The Impact of Queue Features on Customers' Queue Joining and Reneging Behavior: A Laboratory Experiment

by

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This is to certify that I have examined this copy of a master's thesis by

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ABSTRACT

In many service settings, customers encounter waits in queues and have to decide between joining and balking, waiting and reneging. In this study, we investigate customers' queue joining and reneging behaviors by using laboratory experiments in which participants experience several observable queues with different characteristics in terms of queue length and service times and decide to join, balk or renege. The hypotheses of this study concentrate on the effects of queue length, having two levels as long queues and short queues; and encountered service time experience, being deterministic or random. We treat randomness of service times again in two levels; one level having first few service times shorter than the announced mean and other level having first few service times longer than the announced mean.

We observe a significant effect of randomness on people's joining decisions suggesting that joining probability for a random queue is lower compared to a deterministic queue. In our first study with 120 participants, we observe a significant effect of "shorter than the announced mean" service times on people's quitting decisions, yielding lower probability to quit. Also, our findings from our first study suggest that people's probability to quit is greater in long queues compared to short queues. In additional three follow-up studies with 196 participants, we check the robustness of our findings with different service times and service time orderings. Overall, we find a combined effect of experiencing extremely fast service times early on together with an enduring progress effect compared to the deterministic queue on people's patience in the queues.

ÖZETÇE

Günümüzde pek çok servis sisteminde kuyruklar kaçınılmazdır ve kişiler kuyruğa katılma ya da katılmama ile kuyrukta sonuna kadar bekleme ya kuyruğu terk etme arasında bir seçim yapmak durumunda kalırlar. Bu çalışmada, kişilerin kuyruğa katılma ve kuyruğu terk etme kararları laboratuar deneyleriyle araştırılmıştır. Bu deneylerde katılımcılar, servis süreleri ve kuyruk uzunlukları bakımından farklı, gözlenebilir kuyruklarla karşılaşmış ve bu kuyruklar için kuyruğa katılma, kuyruğa katılmama ya da kuyruğu terk etme kararları vermişlerdir. Çalışmanın hipotezleri, uzun ve kısa olmak üzere iki seviyede araştırılmış kuyruk uzunluğu ile belirli ve rassal olmak üzere iki seviyede araştırılmış servis süreleri karakteristiği üzerine yoğunlaşmıştır. Servis sürelerindeki rassallık, yine iki seviyede araştırılmış, "hızlı başlangıç" ve "yavaş başlangıç" olmak üzere iki farklı servis sıralaması tasarlanmıştır. "Hızlı başlangıç"lı kuyruklarda kişiler ilk olarak duyurulan ortalama kişi başı servis süresinden kısa servis süreleri ile karşılaşırken, "yavaş başlangıç"lı kuyruklardaki ilk servis süreleri duyurulan ortalama kişi başı servis sürelerinden uzundur.

Bu çalışmada, servis sürelerindeki rassallığın kişilerin kuyruğa katılma kararları üzerinde anlamlı etkisi olduğu bulunmuştur. Buna göre, kişilerin servis süreleri rassal bir kuyruğa katılma olasılıkları, servis süreleri belirli bir kuyruğa katılma olasılıklarından daha düşüktür. 120 kişinin katılımı ile gerçekleştirilen Çalışma 1'de duyurulan ortalama kişi başı servis süresinden daha kısa servis süreleri tecrübe etmenin kişilerin kuyruğu terk etme kararları üzerinde anlamlı etkisi olduğu görülmüştür. Buna göre, kişilerin terk etme olasılıkları "hızlı başlangıç"lı kuyruklarda daha düşüktür. Buna ek olarak, kişilerin kuyruğu terk etme ihtimallerinin uzun kuyruklarda kısa kuyruklardakine kıyasla daha yüksek olduğu bulunmuştur. 196 kişinin katılımıyla gerçekleştirilen ek çalışmalarda, bu bulguların sağlamlığı farklı servis süreleri ve farklı servis süresi sıralamaları ile test edilmiştir. Tüm bu çalışmaların

sonunda, başlangıçta, duyurulan ortalama kişi başı servis süresinden daha hızlı servis süreleri tecrübe etmenin, kişilerin kuyruklardaki sabırları üzerine olumlu bir etkisi olduğu saptanmış, bu etki adam sayısı cinsinden ilerleme etkisinden (*progress effect*) arındırılamamıştır.

To my beloved family

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Chapter 1

INTRODUCTION

In many service settings, queues are inevitable. We wait for the doctor, we wait in traffic, we wait at the supermarket or at the post office for receiving service. Besides all of these observable queues, there are also many other waiting situations where we do not observe or are not even aware of the queue length, like telephone queues.

Waiting, being the essential part of queuing, is not only important from the point of view of the service seeker but also of the service provider. For organizations, queues lead to low customer satisfaction, lost revenues and low service rates. It is always possible to reduce the waits of their customers for organizations, by adding new service providers that are accompanied with additional costs. Therefore, organizations are facing a trade-off between bearing the costs of additional resources and minimizing the waiting times, while designing their queues. Above all, the designers of the queues should always keep in mind that time spent in queues is wasted time forever, for both service seekers and service providers.

The Danish mathematician Erlang was first to model the queues and to introduce a queuing model with three elements: customers, who wait for service; servers, that provide service and queue, a line of customers who wait to be served (Kharkevich, 2009). With this approach, queues can be modeled in a way that optimizes performance measures like waiting time, balking and reneging rates etc. In queuing systems, a newly arrived customer could start getting service if there is an idle server upon her arrival. If all the servers are busy, s/he could join the queue or balk immediately. After joining the queue, a customer always could renege after some time. So, with the possibility of several decisions that have a great impact on the queue performance, the human part of the queuing settings is critical to understand.

The classical Queuing Theory captures customer's balking and reneging behavior with statistical distributions. For example, in Bacelli and Hebuterne's work (1981), customers are assumed to have threshold values to wait until and if they do not get the service by then, they quit the queue and these threshold values are assumed to come from an arbitrary distribution function. In many other studies with or without Markovian assumptions, several distributions are used to analyze the queue performance. On the other hand, customers could also be modeled as strategic customers in an expected utility framework. In these studies, customers are assumed to have a utility function that they maximize. For example, Naor (1969) models humans as rational agents who seek to maximize their utilities from waiting in a queue and compares individual optimum with socially optimum behavior.

Comprehending human behavior in queuing settings is also the concern of different fields in the literature. Fields like Marketing and Psychology mostly concentrate on people's emotions and stress in waiting situations. Also, the satisfaction of customers and its effects on purchasing behaviors are studied in the Operations Management area. For example, Lu et al. (2013) study the effects of waiting on customers' purchase behaviors in a supermarket in their empirical work.

In all these studies, queues are modeled mostly with assumptions about people's decisions like them being rational utility maximizers who follow a utility function or their decisions are assumed to follow various distributions. Yet, it is important to test the generalizability of these assumptions. For example, in real world situations, reneging occurs in queuing settings while it is not expected for rational utility maximizers, according to Naor's model (1969).

With this purpose, there are several experimental works in this area. For example, Pazgal and Radas (2008) test experimentally whether predictions of Queuing Theory are followed by customers in real world situations or not.

In this thesis work, we investigate experimentally the effects of people's waiting experiences and queue characteristics on people's queue related decisions, in the presence of balking and reneging. Our research questions are centered around the effects of queue length and service time uncertainty on people's queue joining and reneging decisions. In this work, customers are expected to make simple queue related decisions in the laboratory environment. Findings from this study provide insight into how customers' decisions are affected by these queue characteristics. We found a significant effect of randomness on people's joining decisions. Also, we found a significant effect of queue length on people's reneging decision and time to renege, for the same expected waiting time. This result emphasize that customers tend to concentrate on the queue length, more than their expected waiting time.

Additionally, we observe that waiting experience influences people's reneging decisions. Observing extremely fast service times at the beginning of wait compared to the announced mean affect customers' patience in the queues in a positive way.

The findings from this study might guide queue designers in different ways. For example, if the intention is to decrease customer abandonments, the queue might be designed in a way that customers initially experience extremely fast service times creating a progress effect. Or since the queue length seems to drive people's reneging decision besides expected waiting time, the choice of single or multiple lines might be done accordingly.

Thesis Outline

This thesis is organized as follows: The next chapter reviews the current literature. In Chapter 3, hypotheses are developed which are tested in the scope of this experimental study. Chapter 4 explains the design of the study in light of the reviewed literature and developed hypotheses. Further, it describes Focus Group and Pilot studies together with Study 1 with their results and descriptive statistics. Bounded rationality of people in queuing settings is investigated in Chapter 5, for a comparison of experimental data with Naor’s model (1969). In Chapter 6, statistical analyses for hypothesis testing are presented. Finally, Chapter 7 concludes the thesis by discussing the results and suggesting future research directions.

Chapter 2

LITERATURE REVIEW

Queues are inevitable in many service settings, from supermarkets to banks, telephone call centers to hospitals. There is a rich literature on waiting situations and queues that affects many applications such as telecommunication, computer science among others. Queuing Theory, using probabilistic properties extensively, is considered as a stream of Operations Research and deals with mathematical modeling of a system providing service to demands.

Despite the apparent simplicity of queues consisting of basically three elements (service seekers, service providers and queues), queuing models are very complicated without assumptions when the randomness is present. A large variety of queuing models in terms of used probability distributions and made assumptions can be found in Gross and Harris' work (1998). Additionally, incorporating the human part of the queuing systems makes the models even more complicated since it is not possible to predict human behaviors with high accuracy or model them comprehensively (For an extensive overview of these models, we refer reader to Hassin and Haviv (2003)).

In Queuing Theory, customers are generally modeled as entities, not as individuals. This modeling approach leads to several assumptions about the customers that are difficult to ensure considering the variability in human factor. Customers make several decisions in queuing systems, starting with joining or balking decision. When customers join the queue, next they decide between waiting until getting service and reneging. Classical Queuing Theory mostly model customer behavior with several assumptions, using probability distributions. However, these models do not always reflect reality and result in the need for further analysis of humans in queues.

Human factor of queuing systems makes Queuing Theory an interdisciplinary area of operations management, marketing and psychology and one of the most studied research areas of Operations Management. Customer behaviors in queues are studied in different studies with different methods. In this section, existing literature in queuing theory is reviewed, with a particular focus on abandonments from queues.

Modeling Abandonments with Patience Distribution

Queue abandonments is one of the least understood part of the queuing settings and is one of the crucial parts to understand to be able to design queues without loss in terms of customers, money or time. Queue abandonments can be modeled in several ways. Traditional queuing models assume a distribution for abandonment times. Baccelli and Hebuterne (1981) modeled queue abandonments of customers by assuming that each customer has a threshold time to wait and these times come from an arbitrary distribution function. They state that customers wait until reaching their threshold time and if they do not get the service by then, they quit the queue (Baccelli & Hebuterne, 1981). Maximum willingness to wait time is generally independent and identically distributed with an exponential distribution (Gans, Koole, & Mandelbaum, 2003). Brown et al. (2005) and Garnett et al. (2002) use an exponentially distributed patience distribution in their works. Mandelbaum and Zeltyn (2004) investigate in their work the system performance for different patience distributions.

In this work, we analyze experimentally the effects of queue length, randomness and encountered service times on customers' patience in the queues.

Rational Agent Behavior

In a different queue modeling approach, customers are assumed to be rational agents in an expected utility maximization framework. In these models, reneging is not expected in an observable queue, if cost of waiting per minute, value of service, queue length or some of the other queue parameters did not change. If a person decides to join a queue, it indicates that the queue is worth to wait until getting service.

Naor is the first to model strategic customers in a queuing setting (1969). In his seminal paper, he studied a first-come-first-served (FCFS) queue with identical customers who have a linear utility function. In this single server queue, arrival rate is assumed to be Poisson and the service times are assumed to be exponentially distributed. Customers get the reward of the queue R upon completion of service, they have a cost of waiting C per unit time and service times are exponentially distributed with a parameter $1/\mu$. Therefore, with risk neutral customers, it is expected that when $R-(i+1)C\frac{1}{\mu}>0$ (i being the number of customers in the queue upon arrival), a newly arrived customer joins the queue. So, the threshold number of person upon arrival; $n,$ is $n=\frac{R\mu}{C}$, $\frac{R\mu}{C}$ rounded up to closest integer if it is not already integer. In the study, a customer who balks never returns and no reneging is allowed. As a matter of fact, with the assumptions of the study that assume forward looking expected utility maximizer customers and the queue parameters that ensure $R\mu \geq C$, no reneging is expected. Naor's work is followed by researchers and an extensive literature of strategic customers in queues is reviewed by Hassin and Haviv (2003).

Building on Naor's work, the queues with abandonments are studied in a stream of literature. In these studies, assumptions where rational abandonments are possible are made.

Hassin and Haviv (1995) model a single server queue where customers decide to join, balk or renege according to their linear waiting cost function, without any new information. In their study, there is an unobservable queue where the reward of the queue may drop to zero in line with time spent in the queue, leading customer to quit the queue (Hassin & Haviv, Equilibrium strategies for queues with impatient customers, 1995). Mandelbaum and Shimkin (2000) consider a queuing setting with the presence of a fault state and linear waiting cost, in which customers do not know the queue length. As the presence of a fault state induces a probability of never being served, abandonments are expected in this study (Mandelbaum & Shimkin, 2000). In another study, Shimkin and Mandelbaum (2004) analyze the presence of nonlinear waiting costs, allowing to model waiting cost function more flexibly, by taking into consideration psychological aspects of waiting. Customers try to maximize their utility functions which are defined individually (Shimkin & Mandelbaum, 2004). In all of these studies, customers are modeled as applying their initial decisions about the queue. On the other hand in the next study, customers decide dynamically over time while waiting.

Aksin et al. (2013) examine empirically customers of a banking call center in an invisible queue by assuming linear waiting costs. They model the utility of customers in terms of waiting cost and reward of the service and assume that at each time period, customers decide between reneging and waiting. By estimating customers' cost and reward parameters from empirical data, they found a significant difference in waiting time performances between endogenous and exogenous models (Aksin Z. , Ata, Emadi, & Su, 2013). This finding underlines the importance of modeling customers as rational agents while designing service systems with waits.

In this study, we investigate people's quitting behavior experimentally with a linear utility function like in Naor's (1969) paper. Assuming that their initial decisions might change over time with the experience of waiting, customers have the opportunity to quit the queue at any time point during their wait.

Analysis of Waiting Behavior

People's waiting behaviors are studied in several research areas like operations management, psychology and marketing. These studies might provide insight into people's quitting behaviors in queuing settings, since waiting situations induce impatience that leads to quitting.

Osuna states that waiting is stressful; since it is a combination of an economic cost arising from losing time and also a psychological cost arising from stress. He also underlines that stress increases with uncertainty (Osuna, 1985). Osuna's model is built on by Suck and Holling (1997). They include duration of waiting time and waiting time uncertainty to their model, and found that customers become more stressful if duration of waiting time or waiting time uncertainty increases (Suck & Holling, 1997). In our work, duration of waiting time does not differ between different queues; however, we have different treatments for different levels of waiting time uncertainty.

In order to model people's time related decisions, researchers consider people's money related decisions and ask a question: Is time like money (Leclerc, Schmitt, & Dube, 1995)? Leclerc et al. (1995) study customers' time-related decisions in a series of studies and compare them with money-related decisions. They found that customers value their times depending on a contextual setting of the decision situation. When the situation is deterministic, time losses can be modeled with a convex loss function; on the other hand, when the situation is risky, people tend to decide more risk-aversely in the domain of time loss, while they are more risk-seeking in the domain of money loss (Leclerc, Schmitt, & Dube, 1995).

Perception of waiting time has also a critical effect on people's wait-related decisions and experiences. Hornik studies the relation of actual and perceived time empirically (1984). The findings from this study suggest that people overestimate waiting time, especially in passive waits –where level of enjoyment for people is low (Hornik, 1984). Munichor and Rafaeli (2007) investigate the effects of different waiting time fillers; music, apologies and information about queue standing, on satisfaction and people's quitting behaviors. They assert that a sense of progress in the queue increases customer satisfaction (Munichor & Rafaeli, 2007). Bitran et al. provides an overview for the effects of waiting on long term and short term profitability and satisfaction of customers (2008).

In this study, customers' quitting behaviors are investigated without considering customer satisfaction. Total waiting time is not differentiated between queues, however level of service time uncertainty, which leads to total waiting time uncertainty, is manipulated.

Effect of Information

The customers receive additional information while waiting in queues, intentionally provided by the service provider or unintentionally thanks to the nature of the queue (i.e. observable queue). There is a stream of literature that deals with information giving to the customers while waiting and its effects on people's queue related decisions.

In his study, Whitt (1999) investigate two queuing models with and without information that is about the remaining waiting time until getting service, by assuming a threshold value time for quitting for each customer. In these models, balking and reneging is possible. The findings from this study suggest that information giving reduces total waiting time of the system and the number of customer who gets the service (Whitt, 1999). Guo and Zipkin examine the effect of delay information in 3 levels: no information, partial information and full information, and study customers' balking and joining decisions (2009). They found that the effect of information depends on context, and information increases the system performance in some cases but also can hurt some systems (Guo & Zipkin, 2007). These studies concentrate only customer balking decisions and not on reneging decisions.

