows:

- F(.): cumulative discrete uniform distribution for the demand defined on the range $\left[\overline{D} - \frac{w}{2}, \overline{D} + \frac{w}{2}\right] = [150 - 2p_2 + p_1, 250 - 2p_2 + p_1]$ in the first 20 (3.1) seasons and $\left[\overline{D}-\frac{w}{2},\overline{D}+\frac{w}{2}\right]=[100-2p_2+p_1,300-2p_2+p_1]$ in the last 20 seasons (3.2)

- C: total capacity, assumed to be 150 units
- p_1: competitive firm's price, assumed to be 30 in experiment 1, 120 in experiment 2
- w=100 in the first twenty and 200 in the last twenty seasons
- $\overline{D}=K-mp_2+np_1=200-2p_2+p_1$ (3.3)

Variables:

- Price determined for the current company
- Profit obtained
- The ratio of profit to optimal profit
- Expected profit
- The ratio of expected profit to optimal profit

While the distribution of demand is as follows:

$$D=K-mp_2+mp_1+\varepsilon,\ \varepsilon\sim U\left[-\frac{w}{2},\frac{w}{2}\right] \tag{3.4}$$

Accordingly, the lower and upper limits of demand D, $a(p_2)$ and $b(p_2)$ values change as follows:

$$a(p_2)=\overline{D}-\frac{w}{2}=K-mp_2+mp_1-\frac{w}{2} \tag{3.5}$$

$$b(p_2)=\overline{D}+\frac{w}{2}=K-mp_2+mp_1+\frac{w}{2} \tag{3.6}$$

Theoretically, in an environment where two identical competitive firms exist, both firms must solve the following optimization problem:

$$\max_{p_i}\{p_iE[D]\}=\max_{p_i}\left\{p_i\left[\int_{\frac{-w}{2}}^{C-K+mp_i-np_j}\left(K-mp_i+np_j+\varepsilon\right)\frac{1}{w}d\varepsilon+\int_{C-K+mp_i-np_j}^{\frac{w}{2}}C\,\frac{1}{w}d\varepsilon\right]\right\},\qquad i,j=1,2 \tag{3.7}$$

The optimal price in this case is manifested as $p_1^*=p_2^*$. However, the behavioral operations management literature did not study whether human decision-makers can determine their optimal prices while maintaining their rationality, if the other firm does not act rationally and gives prices below or below optimal. According to the parameters set, the optimal price that the subjects should determine in the application of low competitive price (p_1=30) is 60 in first 20 seasons and 64 in last 20 seasons, whereas in the application of high competitive price (p_1=120), the optimal price value is 94 in first 20 seasons and 95 in last 20 seasons.

3.2. Theoretical Model of Experiments 3 and 4

The focus of Experiments 3 and 4 is how to determine the price (p_2) in an environment where the subject encounters a variable competitor price. Customer demand varies depending on the price determined by the subject and the changing price (p_1) of another competitive firm that exists in the environment.

In these experiments, the price of the other firm changes throughout the decision-making process. There were two applications that have changed in directions. In the third experiment, the competitor firm increases its price by thirty monetary units in every ten seasons (p_1 = 30 in the first 10 seasons, 60 in the second 10 seasons, 90 in the third 10 seasons and 120 in the last 10 seasons). Whereas in the fourth experiment, the competitor firm reduces its price by thirty monetary units in every ten seasons (p_1 = 120 in the first 10 seasons, 90 in the second 10 seasons, 60 in the third 10 seasons and 30 in the last 10 seasons).

The focus of both experiments is how the subject will determine the price (p_2). Thus, the achieved outcome is understanding whether decision makers can determine pricing decisions at the right level, as the factor in the environment (i.e. the competitor firm's price) changes dynamically.

In these experiments, the demand distribution range, [a (p_1, p_2), b (p_1, p_2)], is arranged as follows:

For 40 seasons: [a (p_1, p_2), b (p_1, p_2)] = [150 + p_1 - 2 x p_2, 250 + p_1 – 2 x p_2] (3.5)

In both experiments, the price offered by the current firm, p_2, is determined by subjects. The average of the company's customer demand distribution depends on the seat price to be determined by the formula $\overline{D} = K - mp_2 + np_1$. The distribution gap width is fixed at w. In both experiments, after the subject has made the pricing decision, the demand of the random customer takes place and the next round starts with the calculation of the profit obtained and the decision round is concluded. The subjects decide for 43 rounds in total, 3 warm up rounds + 40 rounds. In the third experiment, the competitive price is gradually increased for every ten seasons (p_1 = 30 → 60 → 90 → 120). In the fourth experiment, the competitive price is gradually increased for every ten seasons (p_1 = 120 → 90 → 60 → 30).

Parameters are as follows:

- F(.): $[\bar{D}-\frac{w}{2}, \bar{D}+\frac{w}{2}] = [150-2p_2+p_1, 250-2p_2+p_1]$ this is the range for discrete uniform distribution (3.8)
- C: 150
- p_1: 30→120 or 120→30
- w = 100
- $\bar{D} = K - mp_2 + np_1 = 200 - 2p_2 + p_1$ (3.9)

Variables:

- Price determined for the current company
- Profit obtained
- The ratio of profit to optimal profit
- Expected profit
- The ratio of expected profit to optimal profit

While the distribution of demand is as follows:

$$D = K - mp_2 + mp_1 + \varepsilon,\ \varepsilon \sim U\left[-\frac{w}{2}, \frac{w}{2}\right] \tag{3.10}$$

Accordingly, the lower and upper limits of demand D, $a(p_2)$ and $b(p_2)$ values change as follows:

$$a(p_2) = \bar{D} - \frac{w}{2} = K - mp_2 + mp_1 - \frac{w}{2} \tag{3.11}$$

$$b(p_2) = \bar{D} + \frac{w}{2} = K - mp_2 + mp_1 + \frac{w}{2} \tag{3.12}$$

The theoretical model is the same as in Experiment 2. According to the parameters set, in the application of increasing competitive price (i.e. Experiment 3), the optimal price that the subjects should determine is 60 in seasons 01-10, 71 in seasons 11-20, 82 in seasons 21-30, 93 in seasons 31-40. Whereas in the application of decreasing competitive price (i.e. Experiment 4), the optimal price that the subjects should determine is 93 in seasons 01-10, 82 in seasons 11-20, 71 in seasons 21-30, and 60 in seasons 31-40.

4. EXPERIMENTAL SETUP

4.1. Theoretical Benchmarks of Experiments

The experiment scenarios are based on a one-class airline context (while observing the second airline's competitive price decisions), because revenue management is frequently practiced in airline industry. The subjects acquire the role of an Airline Sales Director and they are asked to determine the price of economy class seats in order to maximize their revenue by observing the price of a competitor airline in the environment. The experiments are designed in such a way that environmental factors are gradually changing. The external parameters are initially kept simple and relatively static, and these parameters are gradually changed more and more to increase the complexity of decision-making environment. The experimental setup is summarized in Table 1. The static competitor price treatment is designed to limit the environmental parameters to one single variable, the distribution gap width, *w*. In the dynamic competitor price treatment, the distribution gap width is kept constant; however, this time, the competitor changes its price linearly by thirty monetary units in every ten seasons, respectively (Table 1).

Table 1 Summary of the Experimental Setup

Static Competitor Price Treatment		Dynamic Competitor Price Treatment	
Experiment 1	**Experiment 2**	**Experiment 3**	**Experiment 4**
$p_1 = 30$	$p_1 = 120$	p_1 =30 for seasons 01-10 60 for seasons 11-20 90 for seasons 21-30 120 for seasons 31-40	p_1=120 for seasons 01-10 90 for seasons 11-20 60 for seasons 21-30 30 for seasons 31-40
w : The distribution gap width *w* =100 for seasons 01-20 200 for seasons 21-40	*w* =100 for seasons 01-20 200 for seasons 21-40	*w* = 100 (fixed)	*w* = 100 (fixed)
Optimal p_2^* = 60 in seasons 01-20 64 in seasons 21-40	Optimal p_2^* = 94 in seasons 01-20 95 in seasons 21-40	Optimal p_2^* = 60 for seasons 01-10 71 for seasons 11-20 82 for seasons 21-30 93 for seasons 31-40	Optimal p_2^* = 93 for seasons 01-10 82 for seasons 11-20 71 for seasons 21-30 60 for seasons 31-40

In the first two experiments, the competitive price is static, with a low price level ($y_1=p_{1,1}$[1]=30) and a high price level ($y_2=p_{1,2}=120$), respectively. The theoretical benchmarks for Experiments 1 and 2 are summarized in Table 2.

Table 2 Theoretical benchmarks for Experiments 1 and 2

		Experiment 1	**Experiment 2**
	The Competitor Price (p_1)	30	120
	Price Decision Interval	[0,140]	[0,140]
Seasons 01-20	**Optimal Price (p_2^*[2])**	60	93
	Demand Range	[60, 160]	[92, 192]
	Expected Demand	110	132
	Potential Revenue	6,600	12,408
Seasons 21-40	**Optimal Price (p_2^*[2])**	64	95
	Demand Range	[2, 202]	[30, 230]
	Expected Demand	102	130
	Potential Revenue	6,528	12,350

In the last two experiments, the competitive price is dynamic and subject to increase ($y_3=p_{1,3}=30 \rightarrow 120$) or decrease ($y_4=p_{1,4}=120 \rightarrow 30$) by thirty monetary units in every ten seasons, respectively. The theoretical benchmarks for Experiments 3 and 4 are summarized in Table 3.

Table 3 Theoretical benchmarks for Experiments 3 and 4

		Experiment 3	**Experiment 4**
	Price Decision Interval	[0,140]	[0,140]
Seasons 01-10	**The Competitor Price (p_1)**	30	120
	Optimal Price (p_2^*)	60	93
	Demand Range	[60, 160]	[84, 184]
	Expected Demand	110	134
	Potential Revenue	6,600	12,462
Seasons 11-20	**The Competitor Price (p_1)**	60	90
	Optimal Price (p_2^*)	71	82
	Demand Range	[68, 168]	[76, 176]
	Expected Demand	118	126
	Potential Revenue	8,378	10,332

[1] $p_{1,j}$=The price value "p_1" determined by the competitive firm during seasons of Experiment "j", j={1,2,3,4}
[2] p^*=The optimum price value determined by the theoretical model

Seasons 21-30	**The Competitor Price (p_1)**	90	60
	Optimal Price (p_2^*)	82	71
	Demand Range	[76, 176]	[68, 168]
	Expected Demand	126	118
	Potential Revenue	10,332	8,378
Seasons 31-40	**The Competitor Price (p_1)**	120	30
	Optimal Price (p_2^*)	93	60
	Demand Range	[84, 184]	[60, 160]
	Expected Demand	134	110
	Potential Revenue	12,462	6,600

In all four experiments the number of seats to be sold is fixed as 150 seats. The customer demand is randomly determined with respect to a discrete uniform distribution on the intervals given in the previous section. This form of demand function is broadly used in environments where two prices define the demand of some good (Akbay and Ayvaz Çavdaroğlu, 2000).

The "demand that subjects observe" and the "amount of seats sold" change according to the price ($p_{2,j}$[3]) set by the airline sales director (i.e. the subject). If the realized demand happens to be greater than the number of seats available, only as many as the total number of seats are sold.

4.2. Profile of Experiment Subjects

All experimental applications were carried out with a group of students from Kadir Has University and Istanbul Technical University. The subjects were chosen among a group of undergraduate students studying in business, international trade and finance, management information systems, industrial engineering, and civil engineering. Candidates were required to have taken and passed basic mathematics and statistics courses as a pre-condition to participate in the experiment. No statistical difference was observed between the experimental performances of students studying in different departments and/or different universities.

[3] $p_{2,j}$=The average price value "p_2" determined by the subject during seasons of Experiment "j", j={1,2,3,4}

4.3. Recruitment Process of Experiment Subjects

Initial announcements to call for voluntary participants were delivered to students through posters posted on university boards and via Twitter social media account called "@hadigeloyna". The poster design can be seen in Figure 1.

The students who were eligible to participate in the experiment were first sent instructions explaining the experiment via electronic mail. They were then asked to fill out a questionnaire to measure their risk appetite, their optimal search motives and their cognitive skills. After filling out the questionnaire, subjects were then invited to the experiment.

4.4. Organization of Experimental Sessions

The experimental sessions were held in the computer laboratories of Kadir Has University. Upon their arrival, subjects were first asked to sign a "Participant Consent Form" and their approval was obtained. Then, the experiment was thoroughly explained once again. The instructions given to the subjects during the experiments are included in Appendix B. It should be noted that the instructions are prepared in Turkish, since the experiments are carried out with subjects whose native language is Turkish.

Experimental sessions lasted an average of one hour; they were carried out by allowing each participant to play the game at the same time and without being affected by or speaking to each other.

Figure 1 Poster design calling for voluntary participants

4.5. Monetary Budget used for Experiments

Since the budget allocated to the subjects within the scope of the budget of the TÜBİTAK research project envisages to give an average of 50 Turkish Liras (TL), pilot experiments were made without the participation fee to a group of undergraduate students tutored by the thesis advisor. Pilot experiments showed that the total budget would be sufficient for conducting all experiments. In order to reach more participants for data collection, the net value of the participation fees is decided as 50 TL on average; the fee varying between 40, 50, 60 or 70 TL according to the subjects' performance on total sales revenue.

4.6. Usage of Software for Data Collection

The experiments are conducted by using Visual Basic for Application (VBA) with Microsoft Office Excel software. The designed interface includes textboxes for the subject to input their name, their school number, and their price value for the corresponding season. The interface also informs the subject about the competitor's price (p_1), the number of available seats (150), the price (p_2) range allowed to enter, as well as the range of customer demand relative to the considered ticket price (p_2).

In the middle of the screen there is a "Decision Support Tool", which helps the subjects to conduct a "what-if" analysis by comparing the demand range to be determined by the ticket price and the corresponding revenue that can be potentially made as a result of possible demand values. The decision support tool provides a list of potential demand values increasing ten by ten, ranging between 0 and 150, i.e. the minimum and maximum number of seats available to be sold. The subject is able to see how many seats they would sell in case of which demand value, and how many seats would then be left empty. The revenue related to the potential demand values are also presented to the decision makers. Once the subject makes their decision, they finalize the price for the corresponding season by pressing the button entitled "Record Ticket Price". An exemplary user interface can be observed in Figure 2. It should be noted that the interface is designed in Turkish language.

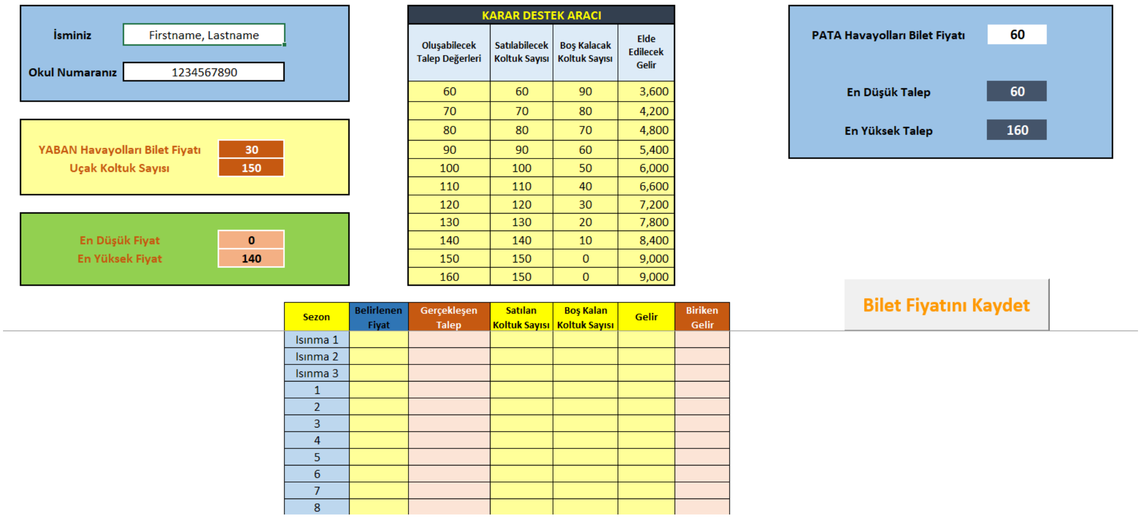

Figure 2 Sample user interface that subjects interact with during experiments

4.7. Statistical Methods Used for Data Analysis

There are three statistical methods used for analyzing the collected data. These are summarized in the following sub-sections:

4.7.1. The Two-Tailed Wilcoxon Signed Rank Test

The Wilcoxon Signed Rank Test is used in order to compare two sets of scores that come from the same sample. Our study contains a static competitor price treatment with two experiments, in which, the distribution gap width is widened at the second half of the treatment. Therefore, the data at the second half of this treatment is generated by the same sample, only with a change in environmental factor, (i.e. "*w*"). The Wilcoxon Signed Rank Test permits the researchers to investigate any change in revenues from the first half to the second half of the treatment, when subjects are faced with a changing environmental condition. The Wilcoxon Signed Rank Test reveals whether there was a difference in realized price average and/or realized revenue under two different demand variance.

For the Wilcoxon Signed Rank Test, both samples must be of equal size. This test is used for the generation of the majority of data presented in the upcoming tables, unless otherwise specified.

4.7.2. The Wilcoxon Rank-Sum Test

When the effects of personality traits are examined, the sample sizes of all four experiments are grouped into two distinctive sub-groups with respect to the subjects' score on cognitive reflection skills, maximizing tendencies, and risk appetites. Because the two sub-groups rarely end up with equal sample sizes, The Wilcoxon Signed Rank Test can no longer be used for conducting a comparative analysis. Therefore, a test that allows comparing two samples with unequal sample sizes is needed, that is the very reason that the Wilcoxon Rank-Sum Test is employed in this study.

The Wilcoxon Rank-Sum Test (a.k.a. The Mann-Whitney U Test) compares whether there is a difference in the dependent variable for two independent groups. For these analyses, the dependent variable is the CRT, MT, and risk scores of the sub-groups. The test controls the distribution of the dependent variable and checks if it is identical in both sub-groups; the presence of identical distribution means that both samples come from the same population.

4.7.3. Linear Regression

Linear regression is an approach to model a relationship between a dependent variable and one or more independent variables. It is a widely-used regression analysis technique to fit a predictive model. This model can then be used when more values of independent variables are collected, in order to forecast the value of the dependent variable. In our study, the independent variables are CRT, MT and risk scores, and a predictive model is fitted in order to estimate future realized price or realized revenue values (i.e. dependent variables) with respect to personality traits, and the expected performance in making good predictions are shown with higher adjusted R-square values.

4.8. Sample Sizes of Experiments

Thirty-two subjects within the scope of Experiment 1 (low competitor price, 30) and thirty-three subjects within the scope of Experiment 2 (high competitor price, 120) participated in the experimental sessions held in the computer laboratories of Kadir Has University. As a result of these first analyzes, all of the experimental data were evaluated as usable, except one subject in Experiment 2. In other words, it was possible to collect healthy and reliable data from 32 and 32 subjects for Experiments 1 and 2 (Table 4).

Thirty-eight subjects within the scope of Experiment 3 (increasing competitor price, 30→120) and thirty-nine subjects within the scope of Experiment 4 (decreasing competitor price, 120→30) participated in the experimental sessions held in the computer laboratories of Kadir Has University. As a result of initial analyzes, one subject in Experiment 3 and two subjects in Experiment 4 were eliminated due to producing unreliable and/or contradictory data. All the remaining experimental data were evaluated as usable. In other words, it was possible to collect healthy and reliable data from 37 and 37 subjects for Experiments 3 and 4 (Table 4).