Armony et al. (2009) study the impact of delay information in an invisible queue. The information giving has two different forms: the delay of the last customer in the queue or the average delay. They say that system performance and delay announcement are in a circle; since system performance is affected by delay announcement and delay announcement is affected by system performance. They suggest that the delay of the last customer in the queue is more reliable than average delay information, resulting in smaller average absolute error (Armony, Shimkin, & Whitt, 2009). Jouini et al. (2011) examine the impact of delay information on customers balking and reneging decisions in a call center. Their findings from this study suggest that customers show sensitivity to delay announcements that leads them to balk and renege. Reneging is even more when the actual waiting time is greater than the announced delay (Jouini, Aksin, & Dallery, 2011).

Aksin et al. (2014) study the effects of delay announcement on customers' behavior and system performance, empirically. Assuming rational agents and dynamic decision making by these customers in the queue, the analysis combines the estimation of customers' utility function parameters with the system queuing performance analysis under delay announcement. The analysis shows that delay announcements have an effect on patience behavior (Aksin, Ata, & Emadi, Impact of Delay Announcements in Call Centers: An Empirical Approach, Working Paper). Similarly, Yu et al. (2014) explore empirically the relation between customer behaviors and delay announcements in queuing settings. They found that customers' waiting costs are influenced by the delay announcements. Their waiting cost per unit time decreases with the announcement and the content of the announcement (Yu, Allon, & Bassamboo, Forthcoming).

In our work, all the queues are observable by the subjects and subjects can track the service time per person. The average service time per person information is available to the subjects before deciding to join. As the queue discipline is FCFS, there is no update about number of people ahead of a person. All other queue parameters like reward of the queue, cost of waiting per unit time and endowment are also constant. So, there is only new information about realized service time per person in random cases.

In the delay announcement literature, different assumptions are made to model customer behavior yet there is no common and agreed upon theory about it. Therefore, our work might contribute to this area since our aim is to understand human behavior in queues.

Human Behavior in the Field

Actual human behavior in queuing settings is also studied by taking advantage of empirical and experimental studies. These studies provide insight into people's real decisions in queuing settings and redefine the assumptions about the human part of the queuing settings, more realistically.

Lu et al. (2013) conduct an empirical study to investigate the relation between queues and customers' purchases in a retail store. Their findings indicate that customers do not use all the available information in queuing systems and they tend to focus more on the queue length than the speed of the queue (Lu, Musalem, Olivares, & Schilkrut, 2013). As an empirical study in a supermarket, there are numerous factors that researchers could not control.

Batt and Terwiesch (2015) evaluate empirically abandonments from queues in an Emergency Department. In their study, the queue is partially observable by the subjects since it is a waiting room in an Emergency Department. The prioritization of the queue is not FCFS but it depends on the urgency of the coming patient. So, subjects have some information about the queue. The findings suggest that waiting time, together with queue length and the pace of the queue have an effect on people's quitting behaviors. Additionally, people process the visual clues in queuing settings, since arrival of a new patient increases people's quit probability in a queue discipline which is not FCFS (Batt & Terwiesch, 2015).

In their experimental work, Pazgal and Radas (2008) study customers' decision-making in queues, where they have the possibility to balk and renege. They find out that customers balk according to a critical number of people in the queue upon arrival and reneging is infrequent. This critical value is estimated differently by the subjects and generally overestimated, so they normalize for heterogeneity in time perception and found again an overestimation of the critical value that led to balking (Pazgal & Radas, 2008). Our study is similar to Pazgal and Radas's considering its experimental design. However, while they concentrate on testing whether customers follow the predictions of Queuing Theory, ours is more specifically interested in the effects of queue length and service time uncertainty on people's queue related decisions.

Janakiraman et al. (2011) examine customers' abandonments with laboratory experiments. In their study, subjects wait for several downloads from a webpage, so there is no queue or queue dynamics. They hypothesize that in waiting situations, people seesaw between *waiting disutility* and *completion commitment*. The findings suggest that people have a tendency to quit the queues in the midpoint of the total waiting time. Also, the presence of several alternative queues together with slowness of these queues decreases people's quitting rates; while having a possibility to track the time internally (on the screen) increases it (Janakiraman, Meyer, & Hoch, 2011).

Differently from other studies that investigate human factor in queuing settings when queues are undesirable, Kremer and Debo (2012) study the queues where queue length is perceived as a signal of service quality and low (high) quality products result in shorter (longer) queues. Similarly to the work of Giebelhausen et al. (2011) that shows experimentally that waiting times affect people's satisfaction and purchases positively and result in a high quality perception, Kremer and Debo's findings suggest that customers who do not know about the product quality are less likely to purchase when the waiting time is short and there are other customers that know the product quality (Kremer & Debo, 2012). Also, the findings from Koo and Fishbach's (2010) study suggest that the attributed value of a product increases when there are more people in the queue and also, more people are added to the line. Additionally, they found that the value of a product increases when people concentrate on the number of people behind them and on the new comers to the line (Koo & Fishbach, 2010). All these studies focus on *positive externalities* of the queues.

Lastly, Conte et al. (2014) conclude from their experimental study that people tend to focus more on the queue length rather than the average service time per person while joining the queue and they choose short queues over long queues. In this work, participants do not actually wait and people's reneging decisions are not investigated. Participants make their decisions only by calculating experimental points.

In this thesis work, customers' behavior in queues are investigated with laboratory experiments that provide better control on data than the empirical studies (Katok, 2011). In our setting, customers first decide between balk and join, then renege and wait and they are assumed to have a linear utility function.

Experimental Methodologies

In Operations Management area, understanding the human behavior is the crucial part for a successful implementation of techniques and for accurate theories (Bendoly, Donohue, & Schultz, 2006). However, using laboratory studies to understand human part of operations is very recent in the literature.

Constituting a bridge between analytical approaches and real world applications, it is of great use to take advantage of experimental studies to relax the assumptions of mathematical models. Laboratory studies are preferable over other experimental studies like field experiments for the possibility of manipulating the focus of study and for the increased control. Therefore, in this thesis work, laboratory experiments are used and they are programmed using z-Tree (Zurich Toolbox for Readymade Economic Experiments) which is a special purpose software package for economic experiments (Fischbacher, 2007).

For an even more increased control and to assure comparability of different experimental groups, randomization procedure should be used in the laboratory experiments. This procedure is basically applicable by assigning the subjects to treatment groups randomly and it is useful to disrupt any systematic relationship between experimental conditions and assignment of subjects (Keppel, 2004). Fisher (1942) considers randomization as the only chance element in an experimental setting, which is exclusively controlled.

Randomization becomes more important when the design of the experiment is between-subject. In a between-subject design, each group of subject experiences only one treatment condition. On the other hand, in a within-subject design, each subject experiences more than one treatment conditions. Both types of designs have their advantages and disadvantages in terms of operational and analytical ease (Keppel, 2004). In this thesis work, both design types are used.

Katok (2011) states that there are three main goals of laboratory experiments: "(1) To test and refine existing theory. (2) To characterize new phenomena leading to new theory and (3) To test new institutional designs." In this thesis work, laboratory experiments are used to refine an existing theory.

Chapter 3

HYPOTHESIS DEVELOPMENT

In this study, we analyze the effects of different queue features on people's queue joining and reneging behaviors and we aim to understand the drivers of people's queue related decisions.

Basing our work on Naor's model (1969), we assume a linear utility function. Differently from Naor's work, we do not have an assumption about people's rationality since it is an experimental work. Both balking and reneging are possible.

3.1. Queue Length

Queue Length, constituting the major part of the queuing settings, plays an important role in customers' queue related decisions. In most service settings in real life, the first information gathered about the queue is queue length. Understanding the effect of queue length on customers' decisions is crucial to be able to design better queues. For this purpose, studies from different disciplines that are useful to interpret the queue length is reviewed and hypotheses about the queue length is developed in this section.

First, the cognitive dimension of interpreting the queue length is reviewed. Cantrell and Smith (2013) investigate in their study that people can evaluate small sets including 1 to 4 items precisely, while they can evaluate large sets imprecisely. Similarly, in another study, it is found out experimentally that people can discriminate the number of several objects up to 6 precisely, by using a different mechanism than used for more crowded sets (Kaufman, Lord, Reese, & Volkmann, 1949). In queueing settings, this finding can be helpful to understand people's behaviors in queues upon their arrival, when they only evaluate the queue length rather than other queue characteristics and decide to join or balk accordingly. Due to the complex interpretation of large sets, long queues in queuing settings, people might base their decisions only on the length of the queue and might chose short queues over long queues.

Besides cognitive aspects of set evaluation, the dominance of queue length over other queue characteristics is underlined in different studies in queuing settings. Carmon (1991) discuss in his study that single lines should be chosen over multiple lines since the average waiting time in single lines is shorter under capacity pooling which occurs in single queue case, according to related Operations Research literature. However, in a study with subjects who are familiar with Operations Research concepts, it is found out that visual cues of queues dominate their decisions since they choose multiple lines over single lines with the presence of an observable queue. On the other hand, they choose single lines over multiple lines as a better queue when there is no visual representation (Carmon, 1991). This finding emphasizes the salience of queue length as a driver of joining or balking decisions in queuing settings.

Additionally, Lu et al. (2013) infer empirically that customers' purchase decisions at a supermarket are influenced by queue lengths more than their expected waiting time. Batt and Terweisch (2013) found out in an empirical study at an Emergency Department that queue length affects people's abandonment decisions besides waiting time. Conte et al. (2014) conclude from their experimental study that a part of the population decide to join the queue by only concentrating on queue length rather than the speed of the service provider, and have a tendency to choose the shorter queue. In their study, subjects are provided two different servers one with lower speed without any entry fee and other with higher speed requiring an entry fee. Optimal decision in terms of *Experimental Currency Units* differs between these two queue types and subjects success rates are compared, success being maximizing the profit (Conte, Scarsini, & Sürücü, 2014).

Debo and Veeraraghavan (2014) state that there is an inverse relationship between queue length and queue joining rates. This statement is in line with Pazgal and Radas's experimental study, where they investigate that people follow benchmarks of queuing theory and balk for queue lengths which are greater than a critical value (2008). These studies do not directly imply that queue length is more significant than other queue characteristics since the critical value calculation for the queue length is related to service times; however, they are important to deduce the salience of queue length processing.

Therefore, gathering all these together, in order to understand the effect of queue length, we hypothesize that:

$\boldsymbol{H_1}$: Joining rates for short queues are greater than joining rates for long queues, where the expected waiting times are the same.

Besides all the studies that are mentioned above, we can also point out two different systems of reasoning that affects people's processing of the queue length, first proposed by Stanovich and West (2000): System 1 and System 2 (Kahneman, Maps of Bounded Rationality: Psychology for Behavioral Economics, 2003). These different systems of reasoning, referred to as Associative and Rule Based respectively in other studies (Sloman, 1996), have different characteristics. Information can be processed via visual representations instinctively in System 1, while System 2 is systematic and requires rule using (Kahneman, 2003). It is also stated that people tend to use System 1 when there is an effortless, easily processable task. One example of System 1 vs. System 2 is given as follows: when you are asked to multiply 2 by 2, it is the System 1 that gives the answer. On the other hand, when these numbers are 17 and 24, it is System 2 that works (Winerman, 2012). So, we can conjecture that in queuing settings, System 1 dominates System 2 and people tend to concentrate on queue length more than they concentrate on their expected remaining service time and decide accordingly in an observable queue, where queue length information is easier to process.

In an experimental study which is mostly focused on people's feelings and satisfaction, people's pleasantness levels before waiting and while waiting are tested and it is concluded that the level of pleasantness increases during the wait (Rafaeli, Barron, & Haber, 2002). Soman and Shi (2003) conclude from their study that the perception of progress has an important effect on consumers' evaluations of services. They state as a managerial implication that in a queuing setting where consumers can observe the rate of progress, their evaluations for service will be higher compared to a queue with unobservable rate of progress (Soman & Shi, 2003). Also, Munichor and Rafaeli's (2007) findings suggest that sense of progress in waiting situations create a higher level of satisfaction for customers, compared to perceived waiting time. Cheema and Bagchi (2011) state that visualizing the goal increases the commitment of the customer, and people's willingness to wait for a service. Researchers suggest in line with their findings as a managerial implication that a progress bar might be used to increase customer satisfaction and goal pursuit (Cheema & Bagchi, 2011). All these studies underline the importance of visualization of goal to increase people's commitment. In a queuing setting, this commitment can be interpreted as low quitting rates.

Different effects can be mentioned here to explain people's decisions in queuing settings. *Goal gradient effect* proposes that people tend to expend more effort when they are closer to their goal (Hull, 1932). In a queuing setting, as processing expected waiting time is more difficult than processing the queue length information, people might concentrate on number of people ahead of them and tend to be more patient –effort in a queuing setting- when this number is smaller.

Therefore, since queue length calculation is easier to process than service time calculation and more salient for subjects, we expect higher quitting rates in long queues than in short queues; for the same expected waiting time.

$\boldsymbol{H_2}$: Reneging rates for long queues are greater than reneging rates for short queues, where the expected waiting times are the same.

$\boldsymbol{H_3}$: People survive longer in short queues compared to long queues, where the expected waiting times are the same.

3.2. Encountered service time experience

Osuna states that waiting is stressful (1985). Suck and Holling (1997) set upon Osuna's work and add that the stress of waiting increases with uncertainty. Therefore, it is expected that people avoid uncertain waits, even if the expected waiting times of deterministic and random queues is the same.

$\boldsymbol{H_4}$: Joining rates for deterministic queues are greater than joining rates for random queues, where the expected waiting times are the same.

When customers decide to join the queue and start to wait, the experience of waiting dominates their reneging decisions. This experience, consisting of realized service times per person directly and the perception of wait and the psychology of waiting indirectly, is important to distinguish since assumptions of the human behaviors in queues are highly related to it. In this section, the studies about people's time perceptions and interpretation of time related randomness is reviewed and hypotheses are developed.

Sun and Wang (2010) investigate in their study that people expect local sample to resemble its parent population in time streaks. They add that people refuse randomness when they face with same outcomes consistently and they do not expect many streaks (Sun & Wang, 2010). So, an implication of this study to queue settings might be that when customers encounter service times that are longer (shorter) than the announced mean, it is expected that they consider all the remaining service times as similar and decide to wait or renege according to their initial experience about the service times.

“Adjustment and Anchoring” effect, first introduced by Tversky and Kahneman (1974) could be used too in queueing settings to understand human behavior where service times are randomly distributed. This effect suggests that people tend to rely on the initial information and insufficiently adjust it, when making further decisions (Tversky & Kahneman, 1974). Thus, first encountered service times experience could affect people’s waiting or reneging decisions in a queuing setting, by creating an anchoring effect. If these service times are preferable, people may tend to show a higher patience in queues. Conversely, if the first encountered service times are worse than the announced mean, high reneging rates may occur with an anchoring effect.

Another effect that can be mentioned is *endowed progress effect*. This effect is defined as “people provided with artificial advancement toward a goal exhibit greater persistence toward reaching the goal” (Nunes & Drèze, 2006). For example in their work, participants are divided into two groups; one group is presented with a loyalty card that requires 8 purchases to get a free one. On the other hand, the other group is presented with a loyalty card with 10 purchases that two of them is already stamped. With this design, they create an endowment progress effect and study the effect of endowed progress on task completion (Nunes & Drèze, 2006). In a queuing setting, fast service times are perceived as “gifts on queue length” or “free progress". When the first few service times are extremely shorter than the announced (or observed) mean, like 2-3 seconds, we could mention an *artificial advancement* in terms of number of people served, even if it is not really *artificial* in a queuing setting since there is a real advancement actually and it still takes time when these service times are shorter than the mean. Thus, in queues where a subject first experience shorter service times, it is speculated that s/he is ready to put more effort and in a queuing setting, this effort can be interpreted as showing patience.

Putting together all these studies from different disciplines that lead to the same interpretation by underlying different aspects, we hypothesize that:

$\boldsymbol{H_{5.1}}$: If the first service times observed after joining are longer than the mean, people are more likely to quit compared to a deterministic queue.

$\boldsymbol{H_{5.2}}$: If the first service times observed after joining are shorter than the mean, people are less likely to quit compared to a deterministic queue.

$\boldsymbol{H_{6.1}}$: If the first service times observed after joining are longer than the mean, people survive shorter in that queue, compared to a deterministic queue.

$\boldsymbol{H_{6.2}}$: If the first service times observed after joining are shorter than the mean, people survive longer in that queue, compared to a deterministic queue.

Chapter 4

DESIGN OF THE EXPERIMENT

4.1. General Design of the Experiment

The laboratory experiments are designed in light of the related literature and hypotheses. In this section, dependent variables, independent variables and control variables of our experiment are introduced.

4.1.1. Dependent Variables

In this study, we test the effects of queue length and service times on people’s joining and quitting decisions in queuing settings.

Join Decision

The first dependent variable is subjects’ joining decisions for each queue. This decision has two possible outcomes: joining or not joining. This decision is taken upon arrival, only observing the length of the queue and information on whether service times are deterministic or random as well as the mean service time.

Quit Decision

The second dependent variable is subjects’ quitting decisions for the queues that they joined. It has also two outcomes: quitting or not quitting. Subjects can decide to quit the queue at any point during the wait. Thus, subjects who quit the queue have another dependent variable which is the time spent in the queue.

Time spent in the Queue, t

Time spent in the queue, denoted by t, represents subjects' time spent in a queue; in case of quit, total time elapsed until quitting decision and in case of getting service, total waiting time of the queue, which is constant.

4.1.2. Independent Variables

The hypotheses that we want to test in the scope of this thesis work is divided into two categories: Queue length and service times. Therefore, we have two independent variables to test our hypotheses that are explained in detail in Chapter 3.

Queue Length

First, we want to test whether people's joining rates are significantly different or not for the same expected waiting time but with different queue lengths. So, in our experiment, we treat this queue length variable at two levels: long queue and short queue. To keep the expected total waiting time the same, average service time per person variable is changed among long and short queues.

Service times

We hypothesize on encountered service times experience. Service times can be deterministic or random; and when service times are random, there are two different sample paths: fast start and slow start. Fast (slow) start queue consists of first few service times which are shorter (longer) than the announced mean. With the same expected total waiting time but different sample paths, we are able to test our hypotheses 3 and 4.

4.1.3. Control Variables

In our study, we consider several factors that might influence our results and we control for them by including these variables into our analyses.

Decision Number of the Subject

In real queuing settings, customers tend to let their prior experiences about a service provider direct their subsequent queue related decisions. Even if the queues are assumed to be independent, a learning effect may be present leading to a variation in people's queue joining rates, as a function of earlier experience.

We design our experiment in a way that aims to make the decisions in the queues independent from each other, and we emphasize this effect by our warnings in the presentation of the experiment. During the presentation, we do not disclose the total number of the queues to the participants (except in the Study 4) but we give notice to the participants that they will have enough time to wait for all the queues. Also, we state that quitting the laboratory is not possible until the end of the session, even if a subject finishes the experiment. Even if we try to minimize it with our warnings, it is still possible that subjects have a cumulative time driven or strategic behavior due to the knowledge of having multiple yet unknown number of queues or some form of learning that leads to non-independent behavior in the queues. So, we include decision number of the subject to our analyses as a control variable. There are three binary variables to capture subjects' decision number: *Decision1forsubject* ,*Decision2forsubject* and *Decision3forsubject*. For example, if it is the first queue that a subject encounters, the values will be equal to 1, 0 and 0 respectively, for the variables described above.

Major of the Subject

In our study, we cannot observe subjects' characteristics in terms of their tendency to follow a expected utility maximizing behavior, as designed in the experiment. However, we know that students can behave significantly different in experimental settings according to their major, especially Economics students ((Frank, Gilovich, & Regan, 1993). Therefore, we collect information of the major of study from each subject. And then we group our subjects who are majoring in Economics or Engineering versus other students. With this control, we aim to have a proxy for personal differences in terms of following a utility function maximizing behavior or more generally, a more quantitative nature allowing the subjects to better focus on utility calculations.

Gender

In the experimental literature, gender is considered as a factor that might influence people's decisions for several emotional and/or characteristic features. Croson and Gneezy (2009) review gender differences in economic experiments and underline that gender plays a role in these experiments. Therefore, we include subjects' gender as a control variable in our analyses.

Risk Aversion

We study subjects' queue joining, balking and reneging decisions in queuing systems with the presence of uncertainty. Hence, as there is a risk involved, participants' risk characteristics are investigated with the Exit Survey and are included in our analyses as a control variable.

4.2. Operationalizing the Design

Before conducting full scale experimental sessions, the feasibility and adequateness of the Experimental Design is tested with Focus Group and Pilot studies, and the study design is improved along several dimensions.

First, a Focus Group study was conducted with a limited number of participants. The experimenter interviewed each participant at the end of the experiment and gathered subjects' opinions about the experimental design. After the Focus Group study, several changes were made and new design was tested with the Pilot Study.

Then, a Pilot Study was conducted. Subjects' feedback about the study was obtained with a survey on paper and after careful consideration; experimental design was transformed into its latest version before the full scale Study 1.

In the following, Focus Group and Pilot studies, together with the changes after these are explained chronologically and the experimental design of the Study 1 is provided.

4.2.1. Focus Group Study

A Focus Group Study is conducted with a limited number of subjects to examine the effects of the planned experimental design. In this section, Experimental Design of the Focus Group Study is provided, and followed by the results and the conclusions from this study.

Experimental Design

Scenario

A scenario is used in the experiments to create a realistic waiting situation perception on subjects. The scenario is chosen to create an optional queue joining situation as opposed to a setting where a task has to be done and joining the queue is inevitable.

Subjects are told upon their arrival to the laboratory that they are going to be a tourist in a city for one day and will have the opportunity to visit several touristic attractions. The number of touristic attractions is not disclosed to the subjects. They are also told that they can gain points if they visit the attractions and for each attraction, they have to wait in a queue. They start each attraction with a budget but they lose points while waiting in a queue. Subjects are told that their purpose during the experiment is to maximize their points.

Presentation of Experiment

The experiment is presented to the subjects by the experimenter using computerized slides.

Variables

Dependent variables

In this study, our dependent variables are subjects' joining and reneging decisions. Additionally, time spent in the queue becomes a third dependent variable for subjects who join the queues. For a detailed explanation of dependent variables, please refer to section 4.1.1.

Independent variables

In this study, the effect of uncertainty on human behaviors in queuing systems is scrutinized and the effect of uncertainty is traced in two variables: the reward at the end of the queue and the waiting time. In the experiment, these two variables having two levels are used to create different treatment groups.

- **Reward of the queue (R):** This variable has two levels: deterministic or random. When the reward is deterministic, subjects know for sure how many points they will get if they wait until the end of the queue and get the service. When the reward is random, subjects can get the high reward with the probability of 50% and the low reward with the probability of 50%. Subjects always know whether the reward is deterministic or random, as well as the possible values and probabilities, before joining a queue as it is described in the scenarios.
- **Service time (1/μ):** The service time variable also has two levels. The first level is that the service times are deterministic. In this level, subjects are told in the scenario that each person in the queue spends equal time in service. So subjects can easily calculate their total waiting time by multiplying the number of people in the queue with the service time. When waiting time is random, subjects are told that each person in the queue spends different amounts of time while getting service and these times come

from an exponential distribution. The experimenter provides a graph of exponentially distributed service times to the subjects, together with an example of possible service times.

Subjects know whether service times are random or deterministic prior to making a decision; the exact service time per person in the deterministic case and the average of the distribution in the random case.

There are four treatment groups according to $2x2$ experimental design, as shown in Table 1.

Table 1: Possible treatment groups according to 2x2 experimental design

<table>
<tr><td colspan="2" rowspan="2">Treatment No</td><td colspan="2">Service Time ($1/\mu$)</td></tr>
<tr><td>Deterministic</td><td>Random</td></tr>
<tr><td rowspan="2">Reward of the Queue (R)</td><td>Deterministic</td><td>Treatment 1</td><td>Treatment 3</td></tr>
<tr><td>Random</td><td>Treatment 2</td><td>Treatment 4</td></tr>
</table>

In addition to uncertainty of reward and the service time of the queue; queue length and service time ordering as a level of service time uncertainty are added to the design to moderate the effects.

- **Queue length:** All the queues are observable in the experiment. Queue length is a between-subject variable with two different levels: long queue and short queue.
- **Service time ordering:** To manipulate subjects' service time experiences, service time ordering in the queues is differentiated. Two different service time orderings are created in the random service time treatment. Subjects first see service times which are longer than the mean, and then the service times which are shorter than the mean in the Slow Start treatment. In the Fast Start treatment, subjects first see service times which are shorter than the mean and then they see service times which are longer than

the mean. Service time ordering is a between-subject variable; a subject experiences always Fast Start or Slow Start queue in random cases.

Determining the parameters

Queue Values

In Naor's model and some models that build on Naor, in queueing settings, people are expected to calculate their utility functions and to make their decisions accordingly (Naor, 1969) before joining the queue. They subtract the total cost of waiting from the reward of the queue. If the result is positive, they join the queue and wait until getting service. However, in real life, people often quit the queues. Quitting may occur for several reasons: there might be changes in the system, the perception might differ from the actuality or there might be other factors that the utility function does not capture.

The first assumption of this study is that people have a linear utility function. The parameters of the utility function are; **R**, reward of the queue, **c**, cost of waiting, **n**, number of people in the queue and **1/μ**, mean service. Also, all subjects start the experiment with a budget, **E**. All parameters are chosen to promote queue joining for utility maximizers, so that we can analyze patience in queues. The parameters are chosen such that it is optimal to join based on the expected utility, i.e. $\boldsymbol{E}+\boldsymbol{R}-\boldsymbol{c}*\boldsymbol{n}*\frac{\mathbf{1}}{\boldsymbol{\mu}}$ is always greater than $\boldsymbol{E}$. If subjects join the queue and wait until getting service, their expected utility will be $\boldsymbol{u}(.)=\boldsymbol{E}+\boldsymbol{R}-\boldsymbol{c}*\boldsymbol{n}*\frac{\mathbf{1}}{\boldsymbol{\mu}}$. If subjects do not join the queue, their utility will be $\boldsymbol{u}(.)=\boldsymbol{E}$.

In the experiment, each subject sees 4 queues. Subjects encounter long queues of 10 people or short queues of 5 people and queue length is a between subject variable. When choosing these queue lengths, two reasons are considered. First, the total time spent in the lab was defined and was not subject to change; because we wanted all subjects to wait the same amount of time during the experiment. Second, with the constraint of total waiting time and the number of queues, we needed meaningful waits and service times to test our hypotheses and to be able to compare different treatment groups. That's why 5 and 10 are chosen as queue lengths, with the mean service times of 2 minutes per person and 1 minutes per person respectively. Note that with these parameter choices, each queue wait lasts 10 minutes if a subject choses to wait until getting service.

Service Times

For random service time cases, we need different service times (10 different service times for the long queue and 5 different service times for the short queue) that satisfy our service time ordering condition. For that purpose, a MATLAB code was run and sets comprising different service times coming from an exponential distribution with an average of 1 minute for a long queue and 2 minutes for a short queue were created with the constraint that ensued the first 4 (or 5) service times will be greater (shorter) than the mean for the long slow (fast) start queue and first 2 service times will be greater (shorter) than the mean for the short slow (fast) start queue. A total of 1000 sets were created for the long queue condition and 1000 other sets were created for the short queue condition. Among all of these sets, 2 sets were chosen to be used for all subjects during the experiment.

Two treatments were used for queue reward: deterministic reward and random reward. A deterministic reward is 32 points. A random reward is 42 points with a probability of 50%, 22 points with a probability of 50%. In these two treatments, the expected value of the reward is the same. The only difference between them is uncertainty.

After determining the service times and queue reward, the cost of waiting per minute was set as constant and 2 points per minute. The budget at the beginning of each queue is 10 points.

Table 2 gives the subjects' gains according to the variables in terms of points.

Table 2: Subjects' gains in points according to different conditions

Subjects who don't join		Service Time (W): Deterministic	Service Time (W): Random
Reward of the Queue (R)	Deterministic	10	10
	Random	10	10

Subjects who join and wait until the end		Service Time (W): Deterministic	Service Time (W): Random
Reward of the Queue (R)	Deterministic	22	22
	Random	12 or 32	12 or 32

There is no uncertainty in Treatment Group 1. This groups is considered as a benchmark. All parameters are determined to motivate people to join the queue, so subjects who do not join the queue in Condition 1 are either those who have an additional term in their utility function not observed by the experimenter or those who make a computational choice error.

Risk Test

In this study, subjects' queue joining, balking and reneging decisions in queuing systems are investigated with the presence of uncertainty. This uncertainty is visible in two variables. The reward at the end of the queue can be uncertain, and can be high or low with equal probabilities. Also, the service times of the queue can be uncertain and come from an exponential distribution when they are random. When a queue has uncertain characteristics, there is risk involved for the participants. People can behave differently when faced with a risky situation. Hence, participants' risk characteristics are investigated with the Exit Survey. The most common and easily understandable survey, the Holt-Laury Risk Test, is used (Holt & Laury, 2002). This test is constructed using monetary amounts in its original context, but for the sake of the experimental context, the monetary amounts are translated into point amounts and at the end of the session, added to participants' total points and translated into cash. The test is applied after participants make all their decisions about the queues and before the Exit Survey. This way, participants' decisions during the experiment are not expected to be influenced by risk concepts.

Payments

During the experiment, participants gain points and are told that their points will be translated into cash and paid to them at the end of the experiment. A conversion factor is used to translate the points into cash. First, the maximum and minimum possible points to be gained across all queues are calculated. If subjects join all the queues and wait until getting service, they get the maximum possible points. On the other hand, if they join the queues and quit them when there is only one person in front of them, they get the minimum possible points. (When reward is random, all subjects get the high reward one time, and low reward the other time for fairness). The maximum amount of points to be gained from the queues is 88 points and the minimum amount of points to be gained is -34 points. Participants' gains from the Risk Test are also added to their points. The maximum amount of points to be gained from the

Risk Test is 38.5 points and the minimum amount of points to be gained from Risk Test is 1 point. Hence, the total points can be 126.5 maximum and -33 minimum.

Each subject who participates in the experiment gains 5 TL at the least, even if they do not join any queues. This 5 TL can be thought as a show-up fee. Participants can earn 15 TL at the most. To satisfy money constraints; two variables, z and t (cumulative time or total time spent in *all* queues) are defined. When $t = 0$, z equals 0.36. When $t \neq 0$, z equals 1. P was used as a subjects' total points from all queues and the Risk Test; therefore the total amount of cash paid equals to $\left(P + (z * 113)\right) * 0.06$. For example if a subject gains a total of 100 points from all queues s/he joined, she/he will get $\left(100 + (1 * 113)\right) * 0.06 = 12.78$ TRY. Subjects are always given rounded down amounts as payments.

Language selection

Our participants are Koç University students. Koç University is a university where all courses are taught in English. Therefore, we think that students can use the English language very well and can easily understand the concept of the experiment. Also, there are many exchange students in Koç University who don't speak Turkish. For these reasons, English is selected as the official language of the experiment and all instructions and explanations during the experiment are made in English.

Results and Conclusion

Two focus group studies are conducted before the pilot study on November 22, 2013 and December 9, 2013 with the explained study design.

Focus Group 1

First Focus Group study is conducted with 4 subjects. In this study, subjects experience three attractions: see a sculpture in a museum, visit city's famous zoo and see a local group's concert, respectively. In the Exit Survey, subjects' interest level over a 7-point Likert scale for each attraction is asked. The table below summarizes subjects' decisions for this study (Table 3).

Table 3: Subjects' decisions for Focus Group 1

	Subject 1	**Subject 2**	**Subject 3**	**Subject 4**
Descriptive				
Gender	Female	Female	Female	Male
Department	MAVA	Industrial Engineering	Industrial Engineering	Mechanical Engineering
Class	Graduate	Graduate	Graduate	Graduate
Birth Year	1990	1989	1990	1984
Risk Preference	Risk-seeking	Risk-averse	Risk-averse	Risk-averse
Decisions (Join/No Join – time spent in queue)				
Queue 1	Join – 600	No Join – 0	No Join – 0	No Join – 0
Queue 2	No Join – 0	Join – 265	No Join – 0	No Join – 0
Queue 3	Join – 600	Join – 600	No Join – 0	Join – 108
Interest Levels (1: not interested, 7: very interested)				
Sculpture	6	5	2	4
Zoo	2	6	6	5
Concert	6	5	5	6
Payment				
Total Gain in TL	9.33	6.53	5.00	6.99

In light of these results, several changes are made in the Experimental Setting:

1) Subjects have different interest levels for different attractions. Naming the attraction can cause no joins for subjects. Therefore, instead of naming specific attractions, attractions will be named as Attraction 1, Attraction 2 and so on in subsequent studies.
2) The last two questions of the Exit Survey are to test whether the subject understands the experiment concepts or not. In Focus Group study, although all the subjects are graduate students, they have difficulties in understanding these questions and give incorrect answers. Thus, one of the questions is eliminated and the other question is updated as follows:

    Q1 (as-is): Suppose it is stated that service time is constant and 2 minutes per person. People in front of you do not quit the queue. In such a queue, how long will you wait until it's your turn if there are 2 people in front of you? (2 min, 1 min, 4 min or 8 min)

    Q1 (to-be): Suppose it is stated that service time is constant and *2 minutes per person.* People in front of you do not quit the queue. In such a queue, if there are *2 people* in front of you, which of the followings will be your waiting time until it is your turn?
3) Number of attractions is increased from 3 to 4 to be able to test the effects of uncertainty on subjects' decisions as a within-subject variable and have more data points with the same number of subjects.

Focus Group 2

Second Focus Group study is conducted with 3 subjects to test the changes made after first Focus Group study. In this study, subjects experience four attractions that are different in terms of reward and service time randomness: deterministic reward-deterministic service time, random reward-deterministic service time, deterministic reward-random service time and random reward-random service time, respectively. When service times are random, first service times are **short**. The Table 4 summarizes subjects' decisions for this study.