Table 4 Sample sizes of the Experiments

	Experiment 1	**Experiment 2**	**Experiment 3**	**Experiment 4**
Experiment Name	Low y	High y	Increasing y	Decreasing y
Initial Sample Size	32	33	38	39
Number of Subjects with unreliable and/or contradictory data	0	1	1	2
Concluding Sample Size	**32**	**32**	**37**	**37**
Subject ID Numbers (#)	1,2,…,32	33,34,...,64	65,66,…,101	102,103,…,138

Each subject participated in exactly one experiment. The results obtained as a consequence of the analysis of these data can be summarized with the figures and tables in the following section.

5. EXPERIMENT RESULTS

5.1. Comparison of Experiment Results with Theoretical Benchmarks

This section presents the comparison of the experiments' results with the theoretical benchmarks. Each subject's experiment performance is averaged over forty seasons; therefore, each data point corresponds to the average performance of a single subject. The sample size "n" for the following hypothesis tests are the number of subjects in Experiments 1, 2, 3, and 4. ($n_1=n_2=32$, $n_3=n_4=37$). Comparisons are made thanks to the usage of the two-tailed Wilcoxon signed rank test.

5.1.1. "Static Competitor Price" Treatment

Hypothesis 1: In the "static competitor price" treatment for both competitor price levels ($y_1=p_{1,1}$[4]$=30$ or $y_2=p_{1,2}=120$), subjects' pricing decisions ($p_{2,j}$[5]) will be as predicted by theory.

Table 5 is comparing the results of experiment performance with the theoretical benchmarks for the "static competitor price" treatment. In both Experiments 1 and 2, the realized price average is decreasing although the optimal price values are increasing. In the first twenty seasons of Experiment 1, the mean price value is rather close to the optimum value. However, the visualization in Figure 3 shows that the mean price during the second half of the experiment is decreasing although the optimal price is supposed to be larger. Therefore, human decision makers tend to fall further away from the optimal price values.

During first half of Experiment 2, subjects tend to determine even lower prices when compared with the optimum value. And as the visualization in Figure 4 reveals, at the second half, the mean price is still decreasing, although the median catches the optimum value (Table 5).

According to the results in Table 5, the subjects did not reach statistically different results from the optimal price on average. However, the actual revenue values deviated

[4] $p_{1,j}$=The price value "p_1" determined by the competitive firm during seasons of Experiment "j", j={1,2,3,4}

[5] $p_{2,j}$=The average price value "p_2" determined by the subject during seasons of Experiment "j", j={1,2,3,4}

significantly from the optimal values. The reason for this situation is that the subjects deviate a lot from the optimal in the positive and negative direction in their season-based decisions, while attaining the correct price on average. This situation is also observed in Figures 3 and 4. In the first experiment, the subjects set prices below and above 60 which is the optimal price in the first 20 seasons; in the second 20 seasons, they made price decisions generally below the correct price of 64. In the second experiment, the subjects made pricing decisions that are generally lower than 94 and 95, which are the optimal prices. The same situation is confirmed by individual analyzes shown in Table 6. In fact, although the subjects gave correct prices on average, they were only able to give the correct price individually by approximately 50%, sometimes 34-37%.

One can conclude that there is no sign of a significant learning effect in pricing decisions of subjects when the demand range widens. Except during the second half of Experiment 1, individual deviations are significant in both experiments due to high p-values in realized price averages (Table 5).

Table 5 Comparison results of experiment performance with the optimal thresholds in Experiments 1 and 2

			Experiment Data						Optimal Price	P-value
			N	Min	Max	Mean	Std. Dev.	Median		
Realized Price Average	Experiment 1 (Low y=30)	Seasons 01-20	32	41.45	84.65	60.6031	9.5168	60.25	60.00	0.6671270
		Seasons 21-40	32	33.75	89.70	59.1813	12.4556	60.10	64.00	0.0225290
	Experiment 2 (High y=120)	Seasons 01-20	32	73.40	117.90	92.4906	11.1540	92.25	94.00	0.2950000
		Seasons 21-40	32	49.00	116.85	91.4797	14.6640	94.93	95.00	0.2780950
			Experiment Data						Potential Revenue	P-value
			N	Min	Max	Mean	Std. Dev.	Median		
Realized Revenue	Experiment 1 (Low y=30)	Seasons 01-20	32	4,177.89	6,190.40	5,749.12	463.14	5,919.30	6,600.00	0.0000008
		Seasons 21-40	32	4,065.00	6,965.29	5,825.90	621.82	5,953.76	6,528.00	0.0000040
	Experiment 2 (High y=120)	Seasons 01-20	32	9,094.05	11,466.20	10,642.99	652.28	10,875.38	12,408.00	0.0000008
		Seasons 21-40	32	7,004.25	11,620.00	10,115.16	814.77	10,340.73	12,350.00	0.0000008

P-values are obtained from two-tailed Wilcoxon signed ranked test. [Sample size is 32 for low y=30 and for high y=120.]

An individual level analysis presented in Table 6 reveals that pricing decisions of subjects tend to vary even more, when the demand range is largened. This is another sign of the lack of learning effect, that one would expect to see. The average price over the periods for experiment 1, visualized in Figure 3, show that there are significant deviations even on the seasonal average level. At the first half of the experiment, the average price fluctuates above and below the optimum price, and at the second half, the average price consistently falls under the optimum. A similar observation applies to Experiment 2, as displayed in Figure 4.

Table 6 Individual level comparison of pricing decisions with the optimal in Experiments 1 and 2

			# of Subjects with		
			P Value ≤ 0.05	P Value > 0.05	Total
Experiment 1 (Low y=30)	Realized Price Average	Seasons 01-20	17	15	32
		Seasons 21-40	11	21	32
Experiment 2 (High y=120)	Realized Price Average	Seasons 01-20	12	20	32
		Seasons 21-40	16	16	32

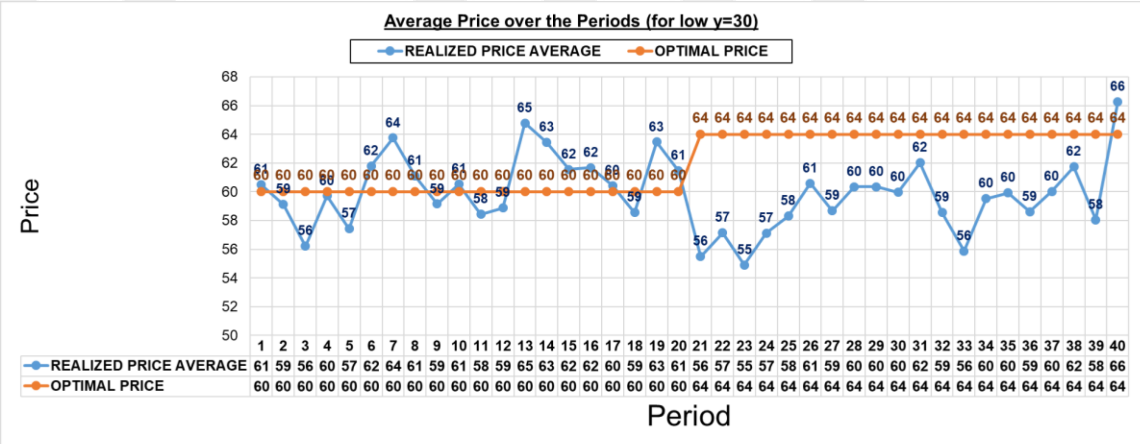

Figure 3 Average price over the periods for Experiment 1

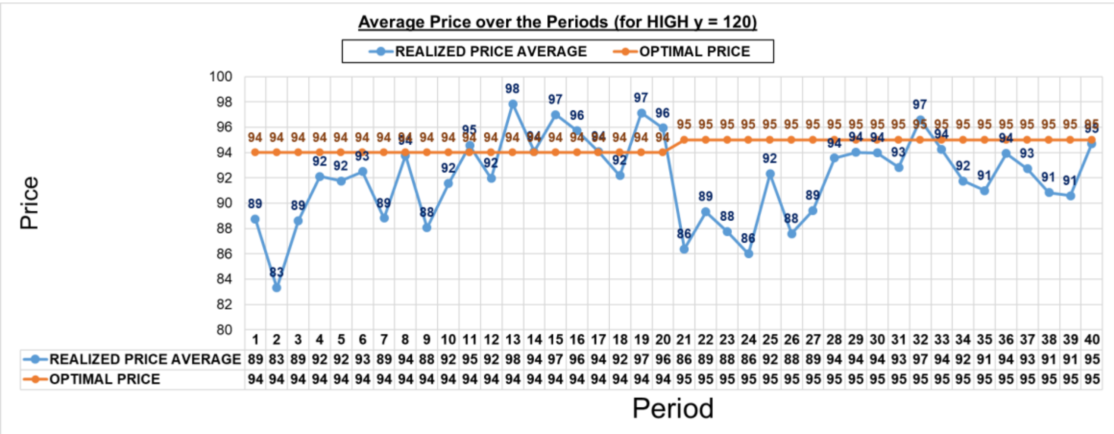

Figure 4 Average price over the periods for Experiment 2

Overall, Hypothesis 1 found rather weak support on the average data; besides, the individual level analysis indicated that the hypothesis is again weakly supported. It is because, not only in the first experiment (y = 30), the average price is lower than optimal, but also in the second experiment (y = 120) the average price is still lower. On top of that, human decisions cause the average price to decrease further in the second half of both experiments.

Hypothesis 2: In the "static competitor price" treatment for both competitor price levels, subjects' realized revenues will be as predicted by theory.

In terms of realized revenue, the mean realized revenue values fall behind the potential revenue values in both experiments. Although one can see the positive signs of a learning effect in terms of an increased realized revenue, when comparing the mean values at the first and second half of Experiment 1, the difference between theoretical prediction and the realized revenue average are significant.

When there is no significant deviation from the optimal prices and the demand is random instead of being consistently lower than expected, the presence of low realized revenues indicates that pricing is consistently incorrect. Even though subjects gave the correct price on average, the total revenue remained low due to season-to-season variations. Since realized demand values are determined under a discrete uniform distribution, the visualization of demand values in Figure 5 and Figure 6 is logical and predictable.

Thanks to the discrete uniform distribution of demand values, one can observe the presence of realized revenues approximate to the potential revenues, as depicted in Figure 7. The mean realized revenue at the second half of experiment 2 is even less than the mean at the first half, this trend can also be observed in Figure 8.

The terms used in Figures 7 and 8 are defined as follows. "Realized Revenue" is calculated by multiplying the realized price average and the realized demand average in corresponding season. "Potential Revenue" is calculated by multiplying the theoretically optimal price and the theoretically expected demand for the corresponding season. Lastly, "Optimal Realized Revenue" is the value obtained by multiplying the theoretically optimal price and the realized demand average in corresponding season.

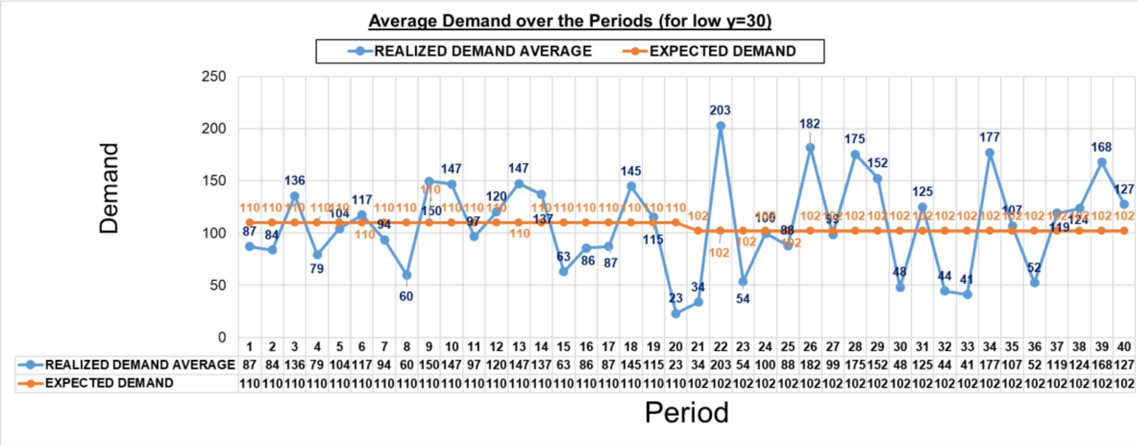

Figure 5 Average demand over the periods for Experiment 1

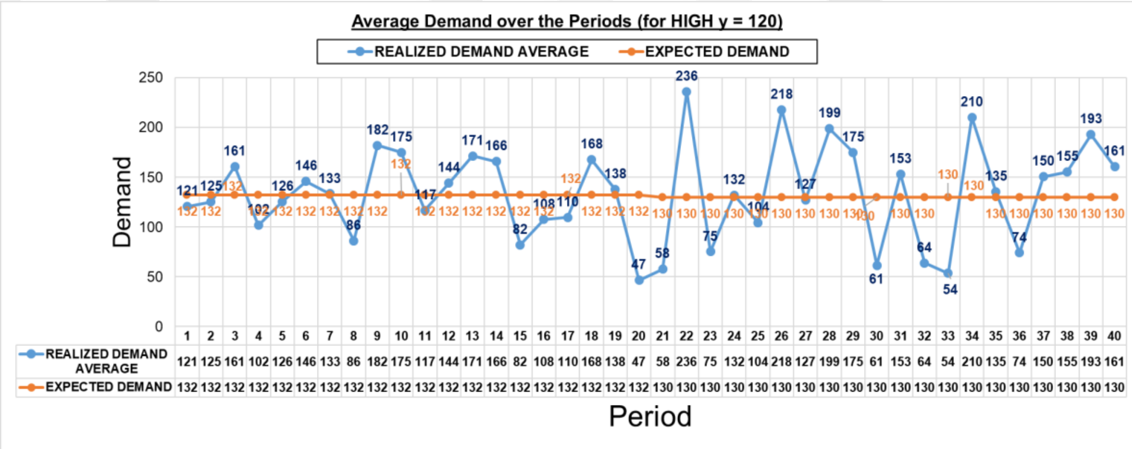

Figure 6 Average demand over the periods for Experiment 2

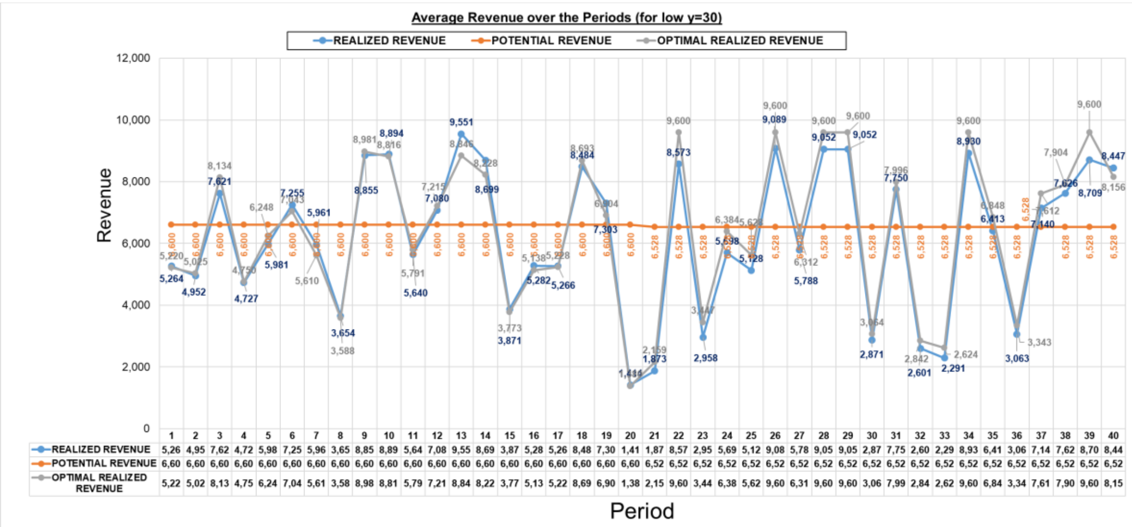

Figure 7 Average revenue over the periods for Experiment 1

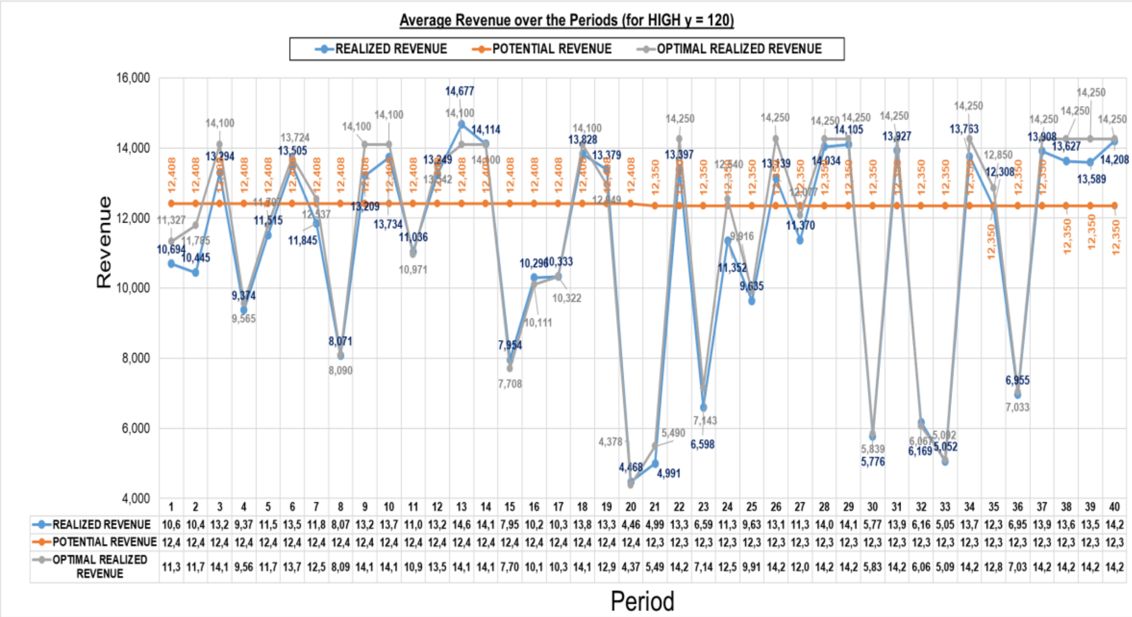

Figure 8 Average revenue over the periods for Experiment 2

Consequently, since realized revenue averages consistently fail to reach the potential revenue values, Hypothesis 2 is strongly rejected.

Hypothesis 3: The value of the competitive firm price given in the "static competitor price" treatment for both competitor price levels ($y_1=p_{1,1}$[6]$=30$ or $y_2=p_{1,2}=120$), do not affect the pricing decisions ($p_{2,j}$[7]) determined by the subjects.

Since no significant anchoring effect was observed in the "static competitor price" treatment for both competitor price levels, Hypothesis 3 is accepted.

Hypothesis 4: The increase in the variance of the demand distribution in the second twenty seasons of the "static competitor price" treatment, do not affect the pricing decisions of the subjects.

Hypothesis 4 is rejected; because in both Experiments 1 and 2, the subjects set prices such that the deviation from optimal value is more significant in the second 20 seasons

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[6] $p_{1,j}$=The price value "p_1" determined by the competitive firm during seasons of Experiment "j", j={1,2,3,4}

[7] $p_{2,j}$=The average price value "p_2" determined by the subject during seasons of Experiment "j", j={1,2,3,4}

(Figures 3, 4). In addition, the p-values and average prices of pricing decisions in Table 5 are lower for the second 20 seasons. In addition, Table 6 shows that the proportion of correct prices in the first 20 seasons decreased considerably (but in the second trial, the opposite is weakly observed). These findings lead the researchers to reject Hypothesis 4 and to conclude that as the variance increases, pricing decisions made will deviate more from the optimal.

5.1.2. "Dynamic Competitor Price" Treatment

Hypothesis 5: In the "dynamic competitor price" treatments, for both increasing and decreasing price trends ($y_3=p_{1,3}=30 \rightarrow 120$ or $y_4=p_{1,4}=120 \rightarrow 30$), subjects' pricing decisions ($p_{2,j}$) will be as predicted by theory and they will not be biased by the trend of the competitor price.

When the realized price averages of Experiment 3 (increasing $y_3=p_{1,3}=30 \rightarrow 120$) in Table 7 are analyzed, the first detection is the fact that anchoring effect is observed over the price of "y". Although the mean price values between seasons 01-10 and 11-20 fall under the optimum values of 60 and 71, respectively; when the optimum "y" is equal to 82 between seasons 21-30, subjects tend to increase their price average up to 5 units above the optimum. Between seasons 31-40, subjects behave more and more aggressively to the changes in "y" by increasing the average up to ten units above the optimum. This trend is obviously observed in Figure 9.

Similarly, results of Experiment 4 (decreasing $y_4=p_{1,4}=120 \rightarrow 30$) confirms this aggressive tendency. Between seasons 01-10, the price determined by subjects is on average 5 units above the optimum. Seasons 11-20 realize an average almost equal to the optimum price, showing a consistency with the theoretical optimal. As the competitor firm decreases their price ("y") even further, the mean value of the subjects show a dramatic decrease, 11 units lower than optimum between seasons 21-30 and 20 units lower than the optimum in seasons 31-40, proving the presence of the anchoring effect over the price of "y". In other words, as the competitor firm updates its price in a linear trend, the human subjects become more likely to make less rational pricing decisions in order to attract more customers (or to minimize the impact of losing customers). This trend is also obvious in

Figure 10. The last quarters of Experiment 4 has a minimum realized price average of 13.40 (subject id#129) that proves the willingness of human subjects to increase demand for their product by decreasing their price over the competitive firm.

Table 7 Comparison results of experiment performance with the optimal thresholds in Experiments 3 and 4

			Experiment Data						Optimal Price	P Value
			N	Min	Max	Mean	Std. Dev.	Median		
Realized Price Average	increasing y	Seasons 01-20	37	35.70	81.30	56.4459	12.1014	57.70	60.00	0.122006000000
		Seasons 11-20	37	41.30	105.00	70.8378	11.1933	73.00	71.00	0.825909000000
		Seasons 21-30	37	67.00	116.90	87.3865	10.3579	88.60	82.00	0.005252000000
		Seasons 31-40	37	69.00	128.90	103.8054	13.2368	103.50	93.00	0.000096000000
	Decreasing y	Seasons 01-20	37	77.00	135.80	97.1946	11.1159	97.40	93.00	0.026745000000
		Seasons 11-20	37	66.40	95.70	82.4541	7.4158	83.60	82.00	0.618562000000
		Seasons 21-30	37	46.30	77.50	60.6027	7.6690	61.10	71.00	0.000000457690
		Seasons 31-40	37	13.40	72.50	40.8162	13.0824	41.70	60.00	0.000000416080
			Experiment Data						Potential Revenue	P Value
			N	Min	Max	Mean	Std. Dev.	Median		
Realized Revenue	increasing y	Seasons 01-20	37	4,798.80	6,423.60	5,877.56	457.7438	6,087.00	6,600.00	0.000000114020
		Seasons 11-20	37	6,022.44	8,364.50	7,935.12	553.9635	8,124.90	8,378.00	0.000000114020
		Seasons 21-30	37	7,367.89	10,042.50	9,612.23	460.5722	9,696.60	10,332.00	0.000000114020
		Seasons 31-40	37	7,733.60	12,134.10	10,815.38	1,105.4162	10,955.00	12,462.00	0.000000114020
	Decreasing y	Seasons 01-20	37	6,104.22	11,651.00	10,777.75	997.1652	11,101.90	12,462.00	0.000000114020
		Seasons 11-20	37	7,885.00	9,725.50	9,304.94	425.7017	9,402.70	10,332.00	0.000000114020
		Seasons 21-30	37	6,242.50	7,875.00	7,344.71	385.8811	7,294.10	8,378.00	0.000000113970
		Seasons 31-40	37	2,010.00	6,516.90	5,117.73	1,072.3149	5,589.80	6,600.00	0.000000114020

P-values are obtained from two tailed Wilcoxon signed ranked test. [Sample size is 37 for both "increasing y" and "Decreasing y".]

When Table 8 demonstrating the "individual level comparison of pricing decisions with the optimal" is analyzed, it is observed that the p-value in second, third and fourth quarters of Experiment 3 is increasing, meaning that the number of decision makers who set prices closer to optimum in Experiment 3 is increasing. However, the p-values in realized price average section of Table 7 demonstrates that on average prices are deviating more from the optimal in these quarters. This means that the decision makers who made wrong pricing decisions deviated significantly from the optimal value, which affected the average prices of the entire subject group.

Table 8 Individual level comparison of pricing decisions with the optimal in Experiments 3 and 4

			# of Subjects with		
			P Value <= 0.05	P Value > 0.05	Total
increasing y	Realized Price Average	Seasons 01-20	21	16	37
		Seasons 11-20	15	21	37
		Seasons 21-30	10	27	37
		Seasons 31-40	8	29	37
Decreasing y	Realized Price Average	Seasons 01-20	14	23	37
		Seasons 11-20	17	20	37
		Seasons 21-30	35	2	37
		Seasons 31-40	34	3	37

Data in Table 8 show that in Experiment 4 ("decreasing y"), 35 subjects out of 37 made the wrong decision in the third quarter, by persistently setting a very low price. This persistence can be proved by the low standard deviation in Table 7, the line corresponding to "decreasing y, seasons 21-30" (7.6690). This observation is another proof that demonstrates the wrongful judgements of human decision makers are widely present and; not only subjects are wrong, but they are also persistent in making those wrong decisions over and over again.

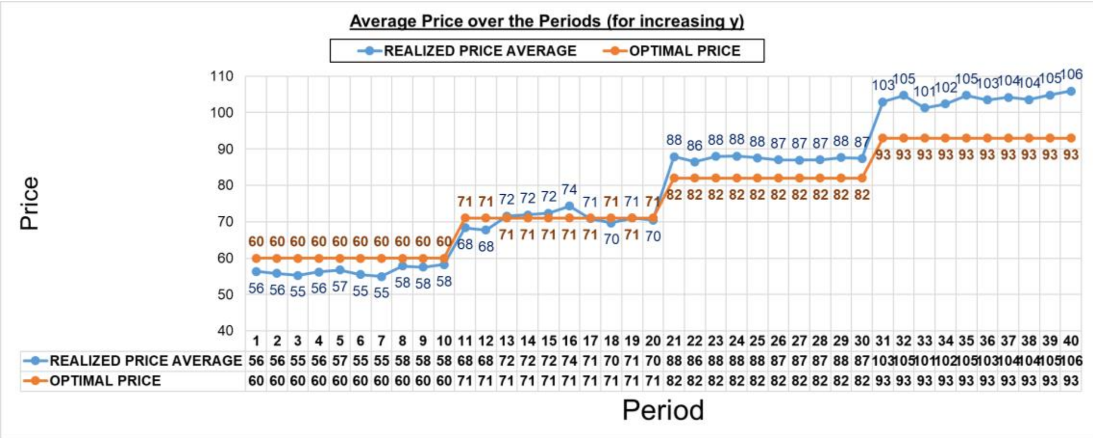


Figure 9 Average price over the periods for Experiment 3

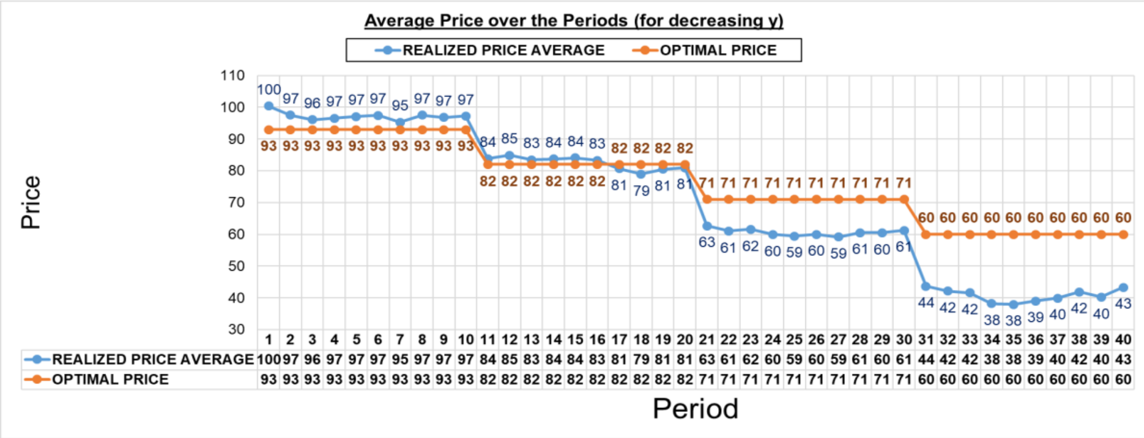


Figure 10 Average price over the periods for Experiment 4

Consequently, the following judgment can be reached: If the price is not changing dynamically, no matter if the competing firm's price is low or high, human subjects successfully get closer to the optimal price. In a dynamic price setting, if the rival's price is constantly changing, the aggressiveness of human subjects is increasing and human decisions are going away from optimal values more and more.

Therefore, Hypothesis 5 is to be rejected. In the "dynamic competitor price" treatments, for both increasing and decreasing price trends ($y_3=p_{1,3}=30 \rightarrow 120$ or $y_4=p_{1,4}=120 \rightarrow 30$), subjects' pricing decisions ($p_{2,j}$) are not as predicted by theory (human decisions are biased by the trend of a dynamic competitor price).

Hypothesis 6: In the "dynamic competitor price" treatment for both competitor price trends, subjects' realized revenues will be as predicted by theory.

Since realized demand values are determined under a discrete uniform distribution, the realized values randomly fall above or below the expected values. Hence, the visualization of demand values in Figure 11 and Figure 12 is logical and predictable. Thanks to the discrete uniform distribution of demand values, one can observe the presence of realized revenues fluctuating above or below the potential revenues, as depicted in Figure 13 and Figure 14. Although there is constant fluctuation, the mean realized revenues almost always fall short of potential revenues, both in experiment 3 and in experiment 4. The realized revenue section of Table 7 show this short-falling when the columns of "Mean" and "Potential Revenue" are compared against each other. In spite of all, Figure 13 depicts an increasing trend in realized revenues from season 1 up until season 40. Likewise, a decreasing trend in realized revenues can also be observed in Figure 14.

In terms of realized revenue values depicted in Table 7, both in experiments 3 and 4 (“increasing y” and “decreasing y”), the third quarter to the fourth quarter, standard deviations triple, meaning the tendency to aggressiveness in making wrong decision increases. Low p-values in Table 7 also prove that realized revenues are significantly different from theoretical optimum values.

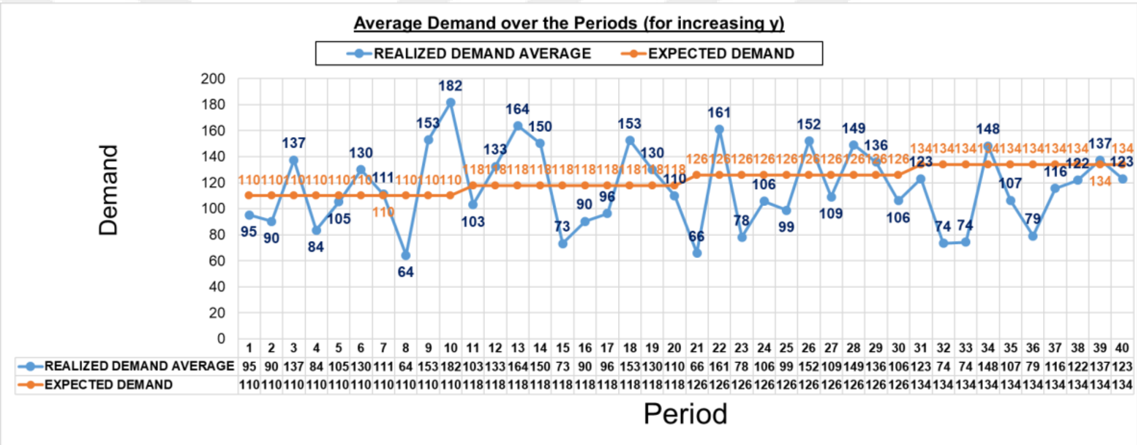


Figure 11 Average demand over the periods for Experiment 3

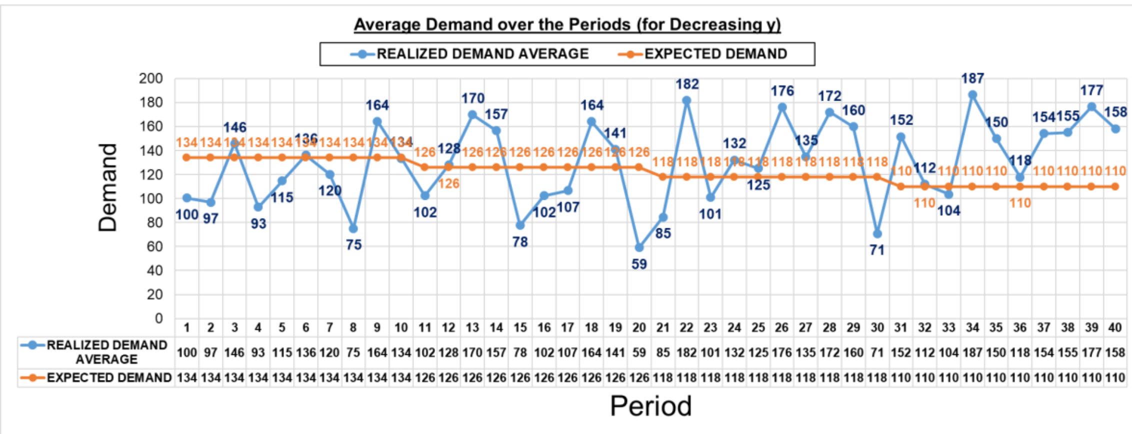


Figure 12 Average demand over the periods for Experiment 4

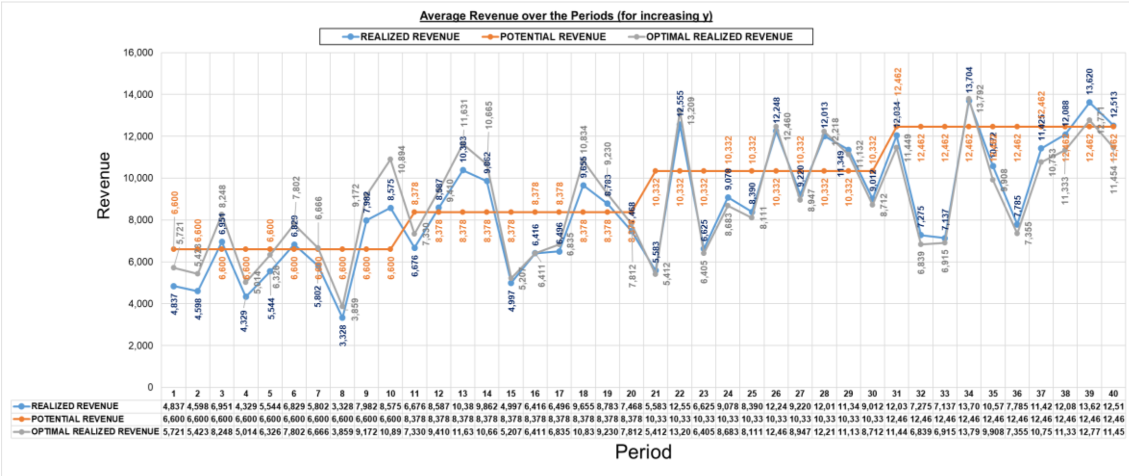


Figure 13 Average revenue over the periods for Experiment 3

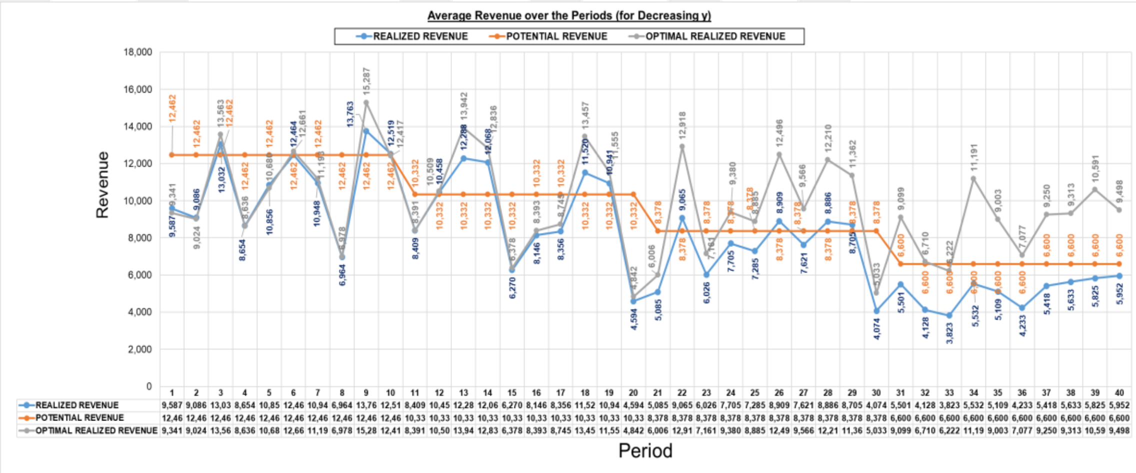


Figure 14 Average revenue over the periods for Experiment 4

As a result, Hypothesis 6 is strongly rejected, because in the "dynamic competitor price" treatment for both competitor price trends, subjects' realized revenues are not realized as predicted by theory.

Hypothesis 7: The value of the competitor firm's price given in the "dynamic competitor price" treatment ($y_3=p_{1,3}=30\rightarrow120$ or $y_4=p_{1,4}=120\rightarrow30$), do not affect the pricing decisions ($p_{2,j}$) determined by the subjects.

When the realized price averages of Experiment 3 (increasing $y_3=p_{1,3}=30\rightarrow120$) in Table 7 are analyzed, the first detection is the fact there anchoring effect is observed over the price of “y”. As the competitive firm increases its price, subjects’ average price decisions augments even faster. The same anchoring is observed in Experiment 4, while the competitive firm’s price shows a decreasing trend. This time, subjects tend to undercut prices with greater appetite than the competitor. Since anchoring effect was observed in the “dynamic competitor price” treatment for both competitor price levels, Hypothesis 7 is strongly rejected.

5.2. Effects of Personality Traits

The effect of personal characteristics on the experiment performance is studied with respect to three criteria: (i) cognitive reflection skills, (ii) maximizing tendency, (iii) risk attitude.