Table 4: Subjects' decisions for Focus Group 2

	Subject 1	**Subject 2**	**Subject 3**
Descriptive			
Gender	Female	Female	Female
Department	Industrial Engineering	Industrial Engineering	MAVA
Class	Graduate	Graduate	Graduate
Birth Year	1989	1990	1991
Risk Preference	Risk-neutral	Risk-neutral	N/A
Decisions (Join/No Join – time spent in queue)			
Queue 1	Join – 600	Join – 600	Join – 24
Queue 2	No Join – 0	No Join – 0	No Join – 0
Queue 3	Join – 600	Join – 600	No Join – 0
Queue 4	No Join – 0	No Join – 0	Join – 600
Payment			
Total Gain in TL	11.83	11.83	10.23

After Focus Group 2, the changes made are approved and tested with the Pilot Study.

4.2.2. Pilot Study

The Pilot Study is conducted after the Focus Group studies and before performing the full scale experiments. The design is improved after the Pilot Study with several changes. In this section, Experimental Design of the performed study and the proposed changes with their reasons are discussed.

Experimental Design

Scenario

The same scenario as in the Focus Group studies is used. Subjects are told upon their arrival to the laboratory that they are going to be a tourist in a city for one day and get a chance to visit several touristic attractions. These attractions are numbered from 1 to 4. Total number of attractions is not disclosed to the subjects.

Presentation of Experiment

A video is used for presentation of the experiment. In the presentation, subjects were introduced to the experimental context, then provided with the screens of experiment interface and finally with the point calculation. The script of the presentation can be found in Appendix A.

Variables

Dependent Variables

There is no change of dependent variables between Focus Group and Pilot studies.

The first dependent variable is subjects' joining decisions for each queue, having two possible outcomes: joining or not joining.

The second dependent variable is subjects' quitting decisions for the queues that they joined, with quitting and not quitting options. A detailed explanation for these variables can be found in section 4.1.1.

Independent Variables

The independent variables are kept the same between the Focus Group and Pilot studies. For more details, please refer to section 4.1.2.

- **Reward of the queue (R):** This is a variable with two levels. Reward of the queue can be deterministic or random. This is a within-subject variable.
- **Service time (1/μ):** This is a variable with two levels. Service time per person might be deterministic or random. This is a within-subject variable.
- **Queue length:** All the queues are observable in the experiment. Queue length is a between-subject variable with two different levels: long queue and short queue. This is a between-subject variable.
- **Service time ordering:** In random queues, there are two different service time orderings. In the Slow Start treatment, subjects first see service times which are longer than the mean, and then they see service times which are shorter than the mean. In the Fast Start treatment, subjects first see service times which are shorter than the mean and then they see service times which are longer than the mean. This is a between-subject variable, meaning that a subject experiences only Fast Start or Slow Start queues in all random cases.

Determining the parameters

Queue Values

The parameters of a linear utility function in a queuing setting are assumed as stated in section 4.1.1 and parameter selection is made again to motivate queue joining.

- $\boldsymbol{R\ (reward\ of\ the\ queue) = 22\ or\ 42\ points}$
- $\boldsymbol{E\ (endowment) = 10\ points}$
- $\boldsymbol{c\ (cost\ of\ waiting\ per\ minute) = 2\ points}$
- $\boldsymbol{\frac{1}{\mu}(average\ service\ time\ per\ person) = 1\ or\ 2\ minutes}$
- $\boldsymbol{n\ (number\ of\ people\ in\ the\ queue) = 5\ or\ 10\ people}$

There are 4 different queues in terms of reward and service time uncertainty combination (Table 5).

Table 5: Treatment groups of Pilot Study

Treatment No	Reward	Service time
1	Deterministic	Deterministic
2	Random	Deterministic
3	Deterministic	Random
4	Random	Random

Two different orders are created for this 4 different treatment groups; 1234 and 1324. The first treatment group is considered as a benchmark and we want each subject to experience it at first. Also, before experiencing both random reward and random service times, we want our subjects to experience a random case for both reward and service time. Therefore, random reward-random service time case is put at the last place.

Service Times

We have two different queue lengths; long queue, consisting of 10 people and short queue, consisting of 5 people, with 1 minute and 2 minutes average service times per person respectively. Thus, 10 and 5 different service times are created respectively for long and short queues. The details of this process can be found in section 4.1.1. Service times for different treatments are represented in Table 6.

Table 6: Service Times of Pilot Study in Seconds

Long Queue	*Treatment Group 3*	*Fast Start*	19, 40, 14, 31, 53, 80, 68, 109, 103, 83
		Slow Start	125, 80, 100, 74, 97, 46, 17, 25, 13, 23
	Treatment Group 4	*Fast Start*	15, 40, 22, 30, 17, 169, 85, 65, 97, 60
		Slow Start	150, 60, 100, 80, 85, 45, 20, 4, 31, 26
Short Queue	*Treatment Group 3*	*Fast Start*	60, 25, 220, 135, 160
		Slow Start	180, 120, 200, 70, 30
	Treatment Group 4	*Fast Start*	33, 49, 250, 112, 156
		Slow Start	300, 90, 118, 40, 52

Risk Test

The same Risk Test is used as stated in section 4.2.1.

Payment

During the experiment, participants gain points and are told that their points will be translated into cash and paid to them at the end of the experiment. A conversion factor is used to translate the points into cash. The same methodology is used as described in section 4.1.1. to determine the point conversion equation. So, we define the variable z as follows:

$$z = \begin{cases} z = 1, t \neq 0 \\ z = 0, t = 0 \end{cases}$$

where t is total time spent in all queues. Therefore, the total amount of cash paid equals to $\big(P + (z * 215)\big) * 0.041$, where P is total points gained from all queues.

Language Selection

Our participants are Koç University students. Koç University is a university where all courses are taught in English. So, the official language of the experiment was English together with all instructions and explanations.

Results and Conclusions

The Pilot Study was conducted on December 12 and 13, 2013 with a total of 52 participants.

There are 2 different orderings for the 4 possible treatment groups: 1234 and 1324. These two orderings were experienced by 29 and 23 subjects respectively. Numbers of people for different Queue Length and First Service Times combinations are summarized in Table 7.

Table 7: Number of participants of each group

Queue Length	First Service Times	Number of participants
Long	Short	14
Long	Long	16
Short	Short	10
Short	Long	12
	Total	**52**

Subjects' joining and quitting rates are summarized descriptively in Table 8. This table enables us to interpret the effects of service time and reward uncertainty. The only difference between Treatment 1 and Treatment 3 in terms of experimental manipulations is service time uncertainty. Between these different treatments, we observe decreasing joining rates; from 63% to 47% for long queues and from 82% to 64% for short queues. Similarly, the only difference between Treatment 1 and Treatment 2 in terms of experimental manipulations is reward uncertainty. The joining rate for long queues remain the same for Treatment 1 and Treatment 2 (63%), however, the joining rate for short queues is decreased from 82% to 77% when the reward is random.

We can also compare Treatment 4 with the other groups for several reasons. The comparison of Treatment 4 with Treatment 2 reveals the effect of service time uncertainty with the presence of random reward. The joining rate decreases from 69% to 50% when both service times and reward are random. In the same manner, the comparison of Treatment 4 with Treatment 3 displays the effect of reward uncertainty with the presence of service time uncertainty. The joining rate decreases from 54% to 50% when both variables are random. In these comparisons, the fact that Treatment 4 is always the last queue experienced by the subjects must be taken into consideration, as it might contain order effects.

Table 8: Subjects' joining and quitting rates

	Queue Length	Joining	Quitting	Total	Joining Rate (Joining/Total)	Quitting Rate (Quitting/Joining)
Treatment 1	Long	19	13	30	0.63	0.68
	Short	18	8	22	0.82	0.44
	Overall	37	21	52	0.71	0.57
Treatment 2	Long	19	6	30	0.63	0.32
	Short	17	5	22	0.77	0.29
	Overall	36	11	52	0.69	0.31
Treatment 3	Long	14	7	30	0.47	0.50
	Short	14	8	22	0.64	0.57
	Overall	28	15	52	0.54	0.54
Treatment 4	Long	14	8	30	0.47	0.57
	Short	12	8	22	0.55	0.67
	Overall	26	16	52	0.50	0.62

Table 9 summarizes average time spent in queues. There are 3 possible ways to calculate the average time; "All" includes no joins as 0 seconds spent in the queue, "Only Join" includes time spent of subjects who join the queue, and finally, "Only Quit" calculation is for subjects who join and quit the queue. It is not possible to conclude systematic differences between average time spent in different conditions (Table 9).

Table 9: Average time spent in queues

			Average time spent in seconds		
No	**Reward**	**Service Time**	**All**	**Only Join**	**Only Quit**
1	Deterministic	Deterministic	221	311	91
2	Random	Deterministic	311	449	82
3	Deterministic	Random	176	327	89
4	Random	Random	155	310	128

Next, a binomial logistic regression is conducted to test whether there is an effect of cumulative time spent on subjects' joining decisions. Binomial logistic regression analyzes a binary response with an explanatory variable, by analyzing number of success in a determined number of independent trials (Weisberg, 2005). In our case, the success is subjects' join decision. This analysis is conducted with Join decisions and cumulative t variable. Since the first and last queues of the experiment are always the same in terms of reward and service time uncertainty combination, a systematic effect of cumulative time spent in queues on subjects' joining decisions might prevent us from interpreting the results confidently. We conduct our binomial logistic regression with the independent variable of joining decisions of subjects for Queue 4 where reward and service times are both random. The independent variable is cumulative time spent in all 3 queues. The result of this analysis implies that increasing total time spent in queues has a negative effect on people's joining decisions ($p < 0.05$). This result suggests there may be an ordering effect and we redesign the order of queues for Study 1.

After the descriptive and statistical analyses together with observations, several changes are made on Experimental Design. These changes are summarized below with their reasons.

- Reward uncertainty is investigated in the Focus Group and Pilot studies. However, having two random variables makes the study too complicated for subjects to understand. Also, statistical analyses becomes complex to conduct and interpret. For these reasons, reward uncertainty is excluded from the scope of this thesis study.
- Service time ordering was a between-subject variable in the Focus Group and Pilot studies. However, to reduce the error associated with individual differences, to economize on the total number of subjects with increasing statistical power and to be able to observe the behavior of the same subject for different service time orderings, service time ordering variable is switched to within-subject variable for Study 1. This change was also possible thanks to eliminating reward uncertainty, since by eliminating it, we were able to reduce the number of queues.
- During the Pilot studies, the experimenter observed that subjects do not fully comprehend the experimental concepts and they have a tendency to try the buttons even if they do not mean them. So, to familiarize subjects with the experiment screens and buttons, a training part is added to the presentation of the experiment for Study 1.
- In our experiment, random service times can have a fast start or slow start and we would like to examine the effects of these random waits on subjects' decisions. To make service time easily tractable to the subjects, a clock is added to the experiment interface where subjects can track the time elapsed ever since they join the queue in Study 1 in seconds.
- All of our subjects were Turkish students. That's why the official language of the experiment is switched to Turkish to avoid a possible language barrier and related misunderstandings.

- Having found a significant effect of cumulative time spent in all queues on subjects' joining decisions in the last queue suggests that ordering of queues matters. Thus, queue ordering is randomized between all participants for Study 1.
- The Exit Survey was on paper during the Pilot Study. This causes the subjects to understand the next step of the experiment as it is easily observable in a lab setting whether a subject is filling in a form on paper or is doing the experiment with the computer. Consequently, Exit Survey is moved to an online survey platform.
- Subjects were allowed to leave the lab when they finished the experiment during the Focus Group and Pilot studies. By allowing subjects to leave the lab, subjects who continue the experiment are distracted and more importantly, the decisions of the remaining subjects might be affected by the fact that the experiment will end soon and there is a possibility to leave the room. That's why in Study 1 subjects are told that the duration of the experiment is 1 hour and it is not possible to leave the lab before 1 hour. The winners are presented with a gift card of 50 TRY from a bookstore.
- In the Focus Group and Pilot studies the only reward that subjects can get was their individual rewards, calculated with respect to their gained points in the queues. In Study 1, to further motivate point maximization behavior by subjects, a draw between subjects who get the top 10 points is organized and announced to the subjects during the presentation of the experiment.

4.2.3. Study 1

The Full-scale Study 1 is conducted after the Focus Group and Pilot studies, with the improved experimental design. In this section, the final design of the experiment is presented with descriptive statistics of the results.

Experimental Design

Scenario

The same scenario as in Focus Group and Pilot study is used. Subjects are told upon their arrival to the laboratory that they are going to be a tourist in a city for one day and get a chance to visit several touristic attractions. These attractions are named as Attraction 1, Attraction 2 and Attraction 3 but the total number of attractions is not disclosed to the subjects.

Presentation of Experiment

The experimental concepts are introduced to subjects via an interactive video. Presenting a video is chosen as the presentation method in order to ensure that each subject receive the same amount of information about the experiment and to prevent the experimenter bias. To avoid creating an expectation, different videos are presented to the subjects who are in the long queue condition and subjects who are in the short queue condition, using examples with the same queue length as the subject will encounter in the experiment.

The transcript of the video with the used slides during the experiment can be found in Appendix B in Turkish.

The video consists of three parts. The first part introduces the scenario of the experiment and tells the subjects that they can gain points if they visit the attractions and for each attraction, they have to wait in a queue. Subjects are also told that they start each attraction with a budget but they lose points from this budget while waiting in a queue. Finally, they are told that their purpose during the experiment is to maximize their points. Subjects are not informed about the number of attractions during this touristic day and they only know their gain from each queue at the end of the experiment to prevent end-of-the-day betting effect (Kahneman &

Tversky, Choices, values, and frames, 2008). End-of-the-day betting effect induces a shift in people's risk preferences towards the end of the day when people integrate their previous gains or losses to their decisions. In the experiment, subjects are told that they have enough time to complete all the attractions; thus there is no reason for them to worry about not knowing the exact number of attractions.

The second part of the video is the training part. In this part, the experiment interface starts on subjects' screens and progresses in parallel with the presentation. This part is to make subjects familiar with the joining, reneging and balking concepts. In the training part, subjects encounter 3 queues. They are told to renege in the first queue, to balk in the second queue and finally, to join and wait until getting service in the third queue. This way they experience the outcome of all three alternatives.

Since it is not practical to make subjects wait long times during the presentation, average service times in the presentation are taken to be very short and subjects are warned that they will see different times during the experiment. For the second queue where subjects are told to balk, the queue has an average service time of 6 seconds and service times of 10, 15, 4, 6, 9 and 12 seconds respectively are experienced by subjects. In this way, subjects get a chance to have an idea about randomness and experience it. For the third queue where subjects are told to join and wait until getting service, the service times are deterministic and 2 seconds per person.

The final part of the presentation is about rewards and point calculation of the experiment. Subjects are told how their points will be calculated in case of joining, reneging and balking and are informed that these points will be translated into a monetary reward at the end. To motivate point maximization behavior further, a draw is organized between the subjects who get the maximum points and a gift card of 50 TRY to be used in D&R (bookstores) is presented to 3 subjects.

After the video, participants are allowed to ask their questions about the experiment and given the hard copy of the video presentation to go through it again. If there is a question, the experimenter responds. If there is no question, the experiment starts.

Variables

Dependent Variables

Dependent variables are kept the same throughout the Focus Group and Pilot studies and Study 1. For more details please refer to Section 4.1.1.

Exit Survey

In addition to these dependent variables, at the end of the experiment, all subjects are expected to complete the Exit Survey that consists of 4 different groups of questions: demographic questions, risk aversion questions, consistency checks and questions that probe for motivation and thoughts during the experiment. These questions are mixed up and not grouped this way in the survey. Subjects are only able to complete the Exit Survey after making all their decisions and they cannot return to the experiment at this stage.

Exit Survey responses of subjects are gathered by an online survey software Qualtrics.

First, demographic questions about subjects' gender, nationality, birth date, study year and department are asked.

Then, since people's risk attitudes depend on the context (Leclerc, Schmitt, & Dube, 1995), subjects' risk preferences for different contexts are gathered: Money Gain, Time Loss and

Money Loss, respectively. For each context, different risk aversion questions are asked. Between these questions, irrelevant questions of risk aversion are placed.

Risk Aversion questions are extracted from Leclerc, Schmitt and Dube (1995). In their study, they investigate people's different approaches towards monetary and time-related decisions. Their questions are translated to Turkish in the Exit Survey, with different values. These questions are as follows:

<u>Money Gain</u>

Please choose between the following options.

A. A certain gain of 10 TRY
B. A 50% chance of gaining 20 TRY, a 50% chance of gaining 0 TRY

<u>Time Loss</u>

Please choose between the following options.

A. Having to wait 10 minutes for sure
B. A 50% chance of waiting 20 minutes, a 50% chance of not waiting

<u>Money Loss</u>

Please choose between the following options.

A. A certain loss of 10 TRY
B. A 50% chance of losing 20 TRY, a 50% chance of losing 0 TRY

Third part of the questions is labeled as Consistency Check questions to investigate whether subjects understand randomness and queue length concepts or not.

The last group of questions is for probing motivation and thoughts during the experiment. These questions examine subjects' decision making mechanisms like a threshold determination for wait or point gain, initial point calculation and update. Further, subjects' reasons for their decisions are inquired with multiple-choice and text questions.