The questionnaire filled out by the subjects consists of three sections. The first section includes questions that measure cognitive skills, proposed by Frederick (2005) and Thomson and Oppenheimer (2016). In the second part, based on Schwarz et al. (2002), there are questions that measure satisfaction status and/or seeking the optimal. In the third part, there are questions used to measure the risk appetite in the scales developed in the studies of Holt and Laury (2002). These risk appetite questions were used in other experimental studies in the field of operations management when examining the relationship between the personal characteristics of the subjects and their decisions (Moritz et al., 2013; Moritz et al., 2014; Narayanan and Moritz, 2015).

5.2.1. Cognitive Reflection Test Scores

The term “cognitive reflection” is concerned with a person’s tendency to suppress the quick, effortless, intuitive, automatic and easily-obtainable response (System 1) to allow the conscious, logical, analytical reasoning processes (System 2) take control when faced with an apparently-easy question. Frederick (2005) introduced three questions as the Cognitive Reflection Test (CRT) and he also contemplated on the intuitive answers to these questions. The questions and their intuitive answers can be seen in Table 9. Frederick ‘s CRT questions date back to fifteen years and according to Stieger & Reips (2016), these questions gained popularity over the internet, as a result of which, a familiarity developed; and having prior experience with the CRT or any similar task has a substantial influence on the CRT score.

Thomson (2016) introduced another set of four questions to be followed by the original three. In order to overcome the familiarity of the initial questions and their high tendency to result in higher CRT scores than expected, the second set of questions are also added in the study (Table 9). It should be noted that the Cognitive Reflection Test is translated to Turkish, since the experiments are carried out with subjects whose native language is Turkish. The translated questionnaire can be seen in Appendix A.1.

Table 9 Questions for Cognitive Reflection Test (CRT)

Q1.	A bat and a ball cost $1.10 in total. The bat costs $1 more than the ball. How much does the ball cost?	(intuitive answer: 10 cents; correct answer: 5 cents)
Q2.	If it takes 5 machines 5 min to make 5 widgets, how long would it take 100 machines to make 100 widgets?	(intuitive answer: 100; correct answer: 5)
Q3.	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half the lake?	(intuitive answer: 24, correct answer: 47)
Q4.	If you're running a race and you pass the person in second place, what place are you in?	(intuitive answer: first; correct answer: second)
Q5.	A farmer had 15 sheep and all but 8 died. How many are left?	(intuitive answer: 7; correct answer: 8)
Q6.	Emily's father has three daughters. The first two are named April and May. What is the third daughter's name?	(intuitive answer: June; correct answer: Emily)
Q7.	How many cubic feet of dirt are there in a hole that is 3'deep x 3' wide x 3' long?	(intuitive answer: 27; correct answer: none)

Experiment performances are frequently compared with CRT scores in behavioral operations management. Moritz et al. (2013) study the cognitive reflection in the newsvendor problem context and conclude that demand chasing tendency is reduced with higher cognitive reflection under high profit margin setting and expected profits are also improved. Mortiz et al. (2014) state that forecasting errors are reduced in case of higher CRT scores. Naranayan and Moritz (2015) report that the tendency to underestimate the pipeline inventory is related with cognitive reflection scores and it leads to bullwhip effect.

In order to compute the CRT scores, the number of correct answers among seven questions is counted for each subject. Subjects that have a score lower than 4.5 are grouped as “low CRT group” and the ones that have a higher score than or equal to 4.5 are grouped as “high CRT group”.

This criterion for dividing into two groups show that ten subjects in Experiment 1, 21 subjects in Experiment 2, 12 subjects in Experiment 3, and 12 subjects in Experiment 4 belong to the “low CRT group”. Likewise, 22 subjects in Experiment 1, 11 subjects in Experiment 2, 25 subjects in Experiment 3, and 26 subjects in Experiment 4 belong to the “high CRT group”.

Hypothesis 8: According to the cognitive reflection test results, subjects categorized with high CRT scores give prices closer to optimal than subjects categorized with low CRT scores.

In the first half of Experiment 1, the “high CRT” group’s performance in pricing is not significantly better than the “low CRT” group; however, in the second half, the “high CRT” group gave prices closer to optimal than the “low CRT” group. In Experiment 2, the “high CRT” group did not perform significantly better in pricing decisions. In seasons 11-20 of Experiment 3, the “high CRT” group gave prices closer to optimal; nonetheless, their price decisions during the remaining seasons did not differ from those made by the “low CRT” group. For all seasons of Experiment 4, the prices determined by the “high CRT” group are not significantly closer to optimal when compared with those determined by the “low CRT” group (Table 13).

Linear regression results displayed in Table 14 depict a p-value of 0.062 for CRT Score in the “dynamic competitor price” treatment, suggesting the possibility to reach a significant change with a p-value less than 0.05 in case by obtaining larger sample sizes (This study has a sample size $n_{dynamic} = n_3+n_4 = 37+37 = 74$).

Hypothesis 8 is rejected because higher CRT scores did not lead to better performance in determining price values closer to theoretically optimal values.

Hypothesis 9: According to the cognitive reflection test results, subjects with higher CRT scores will earn higher revenues than those with lower CRT scores.

During the last twenty seasons of Experiment 1, the “high CRT” group earned higher revenues than those earned by the “low CRT” group. Neither in Experiment 2, nor in Experiment 3 or 4, the “high CRT” group earned significantly better revenues when compared with the “low CRT” group. (Table 13).

Although higher CRT scores lead to an increase in earned revenues; when linear regression results displayed in Table 14 are examined, one cannot conclude that higher CRT scores show a significant difference.

Hypothesis 9 is rejected because the “high CRT” group does not significantly perform better in earning higher revenues when compared with the performance of the “low CRT” group.

5.2.2. Maximizing Tendency Scores

Schwarz et al. (2002) introduced the maximizing scale, consisting of thirteen statements that are evaluated on a 7-point Likert scale. The maximizing behavior of all subjects are measured with the statements listed in Table 10. This maximizing scale is initially used by Akbay and Ayvaz Cavdaroglu (2020) in behavioral operations management to connect the experiment performance with maximizing behavior. It should be noted that the Maximizing Tendency Test is conducted in Turkish language, since the experiments are carried out with subjects whose native language is Turkish. The translated questionnaire can be seen in Appendix A.2.

Table 10 Questions for Maximizing Tendency (MT)

Q8.1.	When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program.
Q8.2.	When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I’m relatively satisfied with what I’m listening to.
Q8.3.	I treat relationships like clothing: I expect to try a lot on before I get the perfect fit.
Q8.4.	No matter how satisfied I am with my job, it’s only right for me to be on the lookout for better opportunities.
Q8.5.	I often fantasize about living in ways that are quite different from my actual life.
Q8.6.	I’m a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.).
Q8.7.	I often find it difficult to shop for a gift for a friend.
Q8.8.	When shopping, I have a hard time finding clothing that I really love.
Q8.9.	Renting videos is really difficult. I’m always struggling to pick the best one.

Q8.10.	I find that writing is very difficult, even if it’s just writing a letter to a friend, because it’s so hard to word things just right. I often do several drafts of even simple things.
Q8.11.	No matter what I do, I have the highest standards for myself.
Q8.12.	I never settle for second best.
Q8.13.	Whenever I’m faced with a choice, I try to imagine what all the other possibilities are, even ones that aren’t present at the moment.

In order to compute the maximizing tendency (MT) scores, the 7-point Likert scale points of thirteen statements is arithmetically averaged for each subject. Subjects that have a score lower than or equal to 3.3 are grouped as “low MT group” and the ones that have a higher score than 3.3 are grouped as “high MT group”.

This criterion for dividing into two groups show that 16 subjects in Experiment 1, 18 subjects in Experiment 2, 17 subjects in Experiment 3, and 17 subjects in Experiment 4 belong to the “low MT group”. Likewise, 16 subjects in Experiment 1, 14 subjects in Experiment 2, 20 subjects in Experiment 3, and 20 subjects in Experiment 4 belong to the “high MT group”.

Hypothesis 10: According to the maximizing tendencies, subjects categorized with high MT scores give prices closer to optimal than subjects categorized with low MT scores.

There is no significant increase in pricing decisions’ performances of the “high MT” group observed in Experiment 1, neither in Experiment 2, nor in Experiment 3. On the other hand, the “high MT” group in Experiment 4, perform price decisions closer to optimal; however, their performance during the last thirty seasons is not significantly better than the “low MT” group (Table 13).

Hypothesis 10 is rejected because comparisons between the “high MT” and the “low MT” groups are not significantly different in terms of determining price values closer to optimum prices.

Hypothesis 11: According to the maximizing tendencies, subjects with higher MT scores will earn higher revenues than those with lower MT scores.

In the first twenty seasons of Experiment 1, the “high MT” group earned higher revenues than the “low MT” group. In the last twenty seasons of Experiment 1, the performance of the "high MT" group does not differ significantly from the performance of the "low MT" group. For Experiments 2, 3, and 4, MT does not significantly affect earning higher revenues. (Table 13). Linear regression results in Table 14 do not show a considerable improvement, either.

Hypothesis 11 is rejected because comparisons between the "high MT" and the "low MT" groups are not significantly different in terms of earning higher revenues.

5.2.3. Risk Attitude Scores

In the field of behavioral operations management, risk attitude is often an important determinant of individual choice, but experiments conducted in a laboratory setting to measure risk attitude are often not possible when data are collected by survey. Therefore, having a reliable and validated method for measuring humans' risk attitude in a questionnaire would be rather beneficial for researchers. In recent years, asking for the reservation price of a hypothetical lottery ticket is one of the frequently used methods (Donkers et al., 2001; Hartog et al., 2002; Guiso and Paiella, 2008). The questions in the questionnaire for measuring risk attitude scores are included in Table 11.

Table 11 Questions for Risk Scores

Q9.	A lottery draw will be held where the prize is 1000 TL and only 10 people will participate. How much will you be willing to pay for the lottery ticket?
Q10.	You will receive a free lottery ticket or 100 TL from the drawing above. Which one would you prefer? a) Ticket b) 100 TL
Q11.	You have won a ticket from the above draw and have not paid any fee. Someone very good at bargaining wants to buy tickets from you. What is the lowest price you will sell the ticket?
Q12.	In case of flipping a coin in each of the following situations, you will earn 6 TL. How much money you will lose in case of tails is stated in the following cases. If you do not agree to play the game, you will not lose anything. Please indicate whether you agree to play the game.
Q12.1.	Game 1: TAILS: You lose 2 TL, HEADS: You earn 6 TL.
Q12.2.	Game 2: TAILS: You lose 3 TL, HEADS: You earn 6 TL.
Q12.3.	Game 3: TAILS: You lose 4 TL, HEADS: You earn 6 TL.
Q12.4.	Game 4: TAILS: You lose 5 TL, HEADS: You earn 6 TL.
Q12.5.	Game 5: TAILS: You lose 6 TL, HEADS: You earn 6 TL.
Q12.6.	Game 6: TAILS: You lose 7 TL, HEADS: You earn 6 TL.
Q12.7.	Game 7: TAILS: You lose 8 TL, HEADS: You earn 6 TL.

The answer to question 9 is divided into four categories. A response up to and including 50 TL received 1 point, any answer between 50 - 100 TL received two points, an answer with 100 TL received 3 points and a response more than 100 TL received 4 points. Because the answer to question 10 is a binary variable, the researchers chose to exclude the score received from question 10 in order to calculate the risk appetite. The answer to question 11 is divided into same four categories as question 9. The points for question 12 is determined by counting the number of sub-questions that were answered as "yes". Afterwards, the points received from questions 9, 11, and 12 are arithmetically averaged, the resulting data revealed the risk score of the subject.

This criterion for dividing into two groups, namely "risk-averse" group and "risk taker" group, show that 14 subjects in Experiment 1, 21 subjects in Experiment 2, 21 subjects in Experiment 3, and 17 subjects in Experiment 4 belong to the "risk-averse" group. Likewise, 18 subjects in Experiment 1, 11 subjects in Experiment 2, 16 subjects in Experiment 3, and 20 subjects in Experiment 4 belong to the "risk taker" group.

Hypothesis 12: According to the risk appetites, subjects with higher risk scores set higher prices on average than those with lower risk scores.

The "risk taker" group's performance is not significantly better than the "risk-averse" group in Experiment 1, neither in Experiment 2, nor in Experiment 4. In Experiment 3; however, the "risk taker" group gave prices closer to optimal than the "risk-averse" group between seasons 11-20 and 21-30. The first ten and the last ten seasons of Experiment 3, the "risk taker" group did not perform significantly better (Table 13).

Linear regression results of personality traits indicate that, in a dynamic competitor price setting, the risk score is rather significant in determining realized price values that are higher.

Hypothesis 12 is weakly supported because in general, the "risk taker" group performs better in determining price values closer to optimum prices.

Hypothesis 13: According to the risk appetites, subjects with higher risk scores will earn higher revenues than those with lower risk scores.

Neither in Experiment 1, nor in Experiments 2 or 4, the revenues earned by the “risk taker” group are significantly higher than those earned by the “risk-averse” group. In Experiment 3, the “risk taker” group earned significantly better revenues only between seasons 21-30, except which the group does not earn significantly higher revenues (Table 13). Table 14 does not provide enough evidence to support this hypothesis, either.
Hypothesis 13 is rejected because comparisons between the “risk taker” and the “risk-averse” groups are not significantly different in terms of earning higher revenues.

Table 12 displays the cumulative survey scores of subjects and their relative classes in CRT, MT and risk appetite. The questionnaire translated into Turkish for Cognitive Reflection Test (CRT), Maximizing Tendency (MT) and Risk Scores of test subjects are included in Appendix A.

Table 12 Cumulative survey scores of subjects and their relative classes in CRT, MT and risk appetite

Experiment	ID	CRT Score 1-7	MT Score	Risk Score	CRT Class	MT Class	Risk Class
low y	1	5	3.92	2.33	High CRT	High MT	Risk-Averse
low y	2	4	4.92	3.00	Low CRT	High MT	Risk Taker
low y	3	5	3.62	2.67	High CRT	High MT	Risk-Averse
low y	4	3	3.08	3.33	Low CRT	Low MT	Risk Taker
low y	5	5	1.69	2.33	High CRT	Low MT	Risk-Averse
low y	6	7	3.15	3.00	High CRT	Low MT	Risk Taker
low y	7	6	3.69	3.00	High CRT	High MT	Risk Taker
low y	8	6	2.08	2.67	High CRT	Low MT	Risk-Averse
low y	9	5	2.23	3.00	High CRT	Low MT	Risk Taker
low y	10	7	2.00	2.33	High CRT	Low MT	Risk-Averse
low y	11	3	6.00	3.00	Low CRT	High MT	Risk Taker
low y	12	4	2.85	4.00	Low CRT	Low MT	Risk Taker
low y	13	3	1.15	4.00	Low CRT	Low MT	Risk Taker
low y	14	5	4.62	1.33	High CRT	High MT	Risk-Averse
low y	15	4	1.00	3.33	Low CRT	Low MT	Risk Taker
low y	16	4	1.00	3.67	Low CRT	Low MT	Risk Taker
low y	17	6	3.69	1.67	High CRT	High MT	Risk-Averse
low y	18	6	3.38	3.00	High CRT	High MT	Risk Taker
low y	19	2	2.85	2.67	Low CRT	Low MT	Risk-Averse
low y	20	1	3.46	1.67	Low CRT	High MT	Risk-Averse
low y	21	6	2.77	3.67	High CRT	Low MT	Risk Taker
low y	22	6	3.46	2.00	High CRT	High MT	Risk-Averse
low y	23	5	3.69	3.33	High CRT	High MT	Risk Taker
low y	24	5	4.23	2.33	High CRT	High MT	Risk-Averse
low y	25	5	1.46	3.67	High CRT	Low MT	Risk Taker
low y	26	6	3.15	3.33	High CRT	Low MT	Risk Taker
low y	27	6	3.31	2.67	High CRT	High MT	Risk-Averse
low y	28	5	3.54	3.33	High CRT	High MT	Risk Taker
low y	29	2	3.15	3.00	Low CRT	Low MT	Risk Taker
low y	30	5	3.08	2.67	High CRT	Low MT	Risk-Averse
low y	31	7	3.92	2.00	High CRT	High MT	Risk-Averse
low y	32	6	4.69	3.00	High CRT	High MT	Risk Taker
HIGH y	33	3	3.31	4.67	Low CRT	High MT	Risk Taker
HIGH y	34	2	5.00	1.00	Low CRT	High MT	Risk-Averse
HIGH y	35	4	3.38	3.33	Low CRT	High MT	Risk Taker
HIGH y	36	1	5.46	1.67	Low CRT	High MT	Risk-Averse
HIGH y	37	2	4.00	2.33	Low CRT	High MT	Risk-Averse
HIGH y	38	4	0.69	2.00	Low CRT	Low MT	Risk-Averse
HIGH y	39	4	4.69	2.00	Low CRT	High MT	Risk-Averse
HIGH y	40	3	3.15	2.67	Low CRT	Low MT	Risk-Averse
HIGH y	41	3	1.92	2.33	Low CRT	Low MT	Risk-Averse
HIGH y	42	4	1.85	2.33	Low CRT	Low MT	Risk-Averse
HIGH y	43	4	2.00	3.00	Low CRT	Low MT	Risk Taker
HIGH y	44	4	2.92	2.00	Low CRT	Low MT	Risk-Averse
HIGH y	45	4	3.62	1.67	Low CRT	High MT	Risk-Averse
HIGH y	46	4	3.69	5.00	Low CRT	High MT	Risk Taker
HIGH y	47	4	2.00	3.67	Low CRT	Low MT	Risk Taker
HIGH y	48	7	2.38	3.33	High CRT	Low MT	Risk Taker
HIGH y	49	5	1.62	3.67	High CRT	Low MT	Risk Taker
HIGH y	50	4	3.00	2.67	Low CRT	Low MT	Risk-Averse
HIGH y	51	6	2.92	2.33	High CRT	Low MT	Risk-Averse
HIGH y	52	4	3.69	3.33	Low CRT	High MT	Risk Taker
HIGH y	53	3	1.15	3.67	Low CRT	Low MT	Risk Taker
HIGH y	54	5	2.77	4.33	High CRT	Low MT	Risk Taker
HIGH y	55	7	4.46	1.33	High CRT	High MT	Risk-Averse
HIGH y	56	3	1.08	1.00	Low CRT	Low MT	Risk-Averse
HIGH y	57	6	3.31	1.67	High CRT	High MT	Risk-Averse
HIGH y	58	7	1.38	2.67	High CRT	Low MT	Risk-Averse
HIGH y	59	5	3.62	2.33	High CRT	High MT	Risk-Averse
HIGH y	60	6	4.15	1.33	High CRT	High MT	Risk-Averse
HIGH y	61	4	3.46	2.67	Low CRT	High MT	Risk-Averse
HIGH y	62	7	2.92	3.67	High CRT	Low MT	Risk Taker
HIGH y	63	3	3.23	1.67	Low CRT	Low MT	Risk-Averse
HIGH y	64	6	2.77	2.67	High CRT	Low MT	Risk-Averse