A summarized descriptive representation of Consistency Check and Motivation Probing questions is provided the following Descriptive Statistics section. All Exit Survey questions can be found in Appendix C.

Independent Variables

Service time (1/µ): The service time variable has two levels: deterministic or random. This is a within-subject variable. When the service times are random, subjects are told that each person in the queue spends different amounts of time while getting service. The distribution of these times is not specified but subjects are provided with an example of a queue with random service times in the presentation of the experiment (Please refer to Section 4.1.2. for more presentation details).

Random service time condition has two levels that subjects are not informed about. A random queue with random service times could start with a series of service times that are shorter than the mean or with a series of service times that are longer than the mean. These are labeled as the Fast Start and Slow Start queues respectively, and represent the two levels of the random service time treatment. The nature of service times are summarized in Figure 1. For more details, please refer to section 4.1.2.

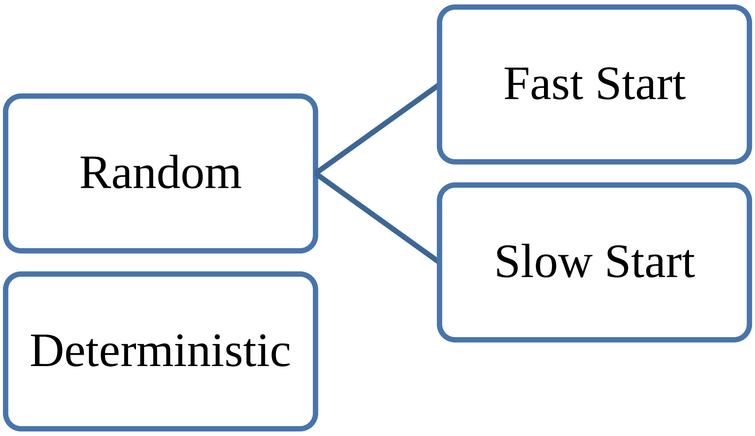

Figure 1: Nature of service times

- **Queue length:** All the queues are observable by the subjects in the experiment. Queue length takes two levels: long, consisting of 10 people or short, consisting of 5 people.

Determining the parameters

Service Times

The queue length variable is a between subject variable and has two levels; long, consisting of 10 people and short, consisting of 5 people. The procedure of determining the different service times in random case is described in section 4.2.1.

Additionally, for a more controlled design, elapsed time for one service completion of the short queue is set equal to the elapsed time of two service completions of the long queue. For example, in a Slow Start long queue, first two service times are 90 and 110, making the time elapsed 200 seconds which is equal to the first service time of a Slow Start short queue. A total of 1000 sets were created for the long queue condition and 1000 other sets were created for the short queue condition. Among all of these sets, 2 sets were chosen to be used for all subjects during the experiment.

The service times used in the experiment are summarized in the table below (Table 10) for long queues and short queues.

Table 10: Service Times of Study 1 in Seconds

Long Queue	*Fast Start*	3, 2, 5, 5, 15, 65, 164, 141, 110, 90
	Slow Start	90, 110, 141, 164, 65, 15, 5, 5, 2, 3
Short Queue	*Fast Start*	5, 10, 80, 305, 200
	Slow Start	200, 305, 80, 10, 5

Queue Values

It is assumed that subjects have a utility function as $\boldsymbol{R + E - c * n * (\frac{1}{\mu})}$. The parameters of this equation are chosen such that joining and waiting until getting service is always optimal for an expected utility maximizer subject. The queue parameters are set as follows:

- $\boldsymbol{R\ (reward\ of\ the\ queue) = 125\ points}$
- $\boldsymbol{E\ (endowment) = 25\ points}$
- $\boldsymbol{c\ (cost\ of\ waiting\ per\ minute) = 10\ points}$
- $\boldsymbol{\frac{1}{\mu}(average\ service\ time\ per\ person) = 1\ or\ 2\ minutes}$
- $\boldsymbol{n\ (number\ of\ people\ in\ the\ queue) = 5\ or\ 10\ people}$

These variables are chosen such that $\boldsymbol{c * \frac{1}{\mu} * n}$ always equals to $\boldsymbol{100\ points}$.

Payments

During the experiment, participants gain points and are told that their points will be translated into cash and paid to them at the end of the experiment. A conversion factor is used to translate the points into cash.

Each subject who participates in the experiment gains 5 TRY at the least. This 5 TRY can be considered as a show-up fee. Participants can earn 15 TRY at the most. Additionally, subjects who do not join any of the queues gain 5 TRY too. To satisfy money constraints two variables, z and t (total time spent at *all* queues) are defined. When $t = 0$, z equals 0.27. When $t \neq 0$, z equals 1. P was used as a subjects' total points from all queues; therefore the total amount of cash paid equals to $\left(P + (z * 350)\right) * 0.03$. For example, if subjects do not join any of the queues, they will only get their endowment points from 3 queues and z will be equal to 0.27. So, the monetary reward will be $\left(75 + (0.27 * 350)\right) * 0.03 = 5.08$ TRY. As a second example, if a subject gains 94 points from all the queues, his/her monetary reward will be $\left(94 + (1 * 350)\right) * 0.03 = 13.32$ TRY.

Language selection

In the Focus Group and Pilot studies, the official language of the experiment, together with all instructions and explanations were in English. However, our participants are Turkish and this creates a language barrier for them as experienced in Focus Group and Pilot studies. Consequently, in the Study 1, the experiment interface as well as instructions and explanations are in Turkish.

Results and Conclusion

Study 1 sessions were conducted on March 20, 21, 25 and May 8 and 9 at Koc University Behavioral Lab. A total of 120 students participated in the experiment. Minimum and maximum cash rewards paid to the participants were 5 TRY and 15 TRY respectively. The average payment was 11 TRY.

The detailed statistical analyses are provided in Chapter 5 and Chapter 6. In this section, only descriptive analyses of Study 1 are presented.

Descriptive Statistics

First, the data from our initial study is analyzed descriptively. The data for these analyses are gathered from subjects' decisions during the experiment and from their Exit Survey responses.

Table 11 summarizes the number of subjects for different experimental conditions. Queue Length is a between subject variable in our experiment. Additionally, as there are 3 different queues in terms of service times (Deterministic, Fast Start, Slow Start), the order of these queues are randomized to avoid order induced biases. There are 6 possible orders for 3 different queues labeled as groups in Table 11 and each group has a minimum of 16 subjects.

Table 11: Number of people for different experimental conditions

		Number of people		
Group No	**Queue Order**	**Long Queue**	**Short Queue**	***Total***
1	Det-Fast-Slow	10	6	***16***
2	Det-Slow-Fast	9	12	***21***
3	Fast-Det-Slow	11	11	***22***
4	Fast-Slow-Det	10	17	***27***
5	Slow-Det-Fast	11	6	***17***
6	Slow-Fast-Det	9	8	***17***
	Total	***60***	***60***	***120***

Table 12 summarizes subjects' descriptive statistics. A subject pool of university students is used to recruit subjects; the majority of students being 2^{nd} year Business Administration (Bus. Adm.) students, as seen in Table 12.

Table 12: Subjects' descriptive statistics

Gender	
Female	***63%***
Male	37%
Department	
Bus. Adm.	***38%***
Economics	16%
Psychology	7%
International Relations	8%
Engineering	21%
Other	10%
Study Year	
Freshman	3%
Sophomore	***38%***
Junior	30%
Senior	29%
Graduate	0%

In Table 13, subjects' risk preferences are summarized. An asymmetry of subjects' risk preferences for money gain and money loss is observed as expected by Prospect Theory (Kahneman & Tversky, Prospect Theory: An Analysis of Decision under Risk, 1979).

Table 13: Subjects' risk preferences

Money Loss		Time Loss		Money Gain	
Risk Averse	32%	Risk Averse	47%	***Risk Averse***	***59%***
Risk Seeker	***68%***	***Risk Seeker***	***53%***	Risk Seeker	41%

In Table 14, subjects' joining and quitting rates are summarized descriptively. In addition to rates, average time spent in queues are included. There are 3 possible ways to calculate the average time; "All" includes no joins as 0 seconds spent in the queue, "Only Join" includes time spent of subjects who join the queue, and finally, "Only Quit" calculation is for subjects who join and then quit the queue.

Table 14: Subjects' joining and quitting rates

		Deterministic	**Fast Start**	**Slow Start**	***Average***
	Queue Joining Rate (%)	60	60	57	***59***
	Queue Quitting Rate (%)	38	31	42	***37***
Average time spent in seconds	All	147	216	120	***161***
	Only Join	245	360	211	***273***
	Only Quit	56	133	71	***83***

Table 15 summarizes Consistency Check questions of the Exit Survey. Subjects are asked to respond to these questions only for the last queue they have experienced. High correct answer rates are observed. For the first question that is about the queue length, when the answers is within a deviation of ±1 person, it is considered to be a correct answer, then the percentages of correct answers become 100% and 86% for short queue and long queue respectively. A deviation of ±1 person might be considered as acceptable in queue length context since there might be a confusion about counting oneself or not. Additionally, subjects' assessment of the queue randomness seems to be correct in higher percentages then their assessment when the queue is deterministic.

Table 15: Consistency Check Questions

Question	Right Answer	Percentage of Correct Answer
How many people were there in the last queue that you've experienced?	Short Queue *(5 people)*	77%
	Long Queue *(10 people)*	69%
Was your waiting time random or deterministic in the last queue that you've experienced?	Random	89%
	Deterministic	74%

The Exit Survey also has questions to probe for motivation and thoughts during the experiment. Subjects are asked about the reasons for their decisions and are provided with multiple reasons as possible answers. They rate each possible answer by using a 5 point Likert scale and the 3 reasons that get the highest average rating are reported in order as "top 3 reasons" for each possible question in Table 16.

Table 16: Top 3 Reasons for decisions

Question	Top 3 Reason
Why did you balk?	I preferred to keep my endowment points.
	I don't like waiting in queues.
	The queue seems long.
Why did you join?	The reward of the queue was greater than the cost of waiting.
	I would like to see the progress of the queue.
	The queue seems short.
Why did you renege?	The queue was progressing slowly.
	My remaining waiting time was uncertain.
	I was bored of waiting.
Why did you wait until the end of the queue?	Waiting was the most profitable option for me in terms of points.
	I wanted to get the reward.
	I have calculated the waiting time and waiting was the best option.

Also, questions about possible update mechanisms and/or a threshold value are asked. Some of these questions and answers are summarized in Table 17. Subjects notice time passing more than their points and the majority of subjects state having a threshold waiting time for their quit decisions upfront.

Table 17: Update and Threshold Questions

	Question	Answer	Percentage
Update	Did you calculate your points while waiting?	No	52%
	Did you watch the time passed while waiting?	Yes	85%
Threshold	Did you plan to quit if waiting time exceeds a certain amount while joining?	Yes	60%

Subjects are also asked about their threshold time. When we analyze subjects' actual waiting time and their reported threshold value, we found an absolute average difference of approximately 109 seconds. However, while 59% of the subjects do not show patience until their threshold time and have an average difference of 122 seconds between their threshold and actual waiting time, 41% of the subjects underestimate their threshold time and show more patience than their threshold time with an average of 90 seconds. These descriptive analyses suggest that people do not stick to their initial decisions during the experiment.

Table 18: Question about the Pace of the Queue

	Question	**Answer**	**Percentage**
Experience	How was the pace of the queue?	Slower / Faster than my prediction	59%

Also, the majority of subjects update their prediction about the pace of the queue while waiting, leading to the conclusion that their prior expectations and predictions about the queue changes during the wait experience (Table 18). When subjects respond to this question for a Slow Start queue, 83% of the subjects claim that the pace of the queue is slower than their prediction and no one claims that the pace of the queue is faster than their prediction. When subjects respond to this question for a Fast Start queue, 10% of the subjects say that the queue is faster than their prediction and 50% of the subjects claim that the pace of the queue is slower than their predictions. Finally, when subjects respond to this question for a Deterministic queue, no one claims that the pace of the queue is faster than their prediction and 88% of the subjects found the queue either exactly like their prediction or slower than their prediction, divided equally.

Chapter 5

ANALYSIS OF BOUNDED RATIONALITY

In this study, we investigate people's queue joining decisions based on a linear utility function. Paralleling Naor's work (1969), we model people's utility as $u(.) = E + R - c * \frac{1}{\mu} * n$. In our experiment, the expected utility is always greater than 0 for a person who joins the queue and waits until getting service. Also, the gain of "joining and waiting until getting service" is greater than the gain of "no join". Therefore, we expect people who maximize expected utility to join all the queues. However, our descriptive analyses show that the joining rate is 59% for Study 1 (Table 8). Additionally, when we combine all the results from Study 1, 2, 3 and 4, we observe a joining rate of 57% among all queues in these studies.

To be able to model people's balking behaviors, we include an error term to the utility function. We redefine subjects' utility functions with this error term that comprises the factors affecting subjects' joining decisions but unobservable by the experimenter.

We treat this error term in the scope of the Quantal Response Equilibrium (QRE) approach. QRE is a generalization of the Nash equilibrium concept developed in order to explain and justify data from experimental economics with the notion of Nash equilibrium. In particular, it addresses the problem that experimental data is rarely a perfect match to what is expected in a theoretical Nash equilibrium. Quantal Response Equilibrium assumes that people behave according to their expected utilities, but they also make some errors while making choices in game theoretic settings (McKelvey & Palfrey, 1995). This is interpreted as a bounded form of rationality. This approach proposes an equilibrium; but differently from Nash equilibrium, it is an imperfect equilibrium including bounded rationality.

As stated before, the expected utility function of subjects is assumed to be:

$$u(.) = E + R - c * \frac{1}{\mu} * n$$

in this study. For Join analyses, this expected utility function is updated to:

$$u^{*}(.) = u(.) + \varepsilon$$

$u^{*}(.)$ being the new function. The error term ε is assumed to follow a logistic distribution.

So, subjects' probability of join is defined according to their expected utility function and formulized as:

$$P_{join} = P(u^{*}(.) > E)$$

Then it can be shown that joining probability takes the form of a logit function as follows (McFadden, 1973):

$$P_{join} = \frac{e^{\frac{R+E-c*w}{\beta}}}{1 + e^{\frac{R+E-c*w}{\beta}}}$$

The β parameter of this function is assumed to be the standard deviation of this function. In this function, R, E, c and w are our queue characteristics and are constant in the experiment; $R + E - c * w = 50$ in all queues and $w = \frac{1}{\mu} * n$. They represent reward of the queue, endowment, cost of waiting per minute and expected total waiting time in minutes, respectively. β is interpreted as the level of subjects' bounded rationality (Huang, Allon, & Bassamboo, 2013). The likelihood function for a person is;

$$l_i = (1 - P_{join})^{(1-y_i)}(P_{join})^{y_i}$$

where y_i is i^{th}person's joining decision and equals to 1 if the subject joins, 0 otherwise. So, the overall likelihood function L of our subjects is formulized as:

$$L = \prod_{i=1}^{n} l_i$$

n being total number of subjects. We write the log-likelihood function used to estimate subjects' level of bounded rationality, β, as follows;

$$\ln L = \ln\left(\prod_{i=1}^{n} l_i\right)$$

$$\ln L = \sum_{i=1}^{n} \ln l_i$$

$$\ln l_i = y_i\left(\frac{R - c * w}{\beta} - \ln\left(e^{\frac{R+E-c*w}{\beta}} + 1\right)\right) - (1 - y_i)ln\left(e^{\frac{R+E-c*w}{\beta}} + 1\right)$$

We use maximum likelihood estimation to estimate β. Different β values for different treatments are estimated with maximum likelihood estimation. β could vary from 0 to ∞, 0 being fully rational and ∞ being random. Note that as $\beta \to \infty$, P_{join}converges to $\frac{1}{2}$, indicating a random join decision. On the other hand, as $\beta \to 0$, P_{join} approaches to 1.

Huang, Allon and Bassamboo propose a ratio to be able to compare different β values, since the unit of β depends on the unit of reward in the study (2013). For this reason, a dimensionless ratio, β/R, is proposed for a straightforward comparison (Huang, Allon, & Bassamboo, 2013). They investigate the literature for different β/R values and find that these values are broadly in the range of [0,5]. In our study, β/R values are in the range of [0,3.5]. β

values with their standard errors in brackets, confidence interval and β/R values are represented in the Table 19. While determining these values, standard errors are clustered by subject to take into account the repeated measures nature of the data (Kremer & Debo, 2012). However, as each subject experiences a deterministic and two random queues in terms of service times because of the within subject design of this variable, β value for Deterministic treatment is determined without clustering.

In these analyses, a combination of all the results from our Study 1 and the follow-up studies, Study 2, 3 and 4 (which are explained in detail in Chapter 6) are presented. The difference between these studies is the service time sequences that are only observable after joining the queue. Since there is no difference for subjects to consider before joining in these studies, we combine them to have more data points and more robust results.

Table 19: The Statistics for the Level of Bounded Rationality

	General	Deterministic	Random	Long	Short
β value	178.38 (42.77)	85.36 (17.10)	375.64 (224.15)	183.48 (50.29)	159.41 (78.93)
95% Confidence Interval	94.55 262.21	51.83 118.87	-63.68 814.96	84.91 282.05	4.71 314.11
β/R	1.43	0.68	3.01	1.47	1.28

	Econ and Engineering Students	Other Students
$\boldsymbol{\beta}$ ***value***	156.17 (50.89)	196.86 (67.33)
95% Confidence Interval	56.43 255.91	64.90 328.82
$\boldsymbol{\beta/R}$	1.25	1.57

We observe relatively high β values overall and several changes in subjects' β values among treatments comparing the mean values. Considering β values as our subjects' level of bounded rationality, we can say that subjects' level of bounded rationality varies across different treatments.

While we cannot state any significance in comparisons, we observe some directional relationships between the average β values estimated for different cases. For example, the β value of Deterministic queues is less than the β value of Random queues. This relation between these two β values suggests that subjects are more affected by unobservable factors in random queues. This is an expected result since randomness is more difficult to interpret than deterministic situations.

For the queue length variable, we observe a greater β value when the queue length is long, implying that people are more boundedly rational in long queues than they are in short queues. However, we do not observe a statistically significant difference between β values of long and short queues, considering their standard errors and confidence intervals. While making this comparison, we keep in mind that even if we randomly assign subjects to different treatment groups, our queue length variable is a between subject variable and comparing β values of subjects in long queues and subjects in short queues would mean comparing different groups' bounded rationality.

Our subjects are from different disciplines. We divide them into two groups: one consisting of Economics and Engineering students and the other group labeled as "Other" consisting of several different disciplines like Management, Psychology, International Relations and Humanities. By grouping the subjects in such a way, we aim to group them according to their quantitative inclinations. Thus, we use their majors as a proxy for personal differences in terms of following a utility function maximizing behavior. The relationship between the β values of Econ and Engineering students and Other groups suggests that Econ and Engineering students are less boundedly rational in the experiment's queuing setting than the students from other disciplines.

Chapter 6

TESTING THE HYPOTHESES

Our hypotheses are developed for three dependent variables. Consequently, statistical analyses for experimental data are investigated for these dependent variables. Join and Quit analyses represent subjects' joining and quitting decisions respectively. t represents subjects' time spent in the queues. In this section, results from Study 1 and three follow-up studies, Study 2, 3 and 4 will be discussed.

We investigate the effects of Queue Length and Randomness, as well as different levels of randomness as Fast Start and Slow Start, on people's joining and quitting decisions and time spent in queues.

Subjects' Join and Quit decisions, together with Queue Length, Randomness, Fast Start, Slow Start variables are binary variables. t, which is in terms of seconds is a continuous variable between 0 and 600, since all the queues in the experiment have a total waiting time of 10 minutes. For this reason, there is a right censoring at 600 seconds in our study.

In the analyses, we choose logit models over ANOVA for two reasons. Our first reason is that our variables are binary. ANOVA compares the means of different groups to test the null hypothesis. ANOVA could still be used for binary variables by interpreting the means as proportions. However, it becomes problematic when interpreting confidence intervals while our variable only takes the values 0 and 1 and confidence intervals could extend this interval (Jaeger, 2008).

Secondly, ANOVA requires equal and sufficiently large sample sizes to ensure normal distribution assumption. However, in our experimental setting since our variables are binary and our groups are not very numerous, it is not possible to satisfy this assumption. Therefore, in our analyses, we use regression models.

Model Selection: probit or logit?

We use regression models in our statistical analyses; since regression model can be used to determine the relationships between dependent and independent variables (Fisher R. A., 1954). A linear regression is modeled as follows (Cook & Weisberg, 1982):

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p + \varepsilon$$

where y is the dependent variable, $x_1, x_2, \ldots, x_p$ are independent variables, βs are coefficients and ε is the error term. In a simple linear regression model, β_i equals to the change in y, when there is a unit change in x_i. However, when y is a binary variable, the only possible change is from 0 to 1 or vice versa. To be able to interpret the effects of independent variables on a binary variable, the equation changes as follows (Wooldridge, 2009):

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k$$

where $\hat{y}$ is the predicted success probability and $\hat{\beta}_i$ is the predicted change in the probability in the case of x_i change by one unit. This model is called Linear Probability Model (LPM).

LPM has some disadvantages of having a constant independent variable and having probabilities that are not between 0 and 1 (Wooldridge, 2009). So, binary response models of the following form are suggested to overcome these disadvantages:

$$P(y = 1|x) = G(\beta_0 + x\beta)$$

where $0 < G(x) < 1$ and $x\beta = \beta_1 x_1 + \cdots + \beta_k x_k$ (Wooldridge, 2009).

To ensure the limitations, $G(x)$ can be modeled as a logistic function or can be a standard normal cumulative distribution function (Wooldridge, 2009). In these cases, the error term ε in the link function $y^* = \beta_0 + x\beta + \varepsilon$, where y^*being an unobservable variable $\binom{y=1;\, if\ y^*>0}{y=0; if\ y^* \leq 0}$, can have a logistic distribution (logit model) or a standard normal distribution (probit model), both being symmetric about zero.

In the probit model, β_i is the amount of change in the z value when there is a unit-change in x_i. In the logit model, coefficients can be interpreted as odds ratios.

In this study, we do not expect the error term to be distributed normally. In addition, logit models are more easily interpretable. For these reasons, in this study, logit models are used in the analyses.

Panel Data Methods: fixed effects or random effects

In our study, Queue Length is a between subject variable; each subject experiences either long queues or short queues. Randomness is a within subject variable; each subject experiences a deterministic and two random queues, one having a fast start and the other one having a slow start.

Having a within subject variable leads us to consider panel data methods for our statistical analyses.

In fixed effects estimation, a variable is used to capture the *unobserved heterogeneity* that does not change over time and assumed to be correlated with independent variables (Wooldridge, 2009). It is easy to get rid of this variable by differencing two different estimations. In our setting, the fixed effects could correspond to subject specific effects that do not change between the first, second and third queues like gender, major of the study or risk preferences. On the other hand, random effects models assume subjects specific effects to be uncorrelated with independent variables. Allowing for individual effects, it is possible to see the effects of time-invariant variables on the dependent variable by using random effects models. In our study, we consider using subject specific random effects since each subject experiences three queues and decide for them. We believe that there are unobserved individual differences that may affect queue joining and reneging behavior.

In these analyses, we test appropriateness of random effects and fixed effects models with statistical tests, as stated by Wooldridge (2009). We use Hausman test for this decision (Hausman, 1978). In this test, the efficiency of two estimators is compared by examining a new estimator and an estimator that is known to be efficient (stata.com).

Additionally, we benefit from the likelihood test of rho=0 to decide between panel estimator and pooled estimator (stata.com).

When all the statistical tests imply that a random effects model should be used, lastly we check the accuracy of quadrature approximation using STATA (stata.com).

A summary of all the statistical tests that take us to our final models is provided in Figure 2.

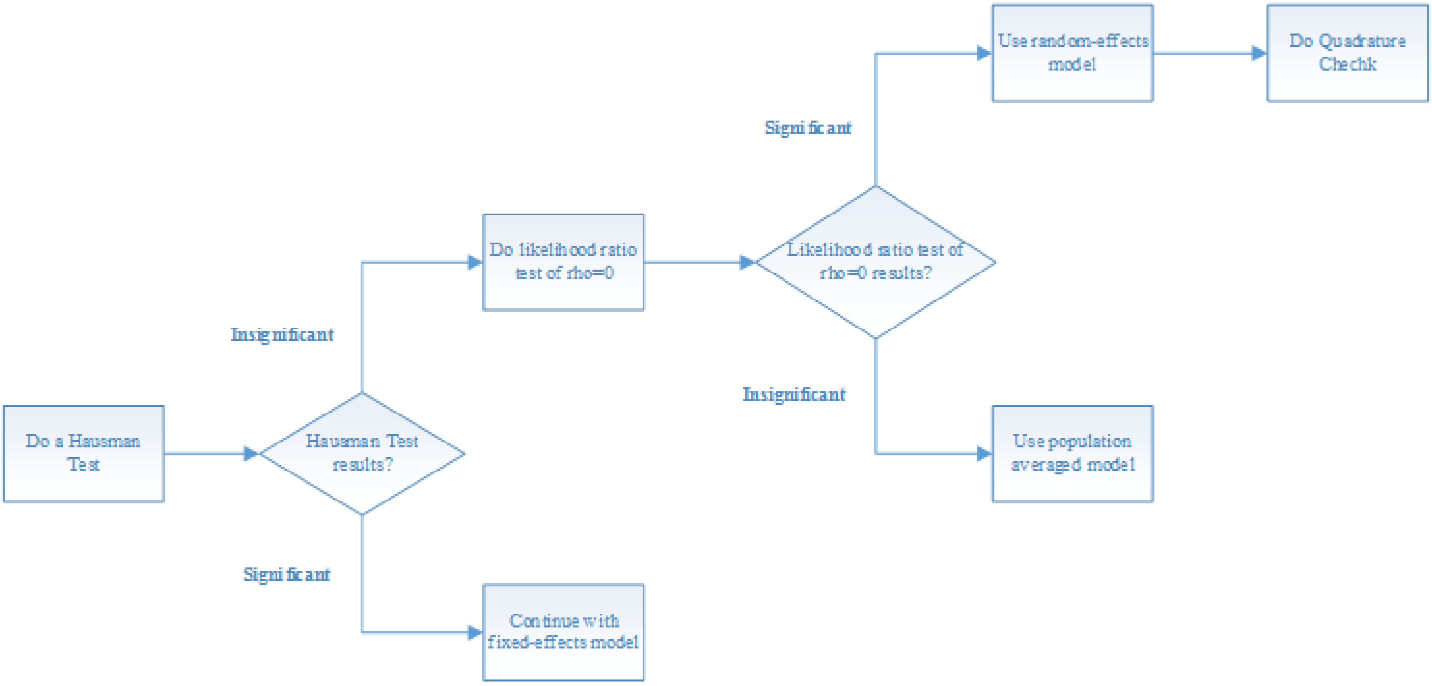

Figure 2: Steps of statistical analyses

6.1. STUDY 1

A total of 120 subjects participated in the Study 1 sessions that are conducted at the Koc University Behavioral Lab. Details and descriptive analysis of Study 1 are provided in the Chapter 4.

6.1.1. Join

Join decision related analyses are mainly investigated in Chapter 5, in the scope of subjects' bounded rationality. The β values that are estimated in Chapter 5 imply that joining is not so rational in the laboratory and converges to randomness in this experimental setting. Even so, we conduct logit analyses for the Join variable by including our independent variables Queue Length and Randomness to see their effects in the presence of our control variables.

The Hausman test and likelihood test of rho=0 imply that a population averaged model is appropriate for this analysis (Table 20).

Table 20: First model for Join decisions of Study 1

```
GEE population-averaged model                   Number of obs      =       351
Group variable:              Overallsub~o      Number of groups   =       117
Link:                               logit      Obs per group: min =         3
Family:                          binomial                     avg =       3.0
Correlation:                 exchangeable                     max =         3
                                                Wald chi2(7)       =      4.67
Scale parameter:                        1      Prob > chi2        =    0.6998
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	.0371462	.2281373	0.16	0.871	-.4099948	.4842872
RandomnessRandom1	-.0620677	.2264213	-0.27	0.784	-.5058453	.3817099
Decision2forsubject	-.2870103	.2617718	-1.10	0.273	-.8000735	.226053
Decision3forsubject	-.2545056	.2623484	-0.97	0.332	-.7686989	.2596878
EconandEng	.3040519	.2490076	1.22	0.222	-.183994	.7920978
GenderF1M0	.2850744	.2487732	1.15	0.252	-.2025122	.7726609
Wait_RiskAverse	.2107881	.2292566	0.92	0.358	-.2385466	.6601229
_cons	.1398678	.3497824	0.40	0.689	-.5456931	.8254288

This is an insignificant model with insignificant variables, so we cannot interpret it.

We run an additional model without our control variables gender and risk aversion.

Again a population averaged model is run as the statistical tests imply.

Table 21: Second model for Join decisions of Study 1

```
GEE population-averaged model                   Number of obs      =       360
Group variable:              Overallsub~o       Number of groups   =       120
Link:                               logit       Obs per group: min =         3
Family:                          binomial                      avg =       3.0
Correlation:                 exchangeable                      max =         3
                                                Wald chi2(5)       =      2.48
Scale parameter:                        1       Prob > chi2        =    0.7794
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	.1016329	.2279821	0.45	0.656	-.3452039	.5484697
RandomnessRandom1	-.0774942	.221725	-0.35	0.727	-.5120672	.3570787
Decision2forsubject	-.3141567	.2561932	-1.23	0.220	-.8162862	.1879728
Decision3forsubject	-.2492049	.2570613	-0.97	0.332	-.7530359	.254626
EconandEng	.178863	.2364301	0.76	0.449	-.2845315	.6422576
_cons	.483671	.2844044	1.70	0.089	-.0737513	1.041093

This is an insignificant model with insignificant independent variables. Therefore, we conclude that our experimental manipulations are not sufficient to explain people's queue joining behaviors in Study 1. So, our hypotheses H_1 and H_4 are not supported.

6.1.2. Quit

We analyze subjects' Quit decisions with 3 independent variables. First one is Queue Length, which is a between subject variable with two levels: long and short. The others are Fast Start and Slow Start queues that are within subject variables and constitute the two levels of Randomness in our experimental setting.

For Quit analyses, we only use the data from participants who join the queues. As each subject experiences 3 queues and we have 120 subjects, there are maximum 360 decisions to be analyzed. As we only use data from participants who join the queues, we have a total of 212 decisions for our Quit analyses.

We conduct Quit analyses with control variables that are described in the Chapter 4. In our experimental setting, we design the queues independent from each other. Subjects are explicitly told that they can consider each queue separately, and that they will have enough time to experience all queues. We do not disclose the total number of queues to the subjects to prevent strategic behavior; however cumulative time spent during the experiment and a learning effect might drive people's decisions progressively in the experiment. Consequently, we include Decision Number variables into our statistical analyses to control for these effects.

Additionally, as we recruit undergraduate students from different disciplines as subjects, the characteristics towards quantitative analyses might differ significantly among subjects. Since we know the major of study for each subject, considering that this information could be useful in determining whether a subject follows a utility function maximizing behavior or not, we introduce a major related control variable. We group Economics and Engineering students together and compare their behavior to the other group that mostly consists of Business Administration, Social Sciences and Humanities students. Lastly, we use subjects' Gender and Risk Aversion behaviors over wait as control variables too.

The Hausman test, the likelihood test of rho=0 and Quadrature Check results imply a population-averaged model for this analysis (Table 22).

Table 22: First model for Quit decisions of Study 1

```
GEE population-averaged model                   Number of obs      =       204
Group variable:              Overallsub~o       Number of groups   =       109
Link:                               logit       Obs per group: min =         1
Family:                          binomial                      avg =       1.9
Correlation:                 exchangeable                      max =         3
                                                Wald chi2(8)       =     32.33
Scale parameter:                        1       Prob > chi2        =    0.0001
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	1.248152	.4060257	3.07	0.002	.4523559	2.043948
Fast	-.7587359	.3059096	-2.48	0.013	-1.358308	-.1591641
Slow	.4469712	.3167523	1.41	0.158	-.173852	1.067794
Decision2forsubject	-.5342834	.3110401	-1.72	0.086	-1.143911	.075344
Decision3forsubject	-.945	.315021	-3.00	0.003	-1.56243	-.3275702
EconandEng	-1.073938	.4190027	-2.56	0.010	-1.895168	-.2527078
GenderF1M0	.0558108	.4284637	0.13	0.896	-.7839627	.8955843
Wait_RiskAverse	-.6038914	.3936981	-1.53	0.125	-1.375526	.1677427
_cons	1.213992	.5324169	2.28	0.023	.1704741	2.25751

Our control variables Gender (*GenderF1M0*) and Risk Aversion over wait (*Wait_RiskAverse*) are not significant, implying that these variables do not explain subjects' Quit decisions. So, we exclude these variables from further analyses in order not to have too many variables in the regression.

The Hausman test, the likelihood test of rho=0 and Quadrature Check results imply again a population-averaged model for the simplified model (Table 23).

Table 23: Second model for Quit decisions of Study 1

```
GEE population-averaged model                   Number of obs      =       212
Group variable:              Overallsub~o      Number of groups   =       112
Link:                               logit      Obs per group: min =         1
Family:                          binomial                     avg =       1.9
Correlation:                 exchangeable                     max =         3
                                               Wald chi2(6)       =     31.63
Scale parameter:                        1      Prob > chi2        =    0.0000
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	1.257258	.3991295	3.15	0.002	.474979	2.039538
Fast	-.7491396	.2992363	-2.50	0.012	-1.335632	-.1626473
Slow	.4182619	.3128379	1.34	0.181	-.1948891	1.031413
Decision2forsubject	-.5061056	.3071924	-1.65	0.099	-1.108192	.0959804
Decision3forsubject	-.8974856	.3080112	-2.91	0.004	-1.501176	-.2937948
EconandEng	-1.234338	.3909493	-3.16	0.002	-2.000584	-.4680914
_cons	1.052577	.3880008	2.71	0.007	.2921092	1.813044

We have a significant model that is interpretable confidently.