Table 12 Continued

Experiment	ID	CRT Score 1-7	MT Score	Risk Score	CRT Class	MT Class	Risk Class
increasing y	65	6	1.85	2.67	High CRT	Low MT	Risk-Averse
increasing y	66	5	3.38	2.67	High CRT	High MT	Risk-Averse
increasing y	67	6	1.54	2.33	High CRT	Low MT	Risk-Averse
increasing y	68	4	3.31	3.33	Low CRT	High MT	Risk Taker
increasing y	69	7	2.38	2.67	High CRT	Low MT	Risk-Averse
increasing y	70	4	0.69	3.33	Low CRT	Low MT	Risk Taker
increasing y	71	5	3.08	3.67	High CRT	Low MT	Risk Taker
increasing y	72	6	5.46	3.67	High CRT	High MT	Risk Taker
increasing y	73	0	4.31	4.00	Low CRT	High MT	Risk Taker
increasing y	74	6	5.31	1.33	High CRT	High MT	Risk-Averse
increasing y	75	7	1.15	4.00	High CRT	Low MT	Risk Taker
increasing y	76	4	3.46	1.00	Low CRT	High MT	Risk-Averse
increasing y	77	4	2.08	2.00	Low CRT	Low MT	Risk-Averse
increasing y	78	7	3.85	3.67	High CRT	High MT	Risk Taker
increasing y	79	5	3.54	2.67	High CRT	High MT	Risk-Averse
increasing y	80	6	4.15	3.00	High CRT	High MT	Risk Taker
increasing y	81	3	3.08	1.33	Low CRT	Low MT	Risk-Averse
increasing y	82	6	4.00	3.67	High CRT	High MT	Risk Taker
increasing y	83	3	2.38	2.67	Low CRT	Low MT	Risk-Averse
increasing y	84	5	2.08	3.33	High CRT	Low MT	Risk Taker
increasing y	85	6	3.54	2.67	High CRT	High MT	Risk-Averse
increasing y	86	4	3.85	1.33	Low CRT	High MT	Risk-Averse
increasing y	87	6	3.77	2.67	High CRT	High MT	Risk-Averse
increasing y	88	6	4.15	3.33	High CRT	High MT	Risk Taker
increasing y	89	5	3.38	2.33	High CRT	High MT	Risk-Averse
increasing y	90	6	5.46	3.67	High CRT	High MT	Risk Taker
increasing y	91	5	2.38	2.33	High CRT	Low MT	Risk-Averse
increasing y	92	6	3.46	3.33	High CRT	High MT	Risk Taker
increasing y	93	6	3.00	1.67	High CRT	Low MT	Risk-Averse
increasing y	94	5	3.08	2.33	High CRT	Low MT	Risk-Averse
increasing y	95	4	3.08	3.00	Low CRT	Low MT	Risk Taker
increasing y	96	3	4.08	4.00	Low CRT	High MT	Risk Taker
increasing y	97	6	1.54	2.67	High CRT	Low MT	Risk-Averse
increasing y	98	6	3.54	3.00	High CRT	High MT	Risk Taker
increasing y	99	4	4.77	2.67	Low CRT	High MT	Risk-Averse
increasing y	100	1	1.00	2.33	Low CRT	Low MT	Risk-Averse
increasing y	101	6	3.00	2.67	High CRT	Low MT	Risk-Averse
Decreasing y	102	6	1.38	2.67	High CRT	Low MT	Risk-Averse
Decreasing y	103	5	4.00	4.00	High CRT	High MT	Risk Taker
Decreasing y	104	6	2.77	3.33	High CRT	Low MT	Risk Taker
Decreasing y	105	4	4.69	3.33	Low CRT	High MT	Risk Taker
Decreasing y	106	5	2.62	1.33	High CRT	Low MT	Risk-Averse
Decreasing y	107	5	4.62	2.33	High CRT	High MT	Risk-Averse
Decreasing y	108	1	3.62	3.33	Low CRT	High MT	Risk Taker
Decreasing y	109	4	2.62	1.33	Low CRT	Low MT	Risk-Averse
Decreasing y	110	7	2.54	3.67	High CRT	Low MT	Risk Taker
Decreasing y	111	4	2.46	3.67	Low CRT	Low MT	Risk Taker
Decreasing y	112	6	4.00	3.00	High CRT	High MT	Risk Taker
Decreasing y	113	6	3.23	2.67	High CRT	Low MT	Risk-Averse
Decreasing y	114	3	3.15	1.33	Low CRT	Low MT	Risk-Averse
Decreasing y	115	6	3.54	2.00	High CRT	High MT	Risk-Averse
Decreasing y	116	6	5.00	2.33	High CRT	High MT	Risk-Averse
Decreasing y	117	5	2.54	2.67	High CRT	Low MT	Risk-Averse
Decreasing y	118	5	3.00	2.33	High CRT	Low MT	Risk-Averse
Decreasing y	119	5	1.31	3.00	High CRT	Low MT	Risk Taker
Decreasing y	120	5	2.38	4.00	High CRT	Low MT	Risk Taker
Decreasing y	121	5	3.38	2.33	High CRT	High MT	Risk-Averse
Decreasing y	122	5	3.85	2.67	High CRT	High MT	Risk-Averse
Decreasing y	123	6	3.69	3.33	High CRT	High MT	Risk Taker
Decreasing y	124	5	3.85	4.00	High CRT	High MT	Risk Taker
Decreasing y	125	5	3.77	3.33	High CRT	High MT	Risk Taker
Decreasing y	126	6	3.38	4.33	High CRT	High MT	Risk Taker
Decreasing y	127	3	4.62	4.00	Low CRT	High MT	Risk Taker
Decreasing y	128	3	3.08	3.00	Low CRT	Low MT	Risk Taker
Decreasing y	129	3	3.00	3.00	Low CRT	Low MT	Risk Taker
Decreasing y	130	4	3.31	2.00	Low CRT	High MT	Risk-Averse
Decreasing y	131	6	3.31	3.33	High CRT	High MT	Risk Taker
Decreasing y	132	6	3.31	1.33	High CRT	High MT	Risk-Averse
Decreasing y	133	5	3.08	2.33	High CRT	Low MT	Risk-Averse
Decreasing y	134	6	3.00	4.33	High CRT	Low MT	Risk Taker
Decreasing y	135	6	2.92	3.33	High CRT	Low MT	Risk Taker
Decreasing y	136	4	3.54	2.67	Low CRT	High MT	Risk-Averse
Decreasing y	137	7	4.00	1.67	High CRT	High MT	Risk-Averse
Decreasing y	138	4	3.77	4.33	Low CRT	High MT	Risk Taker

Table 13 Comparison results of experiments and survey data

Experiment No	Experiment	Seasons		CRT Score			MT Score			Risk Score		
				<4.5	>=4.5		<=3.3	>3.3		<3	>=3	
				LOW Group Median	HIGH Group Median	P Value	LOW Group Median	HIGH Group Median	P Value	RISK-AVERSE Group Median	RISK TAKER Group Median	P Value
1	Low y=30		**# of Subjects**	10	22		16	16		14	18	
		Seasons 01-20	**Optimal Price**	60.00			60.00			60.00		
			Realized Price Median	55.50	60.50	0.392	60.75	60.00	0.385	59.25	62.00	0.216
			Potential Revenue	6,600.00			6,600.00			6,600.00		
			Realized Revenue Median	5,286.25	5,764.00	**0.011**	5,475.50	5,815.75	**0.004**	5,701.75	5,723.75	1.000
		Seasons 21-40	**Optimal Price**	64.00			64.00			64.00		
			Realized Price Median	53.00	63.25	**0.016**	59.50	60.00	0.895	62.25	59.00	0.296
			Potential Revenue	6,528.00			6,528.00			6,528.00		
			Realized Revenue Median	5,980.00	6,584.50	**0.028**	6,295.50	6,555.00	0.356	6,602.50	6,295.50	0.333
2	High y=120		**# of Subjects**	21	11		18	14		21	11	
		Seasons 01-20	**Optimal Price**	94.00			94.00			94.00		
			Realized Price Median	88.00	92.50	0.177	91.50	89.00	0.690	90.50	91.00	0.812
			Potential Revenue	12,408.00			12,408.00			12,408.00		
			Realized Revenue Median	10,914.00	10,770.00	0.416	11,075.50	10,666.50	0.382	11,023.00	10,760.00	0.677
		Seasons 21-40	**Optimal Price**	95.00			95.00			95.00		
			Realized Price Median	95.00	93.00	0.953	99.00	89.50	0.149	92.50	98.50	0.606
			Potential Revenue	12,350.00			12,350.00			12,350.00		
			Realized Revenue Median	11,378.50	11,621.50	0.197	11,635.75	11,126.75	0.271	11,621.50	11,385.00	0.706
3	increasing y		**# of Subjects**	12	25		17	20		21	16	
		Seasons 01-10	**Optimal Price**	60.00			60.00			60.00		
			Realized Price Median	56.70	61.00	0.144	55.00	60.90	0.185	55.00	60.90	0.270
			Potential Revenue	6,600.00			6,600.00			6,600.00		
			Realized Revenue Median	6,043.55	6,093.50	0.871	5,981.00	6,094.25	0.377	6,066.40	6,113.85	0.358
		Seasons 11-20	**Optimal Price**	71.00			71.00			71.00		
			Realized Price Median	67.95	75.50	**0.039**	71.30	77.05	0.247	71.00	77.50	**0.025**
			Potential Revenue	8,378.00			8,378.00			8,378.00		
			Realized Revenue Median	8,037.85	8,136.00	0.270	8,179.50	8,113.05	0.522	8,136.00	8,116.45	0.500
		Seasons 21-30	**Optimal Price**	82.00			82.00			82.00		
			Realized Price Median	83.70	91.90	0.270	84.50	89.85	0.715	84.50	93.45	**0.021**
			Potential Revenue	10,332.00			10,332.00			10,332.00		
			Realized Revenue Median	9,656.95	9,715.50	0.820	9,715.50	9,694.00	0.976	9,752.50	9,568.55	**0.017**
		Seasons 31-40	**Optimal Price**	93.00			93.00			93.00		
			Realized Price Median	102.25	105.60	0.685	106.20	103.20	0.563	102.00	105.90	0.283
			Potential Revenue	12,462.00			12,462.00			12,462.00		
			Realized Revenue Median	10,891.35	10,955.00	0.456	10,761.90	11,211.55	0.807	10,955.00	11,000.70	0.462
4	Decreasing y		**# of Subjects**	11	26		17	20		17	20	
		Seasons 01-10	**Optimal Price**	93.00			93.00			93.00		
			Realized Price Median	98.00	97.15	0.855	92.20	98.55	**0.013**	92.50	98.00	0.170
			Potential Revenue	12,462.00			12,462.00			12,462.00		
			Realized Revenue Median	11,060.60	11,117.45	0.335	11,104.90	11,096.10	0.411	11,104.90	11,071.15	0.692
		Seasons 11-20	**Optimal Price**	82.00			82.00			82.00		
			Realized Price Median	81.70	83.70	0.654	83.60	83.40	0.604	84.30	81.60	0.594
			Potential Revenue	10,332.00			10,332.00			10,332.00		
			Realized Revenue Median	9,411.00	9,395.45	0.595	9,365.80	9,520.15	0.059	9,344.10	9,425.10	0.446
		Seasons 21-30	**Optimal Price**	71.00			71.00			71.00		
			Realized Price Median	58.20	62.30	0.907	64.00	57.15	0.229	56.60	61.85	0.615
			Potential Revenue	8,378.00			8,378.00			8,378.00		
			Realized Revenue Median	7,284.00	7,330.25	0.702	7,414.70	7,260.10	0.512	7,217.00	7,374.15	0.161
		Seasons 31-40	**Optimal Price**	60.00			60.00			60.00		
			Realized Price Median	43.70	41.35	0.973	42.80	40.80	0.626	37.70	45.40	0.063
			Potential Revenue	6,600.00			6,600.00			6,600.00		
			Realized Revenue Median	5,063.20	5,672.85	1.000	5,781.10	5,326.50	0.761	5,231.40	5,607.50	0.190

P-values in Table 13 are obtained from the “Wilcoxon Rank-Sum Test”, also known as “the Mann–Whitney *U* Test”.

Table 14 Personality traits linear regression results

Treatment	Dependent Variable	Realized Price		Realized Revenue	
	Explanatory Variables	**Coefficient**	**P-value**	**Coefficient**	**P-value**
Static Competitor Price	**Intercept**	59.609	**0.000**	5,786.470	**0.000**
	CRT Score	1.239	0.113	52.037	0.269
	MT Score	-1.550	0.150	-36.259	0.576
	Risk Score	-0.292	0.838	-48.092	0.578
	Join High Treatment?	32.434	**0.000**	4,602.764	**0.000**
	Adjusted R-Square	0.755		0.945	
Dynamic Competitor Price	**Intercept**	62.306	**0.000**	8,219.573	**0.000**
	CRT Score	1.078	0.062	43.744	0.279
	MT Score	0.057	0.943	-9.325	0.869
	Risk Score	4.228	**0.000**	54.862	0.422
	Join Decreasing Treatment?	-9.858	**0.000**	-428.406	**0.000**
	Adjusted R-Square	0.426		0.143	

Table 14 indicates that the adjusted R-Square values in the static price competitor treatment are 0.755 and 0.945. These rather-high values mean that 76 percent and 95 percent of the variance in dependent variables "realized price" and "realized revenue", respectively, are explained by movement in chosen independent variables. This shows that linear regression results produced are trustworthy. Furthermore, the significantly high coefficients of the dummy variables called "Join High Treatment?" and "Join Decreasing Treatment?" are simply a natural result of the experiment design: As the prices are higher, the revenues will naturally be higher (although randomly-determined demand values with respect to discrete uniform distribution can overcome the afore-mentioned cause and consequence relationship).

5.3. Individual Behavior Patterns

Bolton and Katok (2008) investigated the presence of anchoring and learning effect in the newsvendor inventory problem. Our study checks whether subjects' pricing decisions are significantly correlated with the demand realized in the previous season. For this analysis, linear regression is conducted and after detecting a significant correlation (along with its tendency of direction) between the decided price and the realized demand, the remaining subjects are categorized with respect to the highest number of price decisions that fall onto above-optimal, near-optimal or below-optimal intervals. The near-optimal interval is defined as the pricing decision that falls between 5% below and 5% above the optimal price. The above-optimal interval is defined as the pricing decision that is more than %5 above the optimal price. Likewise, the below-optimal interval is defined as the pricing decision that is more than %5 below the optimal price. One should note that the mentioned-intervals are determined with respect to the presence of bounded rationality in human decision makers. The subjects that do not show a significant correlation as a result of linear regression analysis are categorized under the interval that has the highest number of decisions over forty seasons. The categorization of the pricing decisions is summarized in Table 15.

Table 15 Explanation of Subject Categories

Category	Explanation of the Behavioral Pattern in Pricing Decisions
Positive	The amounts of deviation of the pricing decisions from the optimal price are significantly (p-value≤0.10) and positively correlated with the demand realization of the previous period.
Negative	The amounts of deviation of the pricing decisions from the optimal price are significantly (p-value≤0.10) and negatively correlated with the demand realization of the previous period.
Above-Optimal	Among the subjects whose pricing decisions do not show a deviation that is significantly correlated with the demand realization of the previous period, the highest number of pricing decisions are more than %5 above the optimal price.
Near-optimal	Among the subjects whose pricing decisions do not show a deviation that is significantly correlated with the demand realization of the previous period, the highest number of pricing decisions fall onto the interval of 5% below and 5% above the optimal price.
Below-optimal	Among the subjects whose pricing decisions do not show a deviation that is significantly correlated with the demand realization of the previous period, the highest number of pricing decisions are more than %5 below the optimal price.

Table 16 shows the number of subjects falling into each category defined above for all four experiments. If the pricing decisions are significantly and positively correlated with the demand, it means that subjects increase their prices after observing a high demand in the previous period. This case would prove the presence of an anchoring effect, and a demand-chasing behavior.

If the pricing decisions are significantly and negatively correlated with the demand, this means that subjects lower the price when the demand of the previous period is high, which presumes that subjects expect the demand at the current period to decrease. In that case, human decision makers fall into the “gambler's fallacy”, because they falsely believe that a high demand can only be followed by a low demand, as a consequence of which, they decide to set up a low price to be able to sell more tickets.

Table 16 Categorization of Subject Behavior

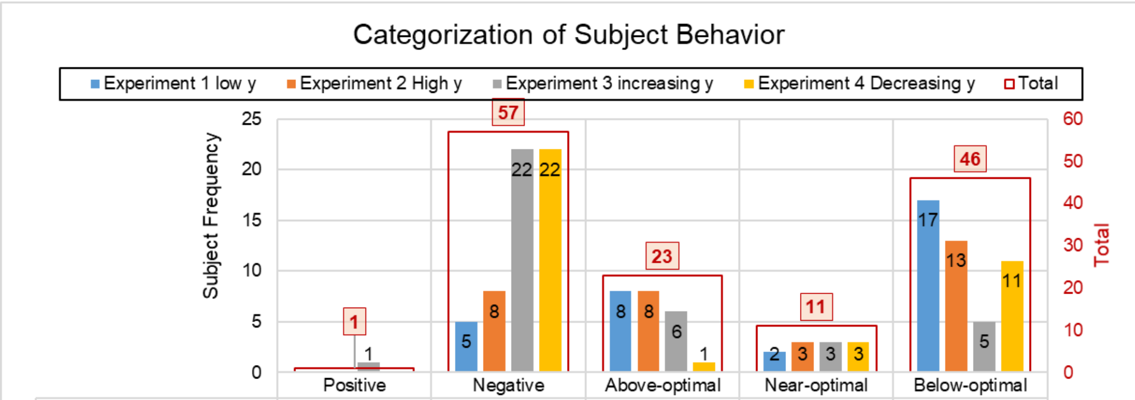
Category	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Total
	low y	High y	increasing y	Decreasing y	
Positive	0	0	1	0	**1**
Negative	5	8	22	22	**57**
Above-optimal	8	8	6	1	**23**
Near-optimal	2	3	3	3	**11**
Below-optimal	17	13	5	11	**46**
Total	**32**	**32**	**37**	**37**	**138**

Data in Table 16 is visualized in Figure 15, the immediate observation to make is the high frequency of subjects that show a negative correlation in pricing decisions with the demand of the previous period. Fifty seven out of 138 subjects fall into the “negative” category, corresponding to a percentage value of 41.3% and this implies a “gambler’s fallacy” type decision bias. They wrongfully expect the demand to decrease after a high realization, or vice versa. Especially in dynamic competitor price treatment (in experiments 3 and 4), subjects display the “gambler’s fallacy” bias with a rate of 59.4 % (22 out of 37 subjects for both experiments). This bias is surely the dominant behavioral pattern observed in a dynamic price setting.

The second most intensive category corresponds to subjects whose pricing decisions are less than the optimal price. One out of three subjects (46 out of 138, in total) decides on prices that are below-optimal. In static competitor price treatment (in experiments 1 and 2), subjects exhibit a higher tendency to underprice. In experiment 4, 11 out of 37 subjects (29.7%) demonstrate the same propensity.

Going forward, our study reveals that only a small minority of the subjects (11 out of 138 subjects) are able to make optimum pricing decisions. In fact, when the frequencies of "negative" and "below-optimal" category are analyzed together, since both of these categories depict a low-price tendency, the former depicting a price-lowering attitude, and the latter depicting a persistence in making below-optimal pricing decisions, 103 out of 138 subjects (corresponding to 74.6% of the sample) make wrongful judgments and set up low prices with respect to theoretical optimal.

The "positive" category contains only in one subject in Experiment 3; meaning that there is no detected sign of demand-chasing bias.



	Positive	Negative	Above-optimal	Near-optimal	Below-optimal
Experiment 1 low y	0	5	8	2	17
Experiment 2 High y	0	8	8	3	13
Experiment 3 increasing y	1	22	6	3	5
Experiment 4 Decreasing y	0	22	1	3	11
Total	1	57	23	11	46

Figure 15 Categorization of Subject Behavior

6. DISCUSSION

6.1. Comparing the potential and realized revenues

The average profitability and the tendency to reach that profitability in terms of percentage of potential revenue is compared in the table below.