Having a significant and a positive coefficient means that an increase in that independent variable results in an increase in the dependent variable. In our case, this result suggest that Queue Length affects subjects' quitting decisions: long queues decreases subjects' patience and leads to higher quitting probabilities, supporting our hypothesis H_2.

When service times are random, experiencing several "faster than the mean" service times early on leads to higher persistence in queues, supporting our hypothesis $H_{5.2}$. On the other hand, there is no statistically significant difference between experiencing deterministic service times and "lower than the mean" service times at the beginning, on subjects' quitting decisions. Our hypothesis $H_{5.1}$ is not supported. This asymmetry should be explored further with different parameters.

The Decision number control also has a significant effect on people's quitting decisions. People become more and more patient (i.e. less likely to quit) as decision numbers increase. Decision2forsubject and Decision3forsubject are also control variables for different queue orders, since we randomize the three types of queues (Deterministic, Fast Start and Slow Start) among all participants. Having significant Queue Length and Fast variables in the presence of these control variables confirms the effects of our independent variables.

Lastly, the subjects majoring in Economics and Engineering have a lower probability of quitting compared to other students majoring in Psychology, International Relations or Humanities. This finding confirms our decision to include subjects' major into our analyses as a proxy for personal differences in terms of decision making styles.

6.1.3. Time spent in queue, t

The dependent variable t represents time spent in a queue for a subject. Differently from other dependent variables, this variable is a continuous variable that can take values between 0 and 600 (in seconds). The t variable only exists for subjects who join the queue. Subjects who do not join the queue have a t value that equals to 0 and they are not included in these analyses.

First, we analyze time spent in the queues data descriptively (Table 24). As we have 120 subjects and each subject experiences 3 different queues; we have a total of 360 join-no join and a total of 212 renege-continue to wait decisions. For the analyses of the t variable, we are only interested in subjects' decisions while waiting. So, 212 of 360 decisions which resulted in joining are analyzed in this section.

The mean time spent in the queues is approximately 273 seconds for people who join the queues. We define failure as a Quit decision and approximately 63% of the decisions are Quit decisions and remaining 37% result in waiting until the end of the queue.

Table 24: Descriptive analyses of t for Study 1

		per subject			
Category	**total**	**mean**	**min**	**median**	**max**
(first) entry time		0	0	0	0
(first) exit time		273.256	1.918	133.8805	600
failures	133	0.6273	0	1	1

Hazard Ratio

Hazard is the probability of failure in a very short time interval and can be defined as:

$$h(t) = \frac{f(t)}{1 - F(t)}$$

where $f(t)$ and $F(t)$ are probability density and cumulative distribution functions of failure respectively. In other words; hazard, defined by $h(t)$, is the probability of the event occurrence for a person who has already survived until the time t. On the other hand, hazard ratio is a ratio of failures to the surviving units and is an expression of rate at which events happen.

The following figure (Figure 3, together with Table 25) is based on a weighted kernel smoothing (Hosmer, Lemeshow, & May, 2008) of the estimated hazard contributions, $\Delta H(t_j) = H(t_j) - H(t_{j-1})$, using $h = b^{-1} \sum_{j=1}^{D} K_t \left(\frac{t-t_j}{b}\right) \Delta H(t_j)$ where K_t is Kernel function, b is bandwidth, and the summation is over the D times at which failure occurs (stata.com).

Table 25: Descriptions for Figure 3

Group No	Queue Length	Deterministic
1	0 (=short)	0 (=random)
2	0	1 (=deterministic)
3	1 (=long)	0
4	1	1

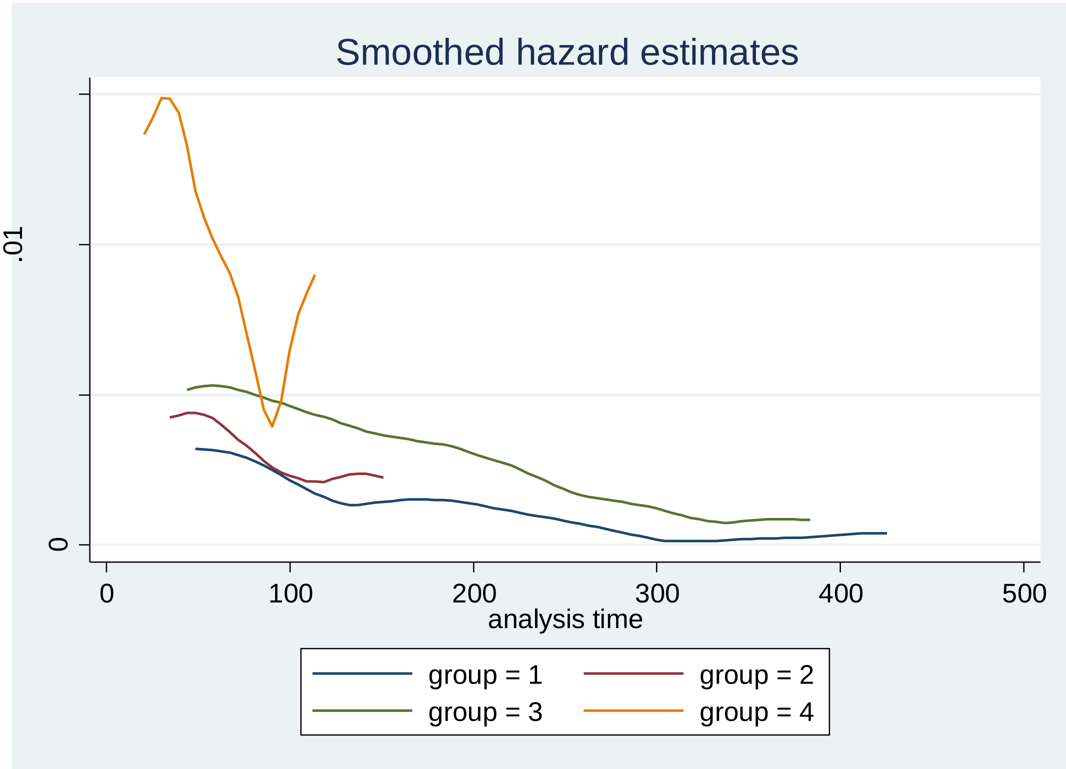

Figure 3: Hazard estimates for different treatment groups

With this figure by estimating the smoothed hazard function and not the function itself (Hosmer, Lemeshow, & May, 2008), we have a visual impression that when service times are deterministic, hazard function is smaller for short queues than long queues, meaning that subjects are less likely to quit short queues when service times are deterministic.

When service times are random, people are less likely to quit the queues as hazard rates decreases both for long and short queues overtime. Also, people are less likely to quit long queues when service times are random.

Kaplan Meier Estimator

In time to event testing, the aim is to observe subjects over time and determine when they encounter the concerned event. In our study, we observe subjects during the experimental sessions for their Quit decisions.

With the Kaplan- Meier estimator, the survival curve of a population can be estimated over time by calculating the survival probability for each time interval. The formula for calculating the survival probability at time t is given below (Kaplan & Meier, 1958):

$$S(t) = \prod_{t_i < t} (1 - \frac{d_i}{n_i})$$

where d_i is the number of deaths (Quits in our case) at t_i and n_i is the number of subjects who survive before t_i.

In our study, there is a time-defined probability which is the probability of quitting. Also, we have censored data since the maximum waiting time for a queue is censored by service at 600 seconds.

We use Kaplan-Meier curves in our analyses to compare different treatment groups visually and make the same comparison statistically with log-rank test of equality.

Log-rank test for equality is a nonparametric test that compares event rates between different groups at each distinct event time (In our case, the event is Quit decisions). The test compares observed events O with expected events E with a chi-squred test, by using the sum of $\frac{(O-E)^2}{E}$.

Comparing the test statistics of each group, we are able to say whether the difference between the groups is statistically significant or not (Bland & Altman, 2004).

For the first Kaplan-Meier survival curve (Figure 4), the model is run without including any treatment effect, using all data points. We observe that the survival curve declines until around 200 seconds, flattening out beyond this point at a value between 0.25 and 0.5.

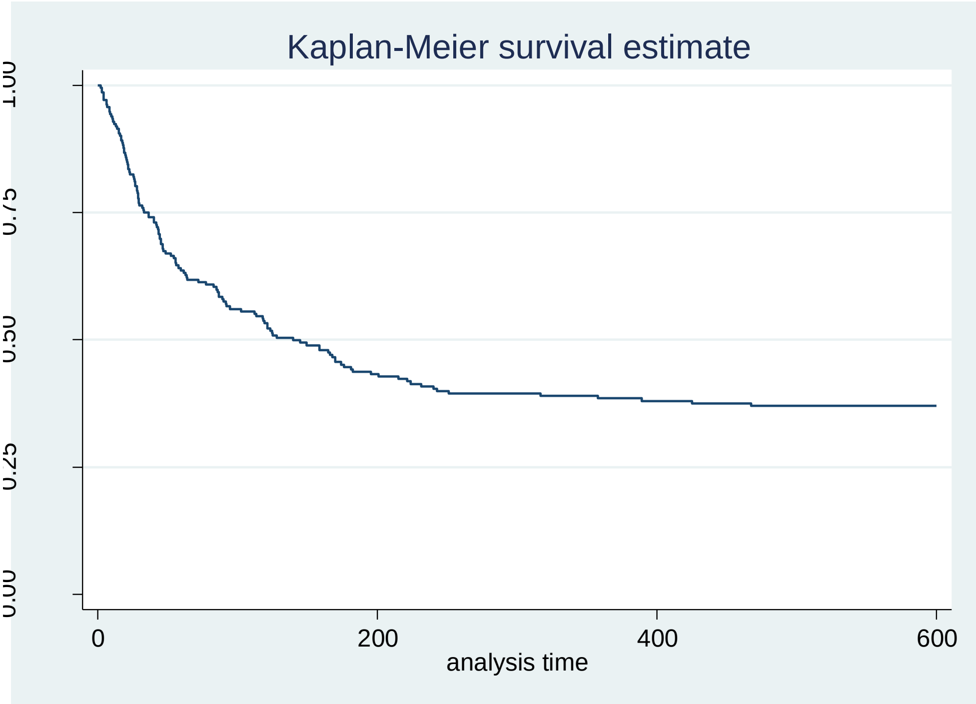

Figure 4: Kaplan-Meier curve for Study 1

Then, Kaplan-Meier survival curves for different treatment groups are included (Figure 5). We have Queue Length and Service Time treatment and accordingly, a total of 6 different treatment groups.

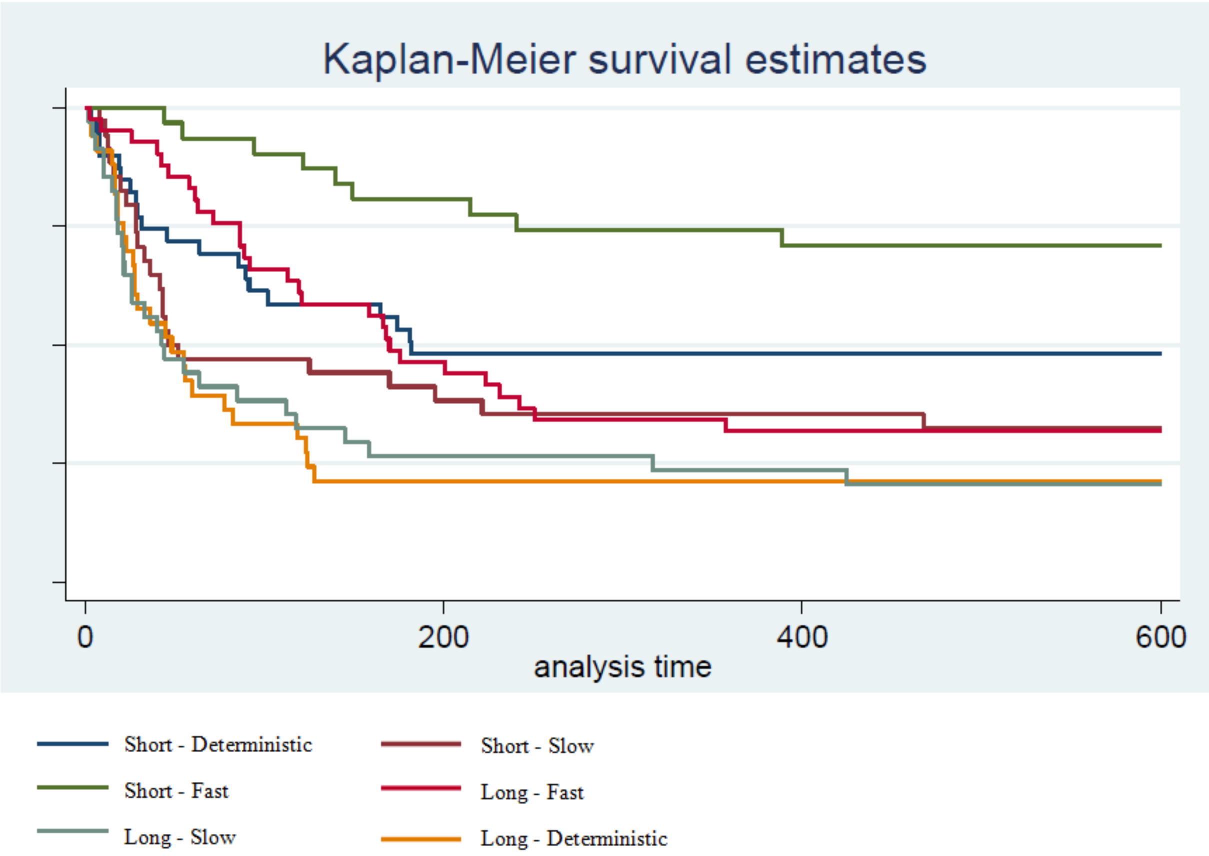

Figure 5: Kaplan-Meier curves for different treatment groups of Study 1

Table 26: Log-rank test for equality of survivor functions

	Events observed	Events expected
Short-Deterministic	20	25.96
Short-Slow Start	23	19.27
Short-Fast Start	9	27.85
Long-Deterministic	26	14.87
Long-Slow Start	27	15.79
Long-Fast Start	28	29.25
Total	**133**	**133.00**

chi2(5)=	31.76
Pr>chi2=	0.0000

It is observable visually that the curves differ from each other, but to be able to interpret it confidently, a log-rank test for equality is conducted (Table 26). This test signifies that all treatment groups are different from each other. However, this is a cumulative test conducted for all groups. For more robust interpretations, pairwise tests are conducted and results are provided in Table 27.

Table 27: Pairwise comparisons of log-rank test for equality

Queue Length	***Comparison***	***Pr>chi2***
Long	Fast Start-Slow Start	0.0266
	Slow Start-Deterministic	0.9961
	Fast Start-Deterministic	0.0127
Short	Fast Start-Slow Start	0.0003
	Slow Start-Deterministic	0.1800
	Fast Start-Deterministic	0.0235

Table 27 shows statistically that subject behavior in queues that have Slow Start and Deterministic service times do not differ from each other both in the long and short queues. On the other hand, subjects' survival times differ significantly in Fast Start queues compared to Slow Start and Deterministic queues, both in long and short queues.

Kaplan-Meier survival estimates allow us to compare the different treatment groups and to see whether their estimates are significantly different from each other. However we cannot see the effect of different variables in combination with this type of an analysis. For such an analysis, we use Cox Proportional Hazards Model which provides estimates for β values for the coefficients of our independent variables which indicating their relationships to the time spent in queues variable in our case (Therneau & Grambsch, 2000) .

Cox Proportional Hazard Model

Cox proportional hazard model is a survival model. In this model, the hazard is modeled as (Cox, 1972):

$$h(t) = h_0(t) exp\ (\beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)$$

The model estimates β values together with their variance and covariance values, as an addition to their baseline hazard $h_0(t)$ without estimating it directly. As stated by Hosmer et al. (2008), when comparing the effect of two different treatments, the ratio of hazard functions eliminate baseline hazard function. Therefore, in this semiparametric model, the baseline hazard function is not important to estimate (Hosmer, Lemeshow, & May, 2008).

Our Cox proportional hazards model is:

$$\begin{aligned} h(t) = h_0(t)\mathrm{exp}\ (&\beta_1 QueueLength + \beta_2 FastStart + \beta_3 SlowStart \\ &+ \beta_4 Decision2forsubject + \beta_5 Decision3forsubject \\ &+ \beta_6 EconandEng) \end{aligned}$$

We do not include Gender and Risk Aversion controls into this analysis because we observe no effect of these variables on people’s Join and Quit decisions. The analysis can be found in Table 28.