Table 17 The profitability of mean realized revenue with respect to potential revenue due to decisions of human decision makers

Experiment No	Experiment	Seasons	Potential Revenue	Mean Realized Revenue	Percentage
1	Low y=30	Seasons 01-20	6,600.00	5,749.12	87%
		Seasons 21-40	6,528.00	5,825.90	89%
2	High y=120	Seasons 01-20	12,408.00	10,642.99	86%
		Seasons 21-40	12,350.00	10,115.16	82%
3	increasing y	Seasons 01-10	6,600.00	5,877.56	89%
		Seasons 11-20	8,378.00	7,935.12	95%
		Seasons 21-30	10,332.00	9,612.23	93%
		Seasons 31-40	12,462.00	10,815.38	87%
4	Decreasing y	Seasons 01-10	12,462.00	10,777.75	86%
		Seasons 11-20	10,332.00	9,304.94	90%
		Seasons 21-30	8,378.00	7,344.71	88%
		Seasons 31-40	6,600.00	5,117.73	78%

The profitability of human decision makers is compared in Table 17. The observations show that, in Experiments 1 and 2, while the competition price is fixed, there is no significant difference between potential revenue and realized revenue. In Experiments 3 and 4, when the competition price is changing dynamically, the realized revenue falls further away than the potential revenue (Figure 16).

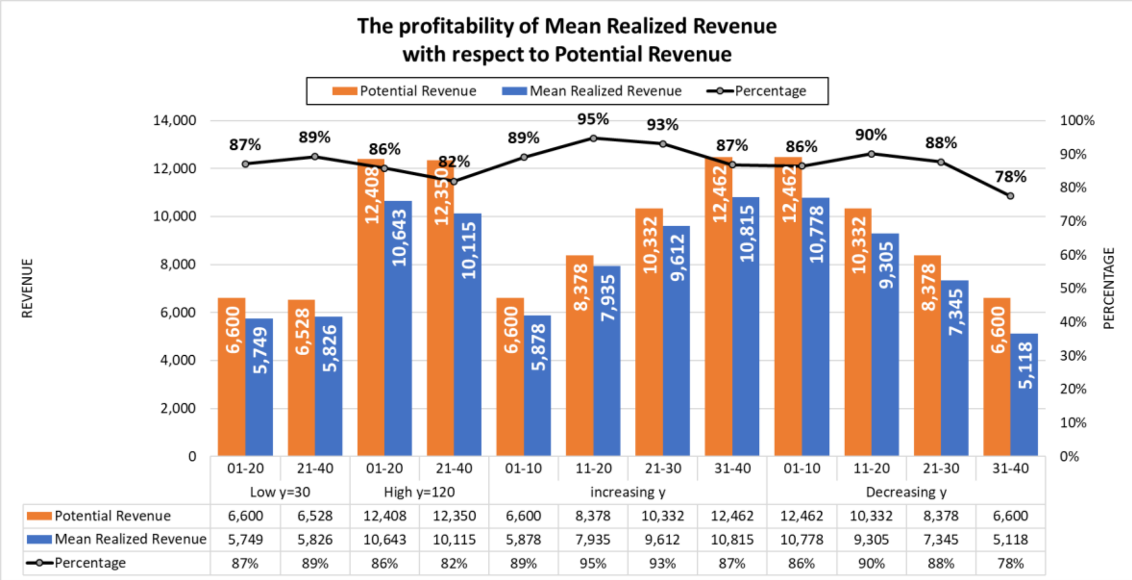


Figure 16 The profitability of mean realized revenue with respect to potential revenue

6.2. Summary of Hypotheses and Conclusions Reached

This study is conducted in a laboratory setting to carry out four computer-based experiments based on different assumptions. This thesis presented an experimental study of the pricing strategies in one-class revenue management problem. The main focus was to measure the consistency of pricing decisions made by human decision makers in obtaining the theoretical revenue management benchmarks. Although subjects were frequently able to reach the optimum price values in a static competitor environment, their decisions tend to deviate more and more in a dynamic competitor environment and subjects start to perform poorly. The hypotheses of the study and the conclusions reached are summarized in Table 18.

Table 18 Summary of the hypotheses and conclusions reached

	Hypothesis	Conclusion
1	In the “static competitor price” treatment for both competitor price levels, subjects’ pricing decisions will be as predicted by theory.	Weakly accepted
2	In the “static competitor price” treatment for both competitor price levels, subjects’ realized revenues will be as predicted by theory.	Rejected
3	The value of the competitive firm price given in the “static competitor price” treatment for both competitor price levels, do not affect the pricing decisions determined by the subjects.	Strongly accepted
4	The increase in the variance of the demand distribution in the second twenty seasons of the “static competitor price” treatment, do not affect the pricing decisions of the subjects.	Rejected
5	In the “dynamic competitor price” treatments, for both increasing and decreasing price trends, subjects’ pricing decisions will be as predicted by theory and they will not be biased by the trend of the competitor price.	Rejected
6	In the “dynamic competitor price” treatment for both competitor price trends, subjects’ realized revenues will be as predicted by theory.	Rejected
7	The value of the competitive firm price given in the “dynamic competitor price” treatment, do not affect the pricing decisions determined by the subjects.	Rejected
8	According to the cognitive reflection test results, subjects categorized with high CRT scores give prices closer to optimal than subjects categorized with low CRT scores.	Rejected
9	According to the cognitive reflection test results, subjects with higher CRT scores will earn higher revenues than those with lower CRT scores.	Rejected
10	According to the maximizing tendencies, subjects categorized with high MT scores give prices closer to optimal than subjects categorized with low MT scores.	Rejected
11	According to the maximizing tendencies, subjects with higher MT scores will earn higher revenues than those with lower MT scores.	Rejected
12	According to the risk appetites, subjects with higher risk scores set higher prices on average than those with lower risk scores.	Weakly accepted
13	According to the risk appetites, subjects with higher risk scores will earn higher revenues than those with lower risk scores.	Rejected

6.3. Main Findings of the Study

The main findings of the conducted experiments are the following:

- Although in static competitor price treatment (in experiments 1 and 2), subjects exhibit a higher tendency to underprice, decision makers are somewhat better at making pricing decision when the competitor's price is low.
- The "gambler's fallacy" bias is surely the dominant behavioral pattern observed in a dynamic price setting. The second most intensive category corresponds to subjects whose pricing decisions are less than the optimal price.
- In case where the competitor's price is dynamically changing, the subjects show an anchoring effect towards the competitor price and tend to increase (or decrease) their price even further away from the optimum. Hence, the need for a "decision support tool" that effectively shows possible outcomes of the pricing decisions beforehand is a necessity to guide human decision makers in a more consistent way.
- An important notion to consider is the presence of bounded rationality that definitely affects the consistency of meeting the optimum price values. Only a small minority (8%) of the subjects are able to make optimum pricing decisions.
- The subjects with higher cognitive reflection skills perform somewhat better than those with lower cognitive reflection skills (although not significantly better). In case of a dynamic competitor price setting, the bounded rationality phenomenon gains even more importance.
- On the other hand, the high scores of maximizing tendency does not create a significant boost in performing better in meeting neither the optimum price, nor the potential revenue.
- Human decision makers with higher risk scores tend to make better decisions in a dynamic competitor price setting. The risk appetite of subjects significantly affects their pricing decisions and result in price values closer to optimal.
- The impact of learning effect is not clearly present in the findings of carried-out experiments. Despite the fact that subjects are able to improve their performance in price decisions and revenue-making, the increase in performance does not survive for a long time and subjects tend to deviate from the theoretical benchmarks at some point. Revenue management literature covers a parallel conclusion stating that humans carry the risk of becoming overconfident with wrong decisions and this results in persistence in poor performance.

- Demand-chasing bias is not a prevalent observation in our study.

This study proves how important the presence of decision support tools that would help in refining the decision making process in order to maximize the theoretical monetary gain is. Ramachandran et al. (2018) mentions this need boldy. The current decision support tools can only provide forecast figures; however, they are not able to warn the user in case of a persistent shortfall in reaching theoretical optimums. The lack of a more intelligent software, a systematic patch that would act as an artificial intelligence package, is crucial in real-life settings where the environmental factors change dynamically. The decision-making processes should be re-designed to allow limited human interference and to automatize a significant portion of the vital steps in profit maximization. Human decision makers are flawed and carry a strong tendency towards developing overconfidence or aggressiveness in decision making. The lack of a more effective decision support tool becomes more and more crucial as time progresses with wrongful judgements made by humans.

7. CONCLUSION

The behavior patterns of the subjects and the degree of deviation of these behaviors from optimal strategies are analyzed by various statistical methods. The common aim of the experiments examined in this thesis was to understand how successful theoretical Revenue Management models are in explaining real human behavior. In various cases, it has been possible to determine the direction that deviations from theoretical models occur, understand the underlying causes, and the type of information that should be provided to decision makers. In general, especially for dynamic environments where the competitor price is changing from day to day, an efficient “Decision Support Tool” should aid the decision makers in order to prevent them from focusing too much on the rival prices and miss the essence of the market demand function. In all settings, this Decision Support Tool must be designed to warn the decision makers regarding possible underpricing, gambler’s fallacy, or other irrational behaviors by reminding them of the theoretical optimal values based on a historical analysis and future predictions of the market data.

It is obvious how important it is to make pricing decisions, which is one of the decisions that seriously affect the profitability of a company. In this context, this study is very useful in determining the issues that companies aiming to increase their profitability should pay attention to in terms of human factor and the measures they can take to improve these decisions.

7.1. Suggestions for Future Research

This study can be improved by obtaining larger sample sizes to reach a p-value less than 0.05 in CRT scores, to be able to state that higher cognitive reflection skills may cause a significant change. Research can also be broadened thanks to the addition of new parameters.

The experiments can be further conducted with different environmental settings, such as a two-class airline context, two flights on a day to the same route, the possibility of overbooking, etc.

In the next phase of the research, a simple but functional "Decision Support Tool" on Excel interface can be developed that decision makers can easily consult. This decision support tool needs to be designed to analyze the subjects' past decisions and provide feedback by identifying systematic deviations in their behavior.

In an experiment to be carried out with the participation of real subjects, it can be aimed to observe whether there is an improvement in the decision-making performance of the subjects who make decisions according to the "Decision Support Tool".

The literature related to pricing models in revenue management requires a deeper attention and examination from a behavioral operations perspective.

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APPENDIX A Questionnaire for Cognitive Reflection Test (CRT), Maximizing Tendency (MT) and Risk Scores of Test Subjects

A.1 Questions for Cognitive Reflection Test (CRT)

Q1.	A bat and a ball cost $1.10 in total. The bat costs $1 more than the ball. How much does the ball cost?	(intuitive answer: 10 cents; correct answer: 5 cents)
	Bir pinpon topu ve raketinin toplam maliyeti 1,10 TL'dir. Raketin maliyeti, pinpon topunun maliyetinden 1,00 TL fazladır. Pinpon topunun maliyeti ne kadardır?	
Q2.	If it takes 5 machines 5 min to make 5 widgets, how long would it take 100 machines to make 100 widgets?	(intuitive answer: 100; correct answer: 5)
	5 makine 5 ürünü 5 dakikada üretirse, 100 makine 100 ürünü kaç dakikada üretir?	
Q3.	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half the lake?	(intuitive answer: 24, correct answer: 47)
	Bir gölün yüzeyini nilüferler kaplamıştır. Nilüferlerin kapladığı alan her gün 2 katına çıkmaktadır. Eğer nilüferlerin bütün göl yüzeyini kaplaması 48 gün sürerse, gölün yarısını kaplaması kaç gün sürer?	

Q4.	If you're running a race and you pass the person in second place, what place are you in?	(intuitive answer: first; correct answer: second)
	Bir yarışmada koşucusunuz. İkinci olan yarışmacıyı geçtiğinizde kaçıncı sırada olursunuz?	
Q5.	A farmer had 15 sheep and all but 8 died. How many are left?	(intuitive answer: 7; correct answer: 8)
	Bir çiftçinin 15 koyunu vardı ve 8'i dışında hepsi öldü. Kaç tane kaldı?	
Q6.	Emily's father has three daughters. The first two are named April and May. What is the third daughter's name?	(intuitive answer: June; correct answer: Emily)
	Emine'nin babasının üç kızı vardır. İlk ikisinin adı Nisan ve Mayıs'tır. Üçüncü kızının adı nedir?	
Q7.	How many cubic feet of dirt are there in a hole that is 3'deep x 3' wide x 3' long?	(intuitive answer: 27; correct answer: none)
	3 metre eninde, 3 metre boyunda ve 3 metre derinliğindeki bir çukurun içinde kaç metreküp çamur vardır?	

A.2 Questions for Maximizing Tendency (MT)

Q8.1.	When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program.	Televizyonda bir program izlemeye çalışırken bile diğer kanallar arasında zap yaparım.
Q8.2.	When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to.	Arabada radyo dinlerken, dinlediğimden memnun olsam bile diğer istasyonlarda daha iyi bir şey çalıp çalmadığını görmek için sık sık kontrol ederim.
Q8.3.	I treat relationships like clothing: I expect to try a lot on before I get the perfect fit.	İnsanlarla olan iişkilerimde kıyafet seçer gibi davranırım. Mükemmel bir uyum elde edebilmek için çok sayıda deneme gerekir.
Q8.4.	No matter how satisfied I am with my job, it's only right for me to be on the lookout for better opportunities.	İşimden ne kadar memnun olsam da, daha iyi fırsatlar için gözlerimi sürekli açık tutarım.
Q8.5.	I often fantasize about living in ways that are quite different from my actual life.	Şimdiki hayatımdan çok daha farklı şekilde yaşamayı sıklıkla hayal ederim.
Q8.6.	I'm a big fan of lists that attempt to rank things (the best movies, the best singers, the best athletes, the best novels, etc.).	En iyi filmler, en iyi şarkıcılar, en iyi atletler, en iyi romanlar vb. şeyleri sıralayan listeleri severim.
Q8.7.	I often find it difficult to shop for a gift for a friend.	Arkadaşıma uygun hediyeyi alabilmekte çoğu zaman zorlanırım.
Q8.8.	When shopping, I have a hard time finding clothing that I really love.	Alışveriş yaparken çok sevebileceğim kıyafeti bulmakta zorlanırım.
Q8.9.	Renting videos is really difficult. I'm always struggling to pick the best one.	İzleyeceğim filmi seçerken çok zorlanırım. Her zaman en iyisini seçebilmek için uğraşırım.
Q8.10.	I find that writing is very difficult, even if it's just writing a letter to a friend, because it's so hard to word things just right. I often do several drafts of even simple things.	Arkadaşıma sıradan bir mail yazarken bile çok zorlanırım çünkü doğru kelimeleri bulmak bana çok zor gelir. Çoğu zaman basit şeylerin bile taslaklarını yaparım.
Q8.11.	No matter what I do, I have the highest standards for myself.	Her ne iş yaparsam, kendim için yüksek standartlar belirlerim.
Q8.12.	I never settle for second best.	İkinci olmayı kendime asla yediremem.
Q8.13.	Whenever I'm faced with a choice, I try to imagine what all the other possibilities are, even ones that aren't present at the moment.	Ne zaman bir seçim yapmak zorunda kalsam, diğer tüm olasılıkların ne olabileceğini, hatta şu anda mevcut olmayanları bile hayal etmeye çalışırım.

A.3 Questions for Risk Scores

Q9.	A lottery draw will be held where the prize is 1000 TL and only 10 people will participate. How much will you be willing to pay for the lottery ticket?	Ödülün 1000 TL olduğu ve sadece 10 kişinin katılacağı bir piyango çekilişi yapılacaktır. Piyango bileti için ne kadar ödemeye razı olursunuz?
Q10.	You will receive a free lottery ticket or 100 TL from the drawing above. Which one would you prefer? a) Ticket b) 100 TL	Yukarıdaki çekilişten ücretsiz bir adet piyango bileti ya da 100 TL alacaksınız. Hangisini tercih edersiniz? a) Bilet b) 100 TL
Q11.	You have won a ticket from the above draw and have not paid any fee. Someone very good at bargaining wants to buy tickets from you. What is the lowest price you will sell the ticket?	Yukarıdaki çekilişten bir bilet kazandınız ve bilete herhangi bir ücret ödemediniz. Pazarlık yapmada çok iyi olan birisi sizden bilet almak istiyor. Bileti satacağınız en düşük fiyat nedir?
Q12.	In case of flipping a coin in each of the following situations, you will earn 6 TL. How much money you will lose in case of tails is stated in the following cases. If you do not agree to play the game, you will not lose anything. Please indicate whether you agree to play the game.	Aşağıdaki durumların her birinde madeni paranın tura gelmesi durumunda 6 TL kazanacaksınız. Yazı gelmesi durumunda ne kadar para kaybedeceğiniz aşağıdaki durumlarda belirtilmiştir. Oyunu oynamayı kabul etmediğinizde herhangi bir şey kazanıp kaybetmeyeceksiniz. Lütfen oyunu oynamayı kabul edip etmediğinizi belirtiniz.
Q12.1.	Game 1: TAILS: You lose 2 TL, HEADS: You earn 6 TL.	Oyun 1: YAZI: 2 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.2.	Game 2: TAILS: You lose 3 TL, HEADS: You earn 6 TL.	Oyun 2: YAZI: 3 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.3.	Game 3: TAILS: You lose 4 TL, HEADS: You earn 6 TL.	Oyun 3: YAZI: 4 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.4.	Game 4: TAILS: You lose 5 TL, HEADS: You earn 6 TL.	Oyun 4: YAZI: 5 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.5.	Game 5: TAILS: You lose 6 TL, HEADS: You earn 6 TL.	Oyun 5: YAZI: 6 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.6.	Game 6: TAILS: You lose 7 TL, HEADS: You earn 6 TL.	Oyun 6: YAZI: 7 TL kaybedersiniz, TURA: 6 TL kazanırsınız.
Q12.7.	Game 7: TAILS: You lose 8 TL, HEADS: You earn 6 TL.	Oyun 7: YAZI: 8 TL kaybedersiniz, TURA: 6 TL kazanırsınız.

APPENDIX B Instructions given to subjects during the Experiments

B.1 Instructions given during Experiment 1

Merhaba Sayın Satış Direktörüm,
PATA Havayolları sayesinde Türk ticari sivil havacılığı yepyeni bir pazarlama anlayışına kavuştu! Ayrıcalıklı hizmetlerimiz ve rekabetçi fiyat politikamızla pazarı bilmediği yeniliklerle tanıştırmanın gururunu yaşıyoruz.
Her ne kadar adımızın anlamı "berabere kalma" olsa da PATA Havayolları yeni sezonda da pata gelmeyecek ve en yakın rakibimiz olan YABAN Havayolları'ndan çok daha fazla gelir elde edecek. Bu hedefimiz için sizin değerli öngörülerinize ihtiyaç duyuyoruz.
Stratejik Plan'ımızda da belirttiğimiz gibi **YABAN Havayolları'nın yolcu bileti için belirlediği fiyatın istihbaratını aldık: Sezon boyunca 30 PB'den bilet satacaklar! (y=30)**
PATA Havayolu'muzun fiyatını ise belirleyecek olan sizsiniz! Belirlediğiniz fiyata göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecek. Gözlemleyeceğiniz talep, YABAN Havayolu'nun fiyatı olan **y** ile artarken PATA Havayolu'nun fiyatı olan ***p*** ile azalacaktır.
Daha spesifik bir biçimde,

- ilk 20 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [180-2***p***, 280-2***p***] aralığında,
- ikinci 20 sezon boyunca ise [100+y-2***p***, 300+y-2***p***] = [130-2***p***, 330-2***p***] aralığında

ayrık düzgün dağılıma göre gerçekleşecek. Örneğin, fiyatımız ***p=90*** ise ve ilk 20 sezon içerisindeysek, firmamızın gözlemleyeceği müşteri talebi [0, 100] aralığında ayrık düzgün dağılıma göre gerçekleşecektir; bir başka deyişle talep, 0 ile 100 arasında herhangi bir tam sayı değerini eşit olasılıkla alabilir.
Değerli Satış Direktörüm,
PATA Havayolu'nun yöneticisi olarak sizin öngörünüze ihtiyacımız var. En yakın rakibimiz YABAN Havayolu'nun sattığı biletin fiyatını göz önüne alarak PATA'nın bilet fiyatını tespit etmeniz gerekiyor. Belirlediğiniz fiyat ***p***'ye göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecektir. Talebin elinizdeki koltuk sayısından daha fazla olması durumunda, elinizdeki koltuk kadar bilet satılacaktır. Her sezonda satabileceğimiz 150 adet koltuk bulunmakta. Yani:

Bir sezondaki Satılan bilet sayısı = min{gerçekleşen talep, 150}

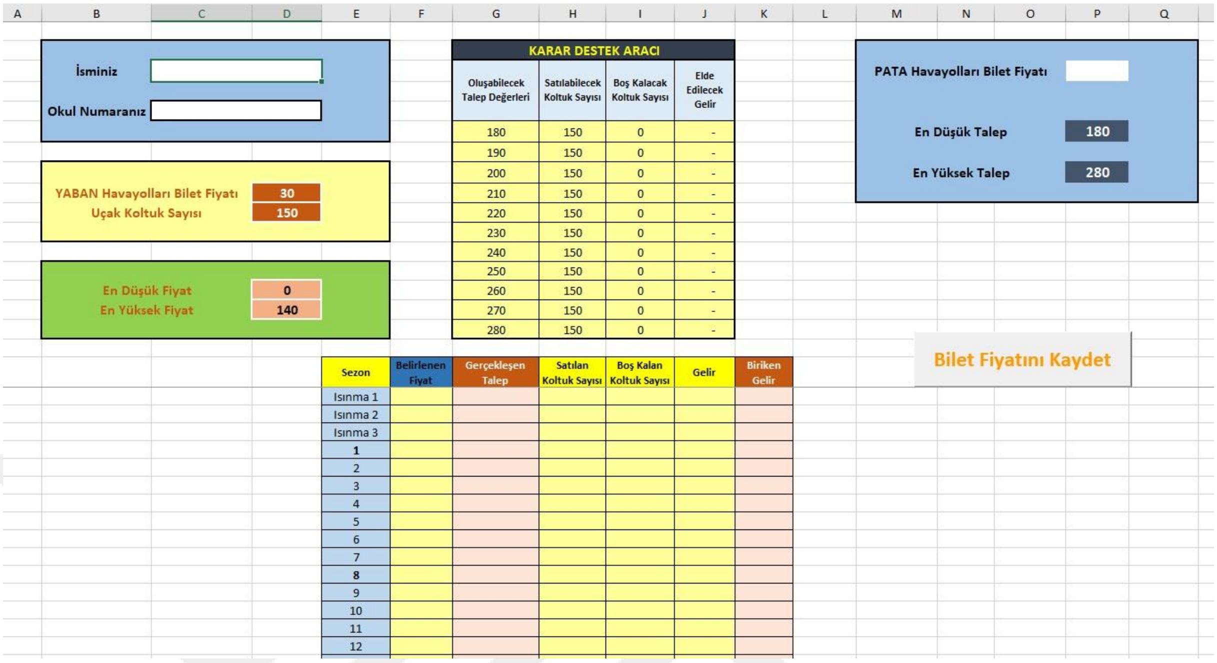
Bu oyunda 40 ardışık periyot boyunca fiyatlandırma kararı vereceksiniz. Her periyot, farklı bir satış sezonuna tekabül etmektedir. Sezonlar birbirinden bağımsızdır ve her sezonda gerçekleşen talep değeri önceki sezonda gerçekleşen talep ile bağlantısızdır; yani trend ya da mevsimsellik gibi durumlar söz konusu değildir. Dolayısıyla her bir sezonda elde edilen gelir, o sezondaki toplam satış miktarı ile fiyatın çarpımına eşit olacaktır:

Bir sezondaki Gelir = ***p*** x min{gerçekleşen talep, 150}

Oyunun sonunda elde ettiğiniz toplam gelir, her sezonda elde edilen Gelir değerlerinin toplamı olarak hesaplanacaktır.
<u>**Sizin hedefiniz, 40 sezonun sonunda kazanacağımız toplam geliri maksimize etmektir.**</u>

SATIŞ EKRANI

Örnek bir Ekran Görüntüsü: Aşağıdaki figür, ekranınızın nasıl göründüğüne bir örnektir:



İsminiz

Okul Numaranız

YABAN Havayolları Bilet Fiyatı 30

Uçak Koltuk Sayısı 150

En Düşük Fiyat 0

En Yüksek Fiyat 140

KARAR DESTEK ARACI

Oluşabilecek Talep Değerleri	Satılabilecek Koltuk Sayısı	Boş Kalacak Koltuk Sayısı	Elde Edilecek Gelir
180	150	0	-
190	150	0	-
200	150	0	-
210	150	0	-
220	150	0	-
230	150	0	-
240	150	0	-
250	150	0	-
260	150	0	-
270	150	0	-
280	150	0	-

PATA Havayolları Bilet Fiyatı

En Düşük Talep 180

En Yüksek Talep 280

Bilet Fiyatını Kaydet

Sezon	Belirlenen Fiyat	Gerçekleşen Talep	Satılan Koltuk Sayısı	Boş Kalan Koltuk Sayısı	Gelir	Biriken Gelir
Isınma 1						
Isınma 2						
Isınma 3						
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						

Figür 1: Satış Ekranı

- Ekranın sol üst köşesindeki mavi kutucuklara isminizi ve okul numaranız bilgisini girmeniz gerekmektedir.
- Ekranın üst bölümünde ortadaki sarı büyük tablo, Karar destek aracıdır (fonksiyonu aşağıda açıklanacaktır).
- Fiyatlandırma kararınızı, ekranın sağ üst köşesindeki mavi kutunun içerisindeki (*PATA Havayolları Bilet Fiyatı* yazılı) beyaz hücreye girmeniz gerekmektedir. Daha sonra talep aralığının minimum ve maksimum değerleri girdiğiniz fiyata bağlı olarak aşağıdaki mavi hücrelerde gösterilecektir.
- Daha sonra Karar Destek Aracı'nda olası sonuçlara bakarak fiyatlandırma kararınızı değerlendirebilirsiniz.
- Kararınızı göndermeye hazır olduğunuzda mavi kutunun alt tarafındaki "**Bilet Fiyatını Kaydet**" düğmesine tıklayınız.

Karar Destek Aracı:

Kararınızı göndermeden önce, Karar Destek Aracını kullanabilirsiniz. Bu araç size fiyatlandırma kararınızın getireceği olası talep değerleri hakkında bilgi sunar. Örneğin, 15. sezonda iken bilet fiyatını **50 PB** seçtiğinizi varsayalım. Minimum müşteri talebi 80, maksimum müşteri talebi ise 180 olacaktır. Figür 2 ise olası talep değerlerine göre bu kararınızın getireceği satış miktarını ve gelir değerlerini listelemektedir. Kırmızı kutudaki satır, talebin 80 olarak gerçekleştiği durumda olacakları göstermektedir; **80 yolcu** elinizdeki 150 koltuktan küçüktür. Bu nedenle 80 koltuk satabileceksiniz ve 150-80 = **70 koltuk ise boş kalacaktır**. (Oyunun doğası gereği sezonlar birbirinden bağımsız olacağından boş kalan koltuklar bir sonraki sezona devredilemez; 16. sezonda elinizde yine 150 koltuk olacaktır.) Eğer talep 80 olarak gerçekleşirse elde edeceğiniz Gelir değeri ise 80 x 50 = 4000 PB'dir.

KARAR DESTEK ARACI			
Oluşabilecek Talep Değerleri	Satılabilecek Koltuk Sayısı	Boş Kalacak Koltuk Sayısı	Elde Edilecek Gelir
80	80	70	4,000
90	90	60	4,500
100	100	50	5,000
110	110	40	5,500
120	120	30	6,000
130	130	20	6,500
140	140	10	7,000
150	150	0	7,500
160	150	0	7,500
170	150	0	7,500
180	150	0	7,500

Figür 2: Karar Destek Aracı

Örnek:

Varsayalım ki 23. sezondasınız ve fiyatınızı 45 PB olarak belirlediniz. Karar Destek Sistemi size göreceğiniz talebin 40 ve 240 arasında olacağı bilgisini verecektir. "**Bilet Fiyatını Kaydet**" düğmesine tıkladıktan sonra varsayımsal talep değeri gerçekleşecek ve bu aralıkta spesifik bir değer alacaktır.

- Örneğin bu değer 123 olarak gerçekleşti diyelim. Bu durumda 23. sezonda 150-123=**27 koltuk boş** kalacaktır. **Elde edeceğiniz gelir** ise 123 x 45 = **5,535 PB** olacaktır.
- Öte yandan, örneğin 182 yolcu bilet talep ederse, bu kez elinizdeki tüm koltukları satacaksınız, ancak talebin tümü karşılanamayacaktır. Bu durumda ise elde edeceğiniz gelir 150 x 45 = **6,750 PB** olacaktır.

Eğer bu sezonda bilet fiyatını **72 PB** olarak belirlemiş olsaydınız, göreceğiniz talep 0-186 aralığında bir değer alacaktı. Gördüğünüz gibi, **verdiğiniz fiyatlandırma kararı talep dağılım aralığını, dolayısıyla elde edeceğiniz geliri etkilemektedir.**

Sayın Satış Direktörüm,
PATA Havayolu'nun sizin tecrübenize ve öngörünüze ihtiyacı var... Bilet satışında birinciliğimizi perçinleyelim ve bir kez daha YABAN Havayolu'nu geride bırakıp, en yüksek gelire sahip havayolu olmaya devam edelim!

B.2 Instructions given during Experiment 2

Merhaba Sayın Satış Direktörüm,
PATA Havayolları sayesinde Türk ticari sivil havacılığı yepyeni bir pazarlama anlayışına kavuştu! Ayrıcalıklı hizmetlerimiz ve rekabetçi fiyat politikamızla pazarı bilmediği yeniliklerle tanıştırmanın gururunu yaşıyoruz.
Her ne kadar adımızın anlamı “berabere kalma” olsa da PATA Havayolları yeni sezonda da pata gelmeyecek ve en yakın rakibimiz olan YABAN Havayolları’ndan çok daha fazla gelir elde edecek. Bu hedefimiz için sizin değerli öngörülerinize ihtiyaç duyuyoruz.
Stratejik Plan’ımızda da belirttiğimiz gibi **YABAN Havayolları’nın yolcu bileti için belirlediği fiyatın istihbaratını aldık: Sezon boyunca 120 PB’den bilet satacaklar! (y=120)**
PATA Havayolu’muzun fiyatını ise belirleyecek olan sizsiniz! Belirlediğiniz fiyata göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecek. Gözlemleyeceğiniz talep, YABAN Havayolu’nun fiyatı olan **y** ile artarken PATA Havayolu’nun fiyatı olan ***p*** ile azalacaktır.
Daha spesifik bir biçimde,

- ilk 20 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [270-2***p***, 370-2***p***] aralığında,
- ikinci 20 sezon boyunca ise [100+y-2***p***, 300+y-2***p***] = [220-2***p***, 420-2***p***] aralığında

ayrık düzgün dağılıma göre gerçekleşecek. Örneğin, fiyatımız ***p=110*** ise ve ilk 20 sezon içerisindeysek, firmamızın gözlemleyeceği müşteri talebi [50, 150] aralığında ayrık düzgün dağılıma göre gerçekleşecektir; bir başka deyişle talep, 50 ile 150 arasında herhangi bir tam sayı değerini eşit olasılıkla alabilir.

Değerli Satış Direktörüm,
PATA Havayolu’nun yöneticisi olarak sizin öngörünüze ihtiyacımız var. En yakın rakibimiz YABAN Havayolu’nun sattığı biletin fiyatını göz önüne alarak PATA’nın bilet fiyatını tespit etmeniz gerekiyor. Belirlediğiniz fiyat ***p***’ye göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecektir. Talebin elinizdeki koltuk sayısından daha fazla olması durumunda, sadece elinizdeki koltuk kadar bilet satılacaktır. Her sezonda satabileceğimiz 150 adet koltuk bulunmakta. Yani:

Bir sezondaki Satılan bilet sayısı = min{gerçekleşen talep, 150}

Bu oyunda 40 ardışık periyot boyunca fiyatlandırma kararı vereceksiniz. Her periyot, farklı bir satış sezonuna tekabül etmektedir. Sezonlar birbirinden bağımsızdır ve her sezonda gerçekleşen talep değeri önceki sezonda gerçekleşen talep ile bağlantısızdır; yani trend ya da mevsimsellik gibi durumlar söz konusu değildir. Dolayısıyla her bir sezonda elde edilen gelir, o sezondaki toplam satış miktarı ile fiyatın çarpımına eşit olacaktır:

Bir sezondaki Gelir = ***p*** x min{gerçekleşen talep, 150}

Oyunun sonunda elde ettiğiniz toplam gelir, her sezonda elde edilen Gelir değerlerinin toplamı olarak hesaplanacaktır.
Sizin hedefiniz, 40 sezonun sonunda kazanacağımız toplam geliri maksimize etmektir.

SATIŞ EKRANI

Örnek bir Ekran Görüntüsü: Aşağıdaki figür, ekranınızın nasıl göründüğüne bir örnektir:

Figür 1: Satış Ekranı

- Ekranın sol üst köşesindeki mavi kutucuklara isminizi ve okul numaranız bilgisini girmeniz gerekmektedir.
- Ekranın üst bölümünde ortadaki sarı büyük tablo, Karar Destek Aracı'dır (fonksiyonu aşağıda açıklanacaktır).
- Fiyatlandırma kararınızı, ekranın sağ üst köşesindeki mavi kutunun içerisindeki (*PATA Havayolları Bilet Fiyatı* yazılı) beyaz hücreye girmeniz gerekmektedir. Daha sonra talep aralığının minimum ve maksimum değerleri girdiğiniz fiyata bağlı olarak aşağıdaki mavi hücrelerde gösterilecektir.
- Daha sonra Karar Destek Aracı'nda olası sonuçlara bakarak fiyatlandırma kararınızı değerlendirebilirsiniz.
- Kararınızı göndermeye hazır olduğunuzda mavi kutunun alt tarafındaki "**Bilet Fiyatını Kaydet**" düğmesine tıklayınız.

Karar Destek Aracı:

Kararınızı göndermeden önce, Karar Destek Aracını kullanabilirsiniz. Bu araç size fiyatlandırma kararınızın getireceği olası talep değerleri hakkında bilgi sunar. Örneğin, 15. Periyotta iken bilet fiyatı olarak **85 PB** değerini seçtiğinizi varsayalım. Minimum müşteri talebi 100, maksimum talep ise 200 olacaktır. Figür 2 ise olası talep değerlerine göre bu kararınızın getireceği satış miktarını ve gelir değerlerini listelemektedir. Kırmızı kutudaki satır, talebin 100 olarak gerçekleştiği durumda olacakları göstermektedir; **100** yolcu elinizdeki 150 koltuktan azdır. Bu nedenle 100 koltuk satabileceksiniz ve 150-100 = 5**0 koltuk ise boş kalacaktır**. (Oyunun doğası gereği sezonlar birbirinden bağımsız olacağından boş kalan koltuklar bir sonraki sezona devredilemez; 16. sezonda elinizde yine 150 koltuk olacaktır.) Eğer talep 100 olarak gerçekleşirse elde edeceğiniz Gelir değeri ise 100 x 85 = 8,500 PB'dir.

KARAR DESTEK SİSTEMİ			
Oluşabilecek Talep Değerleri	Satılan Koltuk Sayısı	Boş Kalan Koltuk Sayısı	Gelir
100	100	50	8,500
110	110	40	9,350
120	120	30	10,200
130	130	20	11,050
140	140	10	11,900
150	150	0	12,750
160	150	0	12,750
170	150	0	12,750
180	150	0	12,750
190	150	0	12,750
200	150	0	12,750

Figür 2: Karar Destek Aracı

Örnek:

Varsayalım ki 23. sezondasınız ve fiyatınızı 65 PB olarak belirlediniz. Karar Destek Sistemi size göreceğiniz talebin 90 ve 290 arasında olacağı bilgisini verecektir. "**Bilet Fiyatını Kaydet**" düğmesine tıkladıktan sonra varsayımsal talep değeri gerçekleşecek ve bu aralıkta spesifik bir değer alacaktır.

- Örneğin bu değer 123 olarak gerçekleşti diyelim. Bu durumda 23. sezonda 150-123=**27 koltuk boş** kalacaktır. **Elde edeceğiniz gelir** ise 123 x 65 = **7,995 PB** olacaktır.
- Öte yandan, örneğin 182 yolcu bilet talep ederse, bu kez elinizdeki tüm koltukları satacaksınız, ancak talebin tümü karşılanamayacaktır. Bu durumda ise elde edeceğiniz gelir 150 x 65 = **9,750 PB** olacaktır.

Eğer bu sezonda bilet fiyatını **92 PB** olarak belirlemiş olsaydınız, göreceğiniz talep 36-236 aralığında bir değer alacaktı. Gördüğünüz gibi, **verdiğiniz fiyatlandırma kararı talep dağılım aralığını, dolayısıyla elde edeceğiniz geliri etkilemektedir.**

Sayın Satış Direktörüm,
PATA Havayolu'nun sizin tecrübenize ve öngörünüze ihtiyacı var... Bilet satışında birinciliğimizi perçinleyelim ve bir kez daha YABAN Havayolu'nu geride bırakıp, en yüksek gelire sahip havayolu olmaya devam edelim!

B.3 Instructions given during Experiment 3

Merhaba Sayın Satış Direktörüm,
PATA Havayolları sayesinde Türk ticari sivil havacılığı yepyeni bir pazarlama anlayışına kavuştu! Ayrıcalıklı hizmetlerimiz ve rekabetçi fiyat politikamızla pazarı bilmediği yeniliklerle tanıştırmanın gururunu yaşıyoruz.
Her ne kadar adımızın anlamı "berabere kalma" olsa da PATA Havayolları yeni sezonda da pata gelmeyecek ve en yakın rakibimiz olan YABAN Havayolları'ndan çok daha fazla gelir elde edecek. Bu hedefimiz için sizin değerli öngörülerinize ihtiyaç duyuyoruz.
Stratejik Plan'ımızda da belirttiğimiz gibi **YABAN Havayolları'nın yolcu bileti için belirlediği fiyatın istihbaratını aldık: İlk 10 sezon boyunca 30 PB'den, sonraki 10 sezon 60 PB'den, sonra 90 PB'den ve son 10 sezon 120 PB'den bilet satacaklar!**
PATA Havayolu'muzun fiyatını ise belirleyecek olan sizsiniz! Belirlediğiniz fiyata göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecek. Gözlemleyeceğiniz talep, YABAN Havayolu'nun fiyatı olan **y** ile artarken PATA Havayolu'nun fiyatı olan ***p*** ile azalacaktır.
Daha spesifik bir biçimde,

- ilk 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [180-2***p***, 280-2***p***] aralığında,
- ikinci 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [210-2***p***, 310-2***p***] aralığında,
- üçüncü 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [240-2***p***, 340-2***p***] aralığında,
- son 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [270-2***p***, 370-2***p***] aralığında,

ayrık düzgün dağılıma göre gerçekleşecektir. Örneğin, fiyatımız ***p=90*** ise ve ilk 10 sezon içerisindeysek, firmamızın gözlemleyeceği müşteri talebi [0, 100] aralığında ayrık düzgün dağılıma göre gerçekleşecektir; bir başka deyişle talep, 0 ile 100 arasında herhangi bir tam sayı değerini eşit olasılıkla alabilir.
Değerli Satış Direktörüm,
PATA Havayolu'nun yöneticisi olarak sizin öngörünüze ihtiyacımız var. En yakın rakibimiz YABAN Havayolu'nun sattığı biletin fiyatını göz önüne alarak PATA'nın bilet fiyatını tespit etmeniz gerekiyor. Belirlediğiniz fiyat ***p***'ye göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecektir. Talebin elinizdeki koltuk sayısından daha fazla olması durumunda, elinizdeki koltuk kadar bilet satılacaktır. Her sezonda satabileceğimiz 150 adet koltuk bulunmakta. Yani:

Bir sezondaki Satılan bilet sayısı = min{gerçekleşen talep, 150}

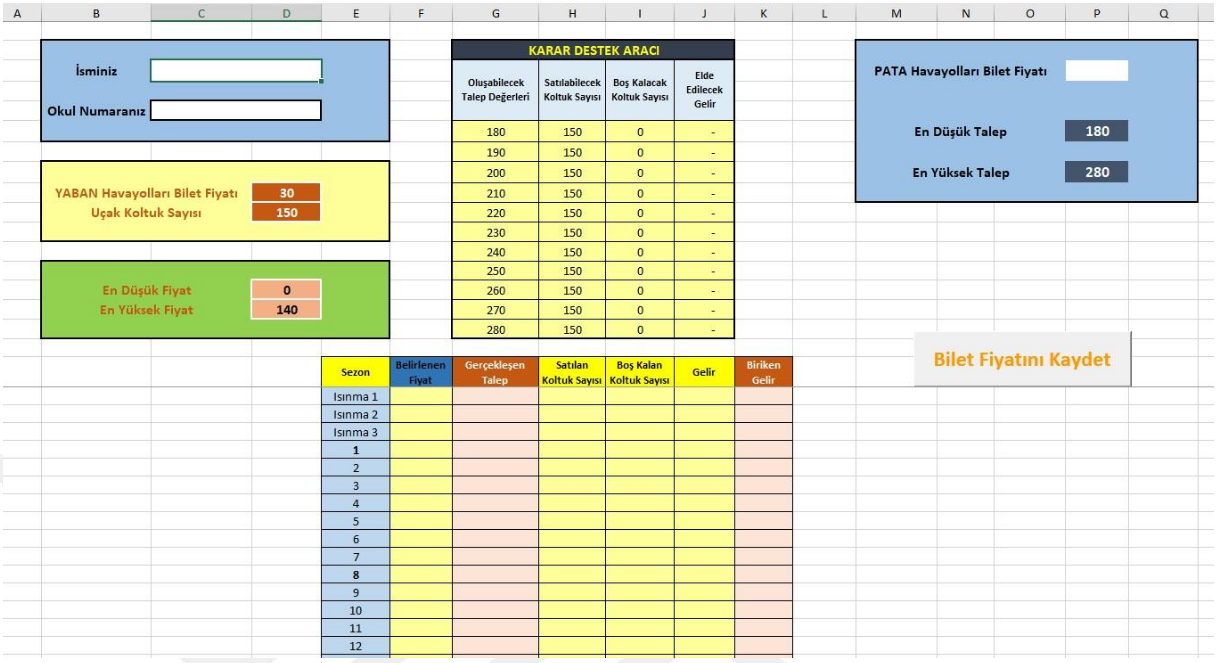
Bu oyunda 40 ardışık periyot boyunca fiyatlandırma kararı vereceksiniz. Her periyot, farklı bir satış sezonuna tekabül etmektedir. Sezonlar birbirinden bağımsızdır ve her sezonda gerçekleşen talep değeri önceki sezonda gerçekleşen talep ile bağlantısızdır; yani trend ya da mevsimsellik gibi durumlar söz konusu değildir. Dolayısıyla her bir sezonda elde edilen gelir, o sezondaki toplam satış miktarı ile fiyatın çarpımına eşit olacaktır:

Bir sezondaki Gelir = ***p*** x min{gerçekleşen talep, 150}

Oyunun sonunda elde ettiğiniz toplam gelir, her sezonda elde edilen Gelir değerlerinin toplamı olarak hesaplanacaktır.
Sizin hedefiniz, 40 sezonun sonunda kazanacağımız toplam geliri maksimize etmektir.

SATIŞ EKRANI

Örnek bir Ekran Görüntüsü: Aşağıdaki figür, ekranınızın nasıl göründüğüne bir örnektir:



Figür 1: Satış Ekranı

- Ekranın sol üst köşesindeki mavi kutucuklara isminizi ve okul numaranız bilgisini girmeniz gerekmektedir.
- Ekranın üst bölümünde ortadaki sarı büyük tablo, Karar destek aracıdır (fonksiyonu aşağıda açıklanacaktır).
- Fiyatlandırma kararınızı, ekranın sağ üst köşesindeki mavi kutunun içerisindeki (*PATA Havayolları Bilet Fiyatı* yazılı) beyaz hücreye girmeniz gerekmektedir. Daha sonra talep aralığının minimum ve maksimum değerleri girdiğiniz fiyata bağlı olarak aşağıdaki mavi hücrelerde gösterilecektir.
- Daha sonra Karar Destek Aracı'nda olası sonuçlara bakarak fiyatlandırma kararınızı değerlendirebilirsiniz.
- Kararınızı göndermeye hazır olduğunuzda mavi kutunun alt tarafındaki "**Bilet Fiyatını Kaydet**" düğmesine tıklayınız.

Karar Destek Aracı:

Kararınızı göndermeden önce, Karar Destek Aracını kullanabilirsiniz. Bu araç size fiyatlandırma kararınızın getireceği olası talep değerleri hakkında bilgi sunar. Örneğin, 5. sezonda iken bilet fiyatını **50 PB** seçtiğinizi varsayalım. Minimum müşteri talebi 80, maksimum müşteri talebi ise 180 olacaktır. Figür 2 ise olası talep değerlerine göre bu kararınızın getireceği satış miktarını ve gelir değerlerini listelemektedir. Kırmızı kutudaki satır, talebin 80 olarak gerçekleştiği durumda olacakları göstermektedir; **80 yolcu** elinizdeki 150 koltuktan küçüktür. Bu nedenle 80 koltuk satabileceksiniz ve 150-80 = **70 koltuk ise boş kalacaktır**. (Oyunun doğası gereği sezonlar birbirinden bağımsız olacağından boş kalan koltuklar bir sonraki sezona devredilemez; 6. sezonda elinizde yine 150 koltuk olacaktır.) Eğer talep 80 olarak gerçekleşirse elde edeceğiniz Gelir değeri ise 80 x 50 = 4000 PB'dir.

KARAR DESTEK ARACI			
Oluşabilecek Talep Değerleri	Satılabilecek Koltuk Sayısı	Boş Kalacak Koltuk Sayısı	Elde Edilecek Gelir
80	80	70	4,000
90	90	60	4,500
100	100	50	5,000
110	110	40	5,500
120	120	30	6,000
130	130	20	6,500
140	140	10	7,000
150	150	0	7,500
160	150	0	7,500
170	150	0	7,500
180	150	0	7,500

Figür 2: Karar Destek Aracı

Örnek:

Varsayalım ki 13. sezondasınız ve fiyatınızı 45 PB olarak belirlediniz. Karar Destek Sistemi size göreceğiniz talebin 120 ve 220 arasında olacağı bilgisini verecektir. "**Bilet Fiyatını Kaydet**" düğmesine tıkladıktan sonra varsayımsal talep değeri gerçekleşecek ve bu aralıkta spesifik bir değer alacaktır.

- Örneğin bu değer 123 olarak gerçekleşti diyelim. Bu durumda 13. sezonda 150-123=**27 koltuk boş** kalacaktır. **Elde edeceğiniz gelir** ise 123 x 45 = **5,535 PB** olacaktır.
- Öte yandan, örneğin 182 yolcu bilet talep ederse, bu kez elinizdeki tüm koltukları satacaksınız, ancak talebin tümü karşılanamayacaktır. Bu durumda ise elde edeceğiniz gelir 150 x 45 = **6,750 PB** olacaktır.

Eğer bu sezonda bilet fiyatını **72 PB** olarak belirlemiş olsaydınız, göreceğiniz talep 66-166 aralığında bir değer alacaktı. Gördüğünüz gibi, **verdiğiniz fiyatlandırma kararı talep dağılım aralığını, dolayısıyla elde edeceğiniz geliri etkilemektedir.**

Sayın Satış Direktörüm,
PATA Havayolu'nun sizin tecrübenize ve öngörünüze ihtiyacı var... Bilet satışında birinciliğimizi perçinleyelim ve bir kez daha YABAN Havayolu'nu geride bırakıp, en yüksek gelire sahip havayolu olmaya devam edelim!

B.4 Instructions given during Experiment 4

Merhaba Sayın Satış Direktörüm,
PATA Havayolları sayesinde Türk ticari sivil havacılığı yepyeni bir pazarlama anlayışına kavuştu! Ayrıcalıklı hizmetlerimiz ve rekabetçi fiyat politikamızla pazarı bilmediği yeniliklerle tanıştırmanın gururunu yaşıyoruz.
Her ne kadar adımızın anlamı "berabere kalma" olsa da PATA Havayolları yeni sezonda da pata gelmeyecek ve en yakın rakibimiz olan YABAN Havayolları'ndan çok daha fazla gelir elde edecek. Bu hedefimiz için sizin değerli öngörülerinize ihtiyaç duyuyoruz.
Stratejik Plan'ımızda da belirttiğimiz gibi **YABAN Havayolları'nın yolcu bileti için belirlediği fiyatın istihbaratını aldık: İlk 10 sezon boyunca 120 PB'den, sonraki 10 sezon 90 PB'den, sonraki 10 sezon 60 PB'den ve son 10 sezon 30 PB'den bilet satacaklar!**
PATA Havayolu'muzun fiyatını ise belirleyecek olan sizsiniz! Belirlediğiniz fiyata göre gözlemleyeceğiniz talep ve yaptığınız satış miktarı değişecek. Gözlemleyeceğiniz talep, YABAN Havayolu'nun fiyatı olan **y** ile artarken PATA Havayolu'nun fiyatı olan ***p*** ile azalacaktır.
Daha spesifik bir biçimde,

- ilk 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [270-2***p***, 370-2***p***] aralığında,
- ikinci 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [240-2***p***, 340-2***p***] aralığında,
- üçüncü 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [210-2***p***, 310-2***p***] aralığında,
- son 10 sezon boyunca müşteri talebi [150+y-2***p***, 250+y-2***p***] = [180-2***p***, 280-2***p***] aralığında,

ayrık düzgün dağılıma göre gerçekleşecektir. Örneğin, fiyatımız ***p=90*** ise ve 31-40. sezonlar içerisindeysek, firmamızın gözlemleyeceği müşteri talebi [0, 100] aralığında ayrık düzgün dağılıma göre gerçekleşecektir; bir başka deyişle talep, 0 ile 100 arasında herhangi bir tam sayı değerini eşit olasılıkla alabilir.
Değerli Satış Direktörüm,
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Bir sezondaki Satılan bilet sayısı = min{gerçekleşen talep, 150}

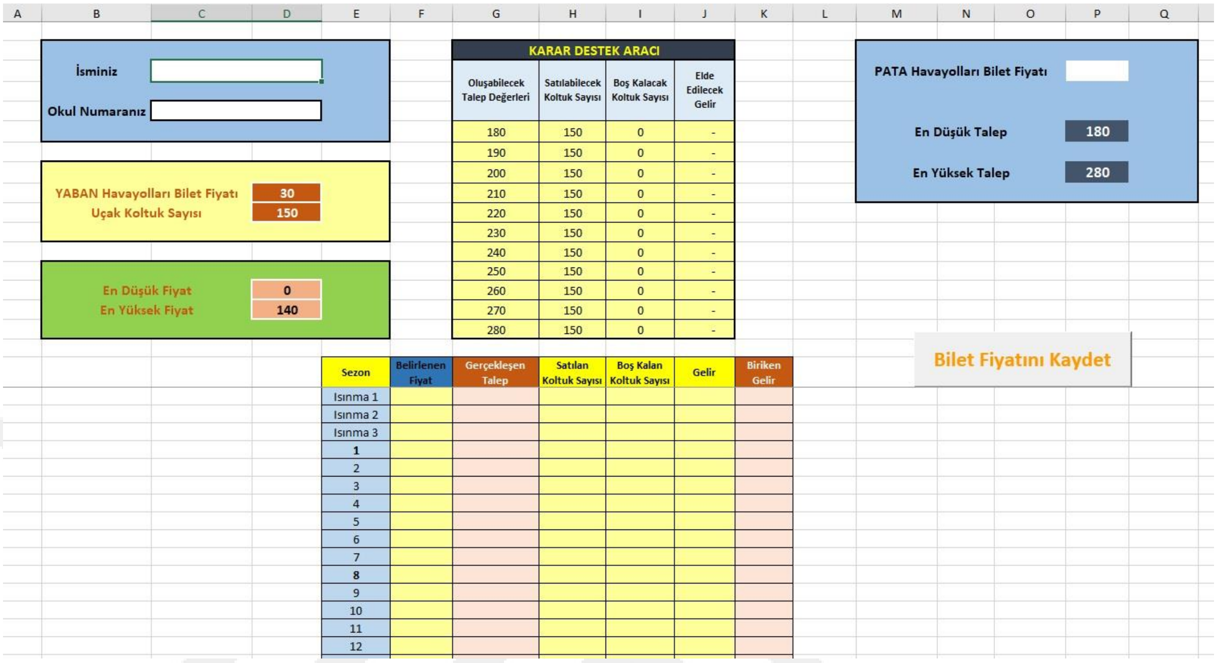
Bu oyunda 40 ardışık periyot boyunca fiyatlandırma kararı vereceksiniz. Her periyot, farklı bir satış sezonuna tekabül etmektedir. Sezonlar birbirinden bağımsızdır ve her sezonda gerçekleşen talep değeri önceki sezonda gerçekleşen talep ile bağlantısızdır; yani trend ya da mevsimsellik gibi durumlar söz konusu değildir. Dolayısıyla her bir sezonda elde edilen gelir, o sezondaki toplam satış miktarı ile fiyatın çarpımına eşit olacaktır:

Bir sezondaki Gelir = ***p*** x min{gerçekleşen talep, 150}

Oyunun sonunda elde ettiğiniz toplam gelir, her sezonda elde edilen Gelir değerlerinin toplamı olarak hesaplanacaktır.
Sizin hedefiniz, 40 sezonun sonunda kazanacağımız toplam geliri maksimize etmektir.

SATIŞ EKRANI

Örnek bir Ekran Görüntüsü: Aşağıdaki figür, ekranınızın nasıl göründüğüne bir örnektir:



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- Ekranın sol üst köşesindeki mavi kutucuklara isminizi ve okul numaranız bilgisini girmeniz gerekmektedir.
- Ekranın üst bölümünde ortadaki sarı büyük tablo, Karar destek aracıdır (fonksiyonu aşağıda açıklanacaktır).
- Fiyatlandırma kararınızı, ekranın sağ üst köşesindeki mavi kutunun içerisindeki (*PATA Havayolları Bilet Fiyatı* yazılı) beyaz hücreye girmeniz gerekmektedir. Daha sonra talep aralığının minimum ve maksimum değerleri girdiğiniz fiyata bağlı olarak aşağıdaki mavi hücrelerde gösterilecektir.
- Daha sonra Karar Destek Aracı'nda olası sonuçlara bakarak fiyatlandırma kararınızı değerlendirebilirsiniz.
- Kararınızı göndermeye hazır olduğunuzda mavi kutunun alt tarafındaki "**Bilet Fiyatını Kaydet**" düğmesine tıklayınız.

Karar Destek Aracı:

Kararınızı göndermeden önce, Karar Destek Aracını kullanabilirsiniz. Bu araç size fiyatlandırma kararınızın getireceği olası talep değerleri hakkında bilgi sunar. Örneğin, 35. sezonda iken bilet fiyatını **50 PB** seçtiğinizi varsayalım. Minimum müşteri talebi 80, maksimum müşteri talebi ise 180 olacaktır. Figür 2 ise olası talep değerlerine göre bu kararınızın getireceği satış miktarını ve gelir değerlerini listelemektedir. Kırmızı kutudaki satır, talebin 80 olarak gerçekleştiği durumda olacakları göstermektedir; **80 yolcu** elinizdeki 150 koltuktan küçüktür. Bu nedenle 80 koltuk satabileceksiniz ve 150-80 = **70 koltuk ise boş kalacaktır**. (Oyunun doğası gereği sezonlar birbirinden bağımsız olacağından boş kalan koltuklar bir sonraki sezona devredilemez; 36. sezonda elinizde yine 150 koltuk olacaktır.) Eğer talep 80 olarak gerçekleşirse elde edeceğiniz Gelir değeri ise 80 x 50 = 4000 PB'dir.

KARAR DESTEK ARACI			
Oluşabilecek Talep Değerleri	Satılabilecek Koltuk Sayısı	Boş Kalacak Koltuk Sayısı	Elde Edilecek Gelir
80	80	70	4,000
90	90	60	4,500
100	100	50	5,000
110	110	40	5,500
120	120	30	6,000
130	130	20	6,500
140	140	10	7,000
150	150	0	7,500
160	150	0	7,500
170	150	0	7,500
180	150	0	7,500

Figür 2: Karar Destek Aracı

Örnek:

Varsayalım ki 23. sezondasınız ve fiyatınızı 45 PB olarak belirlediniz. Karar Destek Sistemi size göreceğiniz talebin 120 ve 220 arasında olacağı bilgisini verecektir. "**Bilet Fiyatını Kaydet**" düğmesine tıkladıktan sonra varsayımsal talep değeri gerçekleşecek ve bu aralıkta spesifik bir değer alacaktır.

- Örneğin bu değer 123 olarak gerçekleşti diyelim. Bu durumda 23. sezonda 150-123=**27 koltuk boş** kalacaktır. **Elde edeceğiniz gelir** ise 123 x 45 = **5,535 PB** olacaktır.
- Öte yandan, örneğin 182 yolcu bilet talep ederse, bu kez elinizdeki tüm koltukları satacaksınız, ancak talebin tümü karşılanamayacaktır. Bu durumda ise elde edeceğiniz gelir 150 x 45 = **6,750 PB** olacaktır.

Eğer bu sezonda bilet fiyatını **72 PB** olarak belirlemiş olsaydınız, göreceğiniz talep 66-166 aralığında bir değer alacaktı. Gördüğünüz gibi, **verdiğiniz fiyatlandırma kararı talep dağılım aralığını, dolayısıyla elde edeceğiniz geliri etkilemektedir.**

Sayın Satış Direktörüm,
PATA Havayolu'nun sizin tecrübenize ve öngörünüze ihtiyacı var... Bilet satışında birinciliğimizi perçinleyelim ve bir kez daha YABAN Havayolu'nu geride bırakıp, en yüksek gelire sahip havayolu olmaya devam edelim!