Table 28: First Cox model for Study 1

```
Cox regression -- no ties

No. of subjects =          212                    Number of obs   =       212
No. of failures =          133
Time at risk    =    57930.276
                                                  LR chi2(6)      =     63.19
Log likelihood  =   -625.80965                    Prob > chi2     =    0.0000
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	2.09692	.3772408	4.12	0.000	1.473835	2.983424
Fast	.4639308	.103906	-3.43	0.001	.2990961	.7196075
Slow	1.193827	.2464826	0.86	0.391	.796524	1.789304
Decision2forsubject	.7515967	.1577212	-1.36	0.174	.4981519	1.133987
Decision3forsubject	.6145577	.1310134	-2.28	0.022	.4046698	.933307
EconandEng	.3767638	.0742881	-4.95	0.000	.2559966	.5545033

Cox regression model assumes that hazard ratio is constant over time. Thus, to validate this assumption and to interpret the results confidently, the null hypothesis of zero slope is tested; that is to test whether log hazard-ratio function is constant over time or not (Table 29).

Table 29: Test for proportional hazards assumption

```
. estat phtest, detail

      Test of proportional-hazards assumption

      Time:  Time
```

	rho	chi2	df	Prob>chi2
QueueLengt~e	0.02047	0.06	1	0.8130
Fast	0.29572	10.89	1	0.0010
Slow	0.05439	0.41	1	0.5229
Decision2f~t	-0.07219	0.70	1	0.4032
Decision3f~t	0.00292	0.00	1	0.9733
EconandEng	0.06126	0.49	1	0.4825
global test		13.72	6	0.0330

A significant result of global test (Prob>chi2=0.0330) suggest that the constant hazard-ratio assumption is violated and that is because of the Fast start variable (Prob>chi2=0.0010). A single hazard ratio for this variable is not appropriate to explain its effects since it appears to be time-dependent. So, we include an interaction variable in the model to account for the time dependency. Our Cox proportional hazards model becomes as follows:

$$h(t) = h_0(t)\exp\{(\beta_1 QueueLength + \beta_2 FastStart + \beta_3 SlowStart$$
$$+ \beta_4 Decision2forsubject + \beta_5 Decision3forsubject$$
$$+ \beta_6 EconandEng + g(t)(\gamma_1 FastStart)\}$$

where t is analysis time and we define $g(t) = t$.

When we rerun the model with this interaction term as a time varying covariate, we obtain (Table 30):

Table 30: Second Cox model for Study 1

```
Cox regression -- no ties

No. of subjects =          212                 Number of obs   =        212
No. of failures =          133
Time at risk    =    57930.276
                                               LR chi2(7)      =      74.48
Log likelihood  =   -620.16568                 Prob > chi2     =     0.0000
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
main						
QueueLength_Code	2.124193	.3813802	4.20	0.000	1.494061	3.020089
Fast	.2295612	.0759571	-4.45	0.000	.1200199	.4390801
Slow	1.205306	.2485981	0.91	0.365	.8045156	1.805761
Decision2forsubject	.7521888	.1576498	-1.36	0.174	.4987986	1.134301
Decision3forsubject	.6146979	.1310536	-2.28	0.022	.4047488	.9335505
EconandEng	.3797243	.0747856	-4.92	0.000	.2581229	.5586118
tvc						
Fast	1.007387	.0023768	3.12	0.002	1.002739	1.012056

Note: variables in tvc equation interacted with _t

In this analysis, hazard ratio implies one unit change in the corresponding variable which is time spent in the queue, t. Hazard ratios which are greater than or equal to 1 are associated with shorter survival times. Hazard ratios which are smaller than 1 are associated with longer survival times. With this significant model, after controlling for subjects' decision numbers and Economics and Engineering students, Queue Length is related with shorter survival times; meaning that subjects survive shorter in long queues, supporting our hypothesis H_3.

On the other hand, queues with a Fast start, having a lower hazard, are related with longer survival times. Subjects' survive longer when the queue starts faster than the mean service times. Hypothesis $H_{6.2}$ is supported. There is no significant effect of Slow start on people's time spent in queues, so hypothesis $H_{6.1}$ is not supported.

Decision2forsubject has not a significant effect on subjects' survival time; however, Decision3forsubject has a significant effect resulting in a lower hazard and longer survival times. This result suggests that subjects become more patient in the 3rd queue.

Controlling for constant hazard ratio assumption and relaxing this for Fast start treatment, a 67% reduction in risk for Fast start queues is found with the analysis (Hazard ratio for Fast start variable is approximately 0.23). This risk increases linearly with t, meaning that subjects are more patient in Fast start queues but their patience decreases with time.

6.2. STUDY 2

In Study 2, our aim is to test whether it is the extremely fast service times that drive the results of Study 1; or more generally faster than the mean service times give a similar effect. To this end, we use different service time values but keep the design of Study 1 the same. We still keep the sequence: first five service times are faster than the mean by more than 50%. However, we avoid extremely short service times like 2, 3 or 5 seconds which were part of the sequence in Study 1. Also, to keep the total waiting time the same, we make our long service times shorter as our short service times become shorter. The Slow Start queue has the same service times as a Fast Start queue but in a reverse order. The service times that are used in Study 2 are presented in Table 31.

Table 31: Service times of Study 2

Fast Start	15, 10, 25, 15, 25, 65, 144, 121, 98, 82
Slow Start	82, 98, 121, 144, 65, 25, 15, 25, 10, 15

As it is like a smoothened version of the service times of Study 1, we call this study as "Not-so-extreme" service times.

This study is conducted only with long queues to reduce the number of groups, so our hypotheses H_1, H_2 and H_3 are not testable in the scope of this study. Long queues are chosen over short queues since it is easier to obtain a variety of service time orderings with long queues. We randomize the order in which subjects experience Deterministic, Fast Start and Slow Start queues and summarize the number of people in these different groups in Table 32.

Table 32: The number of people in different order groups in Study 2

Group No	Queue Order	Number of People
1	Det-Fast-Slow	30
2	Det-Slow-Fast	15
3	Fast-Det-Slow	9
4	Fast-Slow-Det	4
5	Slow-Det-Fast	11
6	Slow-Fast-Det	5

Study 2 is conducted with the participation of 74 subjects, 65% of the subjects being females, 46% of the subjects being risk averse over wait and 36% of the subjects being Economics and Engineering students. The average payment was 12 TRY.

The descriptive statistics for subjects' joining and quitting decisions are provided in Table 33. The significance of these differences are investigated in the following sections.

Table 33: Descriptive statistics of Study 2

JOIN?	Det	FastStart	SlowStart
No	22	34	38
Yes	52	40	36
Joining Rate	0.70	0.54	0.51
QUIT?	**Det**	**FastStart**	**SlowStart**
No	21	23	10
Yes	31	17	26
Quitting Rate	0.60	0.43	0.72

6.2.1. Join

Although in Chapter 5 we conduct analyses of β values for subjects' joining decisions, we conduct logit analyses too for Study 2 to be able to see effects of Randomness on people's joining decisions with the presence of our control variables.

We run a population averaged model with our control variables as the Hausman test and a likelihood test of rho=0 imply (Table 34).

Table 34: First model for Join decision of Study 2

```
GEE population-averaged model                   Number of obs      =       162
Group variable:               OverallSub~o      Number of groups   =        54
Link:                                logit      Obs per group: min =         3
Family:                           binomial                     avg =       3.0
Correlation:                  exchangeable                     max =         3
                                                Wald chi2(6)       =      6.86
Scale parameter:                         1      Prob > chi2        =    0.3344
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-.4828956	.5327351	-0.91	0.365	-1.527037	.5612461
Decision2forsubject	-.4828956	.5327351	-0.91	0.365	-1.527037	.5612461
Decision3forsubject	-.4030926	.5914591	-0.68	0.496	-1.562331	.7561459
EconandEng	-.1917596	.3473497	-0.55	0.581	-.8725525	.4890334
GenderF1M0	.2128944	.3546868	0.60	0.548	-.4822789	.9080677
Wait_RiskAversionAverse1	.2818191	.3302322	0.85	0.393	-.3654241	.9290624
_cons	.7444189	.4384165	1.70	0.090	-.1148616	1.603699

There is no significance in this model; therefore, we cannot interpret it.

As the next step, we rerun a population averaged model as statistical tests imply, by excluding our Gender (*GenderF1M0*) and Wait_RiskAversion (*Wait_RiskAversionAverse1*) controls, since they were not significant either in the previous models (Table 35).

Table 35: Second model for Join decisions of Study 2

```
GEE population-averaged model                   Number of obs      =       222
Group variable:              OverallSub~o       Number of groups   =        74
Link:                               logit       Obs per group: min =         3
Family:                          binomial                      avg =       3.0
Correlation:                 exchangeable                      max =         3
                                                Wald chi2(4)       =      8.83
Scale parameter:                        1       Prob > chi2        =    0.0655
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-.740572	.3246044	-2.28	0.023	-1.376785	-.1043589
Decision2forsubject	-.3881018	.3495116	-1.11	0.267	-1.073132	.2969283
Decision3forsubject	-.114194	.3659606	-0.31	0.755	-.8314636	.6030756
EconandEng	-.144321	.2992617	-0.48	0.630	-.7308632	.4422213
_cons	1.03919	.3127881	3.32	0.001	.426137	1.652244

With this almost significant model, we are able to say that Randomness induces lower joining probabilities. This finding supports our hypothesis H_4. There is no effect of decision number and major of the study on people's joining decisions.

6.2.2. Quit

In Study 2, there are again two levels of Randomness; Fast Start and Slow Start which are only observable if a subject joins the queue. Therefore, for Quit analyses, we have a total of 128 decisions from 66 subjects who join the queues.

First, we run the logit analysis with our control variables as a random effects model since this is what the statistical tests suggest (Table 36).

Table 36: First model for Quit decisions of Study 2

```
Random-effects logistic regression              Number of obs      =        94
Group variable: OverallSubje~o                  Number of groups   =        49

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.9
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(7)       =      8.38
Log likelihood  = -46.201253                    Prob > chi2        =    0.2999
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-2.698906	1.340416	-2.01	0.044	-5.326072	-.0717393
SlowStart	-1.460514	1.451003	-1.01	0.314	-4.304428	1.383399
Decision2forsubject	1.530868	1.197343	1.28	0.201	-.8158816	3.877617
Decision3forsubject	1.279494	1.44527	0.89	0.376	-1.553183	4.112172
EconandEng	-.6511528	1.027602	-0.63	0.526	-2.665216	1.36291
GenderF1M0	.9394643	1.048916	0.90	0.370	-1.116374	2.995303
Wait_RiskAversionAverse1	-2.780423	1.157314	-2.40	0.016	-5.048717	-.5121289
_cons	2.83208	1.40328	2.02	0.044	.0817026	5.582457
/lnsig2u	1.592675	.8971524			-.1657114	3.351061
sigma_u	2.217405	.994675			.920484	5.341629
rho	.5991267	.2154726			.2048001	.8966194

```
Likelihood-ratio test of rho=0: chibar2(01) =     5.88 Prob >= chibar2 = 0.008
```

This model is not significant so we cannot interpret it.

We rerun the model by excluding our control variable for gender that is not significant (Table 37).

Table 37: Second model for Quit decisions of Study 2

```
Random-effects logistic regression              Number of obs      =        94
Group variable: OverallSubje~o                  Number of groups   =        49

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.9
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(6)       =      8.19
Log likelihood  = -46.612027                    Prob > chi2        =    0.2245
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-2.77874	1.366278	-2.03	0.042	-5.456596	-.1008835
SlowStart	-1.520945	1.474329	-1.03	0.302	-4.410578	1.368687
Decision2forsubject	1.599258	1.220079	1.31	0.190	-.7920535	3.99057
Decision3forsubject	1.325132	1.474142	0.90	0.369	-1.564133	4.214398
EconandEng	-.7201015	1.048282	-0.69	0.492	-2.774696	1.334493
Wait_RiskAversionAverse1	-2.828734	1.177516	-2.40	0.016	-5.136622	-.520846
_cons	3.565847	1.314662	2.71	0.007	.9891559	6.142537
/lnsig2u	1.661525	.8752103			-.053856	3.376905
sigma_u	2.295068	1.004333			.9734313	5.411102
rho	.615544	.2071182			.2236183	.8989905

```
Likelihood-ratio test of rho=0: chibar2(01) =     6.54 Prob >= chibar2 = 0.005
```

This is again an insignificant model, with some significant variables. We cannot interpret this model confidently.

To ensure the integrity among the analyses of different studies, the model is run without risk aversion control variable (Table 38).

Table 38: Third model for Quit decisions of Study 2

```
Random-effects logistic regression               Number of obs      =       128
Group variable: OverallSubje~o                   Number of groups   =        66

Random effects u_i ~ Gaussian                    Obs per group: min =         1
                                                                avg =       1.9
                                                                max =         3

Integration method: mvaghermite                  Integration points =        12

                                                 Wald chi2(5)       =     10.83
Log likelihood  = -74.005504                     Prob > chi2        =    0.0550
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-.5427331	.6881652	-0.79	0.430	-1.891512	.8060459
SlowStart	1.398652	.730156	1.92	0.055	-.0324272	2.829732
Decision2forsubject	-.3582778	.6802577	-0.53	0.598	-1.691559	.9750029
Decision3forsubject	-1.649422	.7906006	-2.09	0.037	-3.198971	-.0998733
EconandEng	-1.40988	.8094205	-1.74	0.082	-2.996315	.1765553
_cons	1.569646	.7014481	2.24	0.025	.1948332	2.944459
/lnsig2u	1.44214	.676078			.1170519	2.767229
sigma_u	2.056633	.6952222			1.060272	3.989295
rho	.5624947	.166379			.2546819	.8286914

```
Likelihood-ratio test of rho=0: chibar2(01) =    10.22 Prob >= chibar2 = 0.001
```

This model is almost significant with significant variables. Slow start queues induce high quitting rates compared to deterministic queues. Also, subjects tend to show higher patience in their last queue during the experiment. Subjects who are majoring in Economics or Engineering tend to quit less compared to other students.

Despite the monotonic fast/slow first sequence, we do not find the same effects in Study 2 as we find in Study 1 with more extreme service times. In this study, not having a significant effect of fast start might be because of the reduced feeling of progress with not so extreme service times. On the other hand, we find an effect of slow start on probability to quit, which is the reverse of the effect of fast start in Study 1. Thus, even though they are different, the results seem to be consistent.

6.2.3. Time spent in queue, t

In this section, the variable t, time spent in queues is analyzed for Study 2. It is a continuous variable since it can take the values between 0 and 600 (in seconds), as each queue lasts 10 minutes.

The mean time spent in the queues in Study 2 is approximately 294 seconds and 58% of subjects who join the queue quit. The descriptive analysis for t is provided in Table 39.

Table 39: Descriptive analyses of t for Study 2

		per subject			
Category	**total**	**mean**	**min**	**median**	**max**
(first) entry time		0	0	0	0
(first) exit time		294.5856	1.778	151.51	600
failures	74	0.5781	0	1	1

Next, survival time estimate of all subjects is provided in Figure 6 (i.e. for all treatment groups). In Study 2, we observe slightly higher survival rates and longer survival times over all.

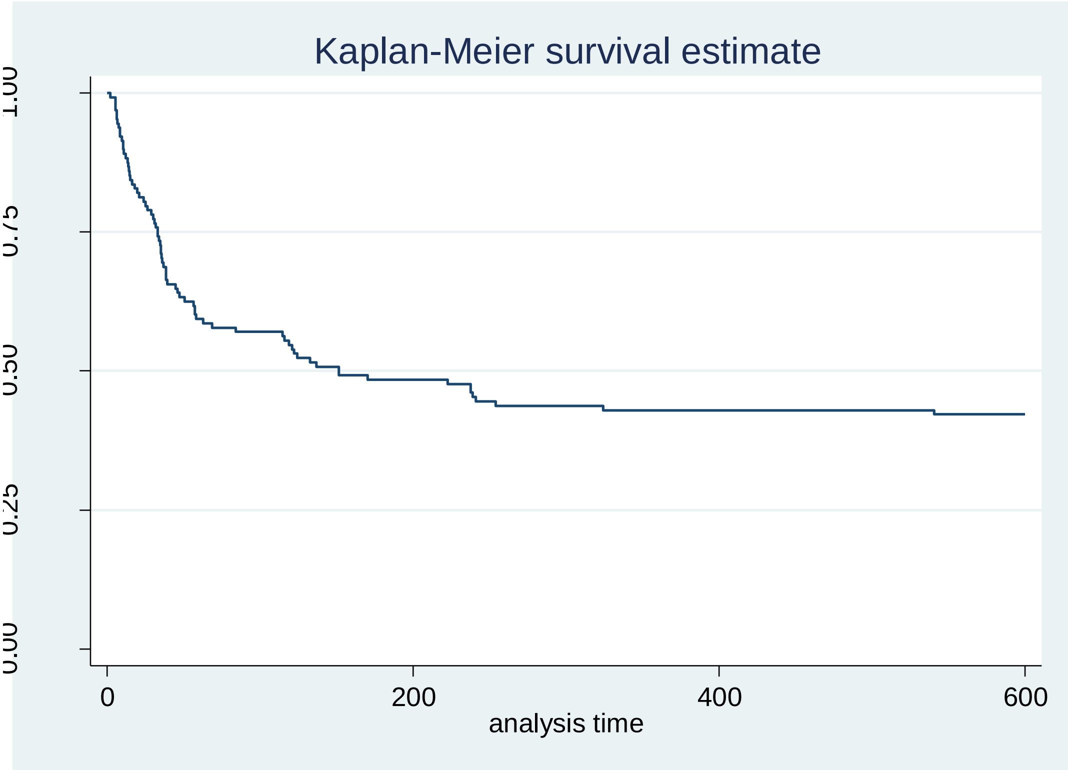

Figure 6: Kaplan-Meier curve for Study 2

Then, the survival estimates are decomposed for different treatment groups, which are provided in Figure 7.

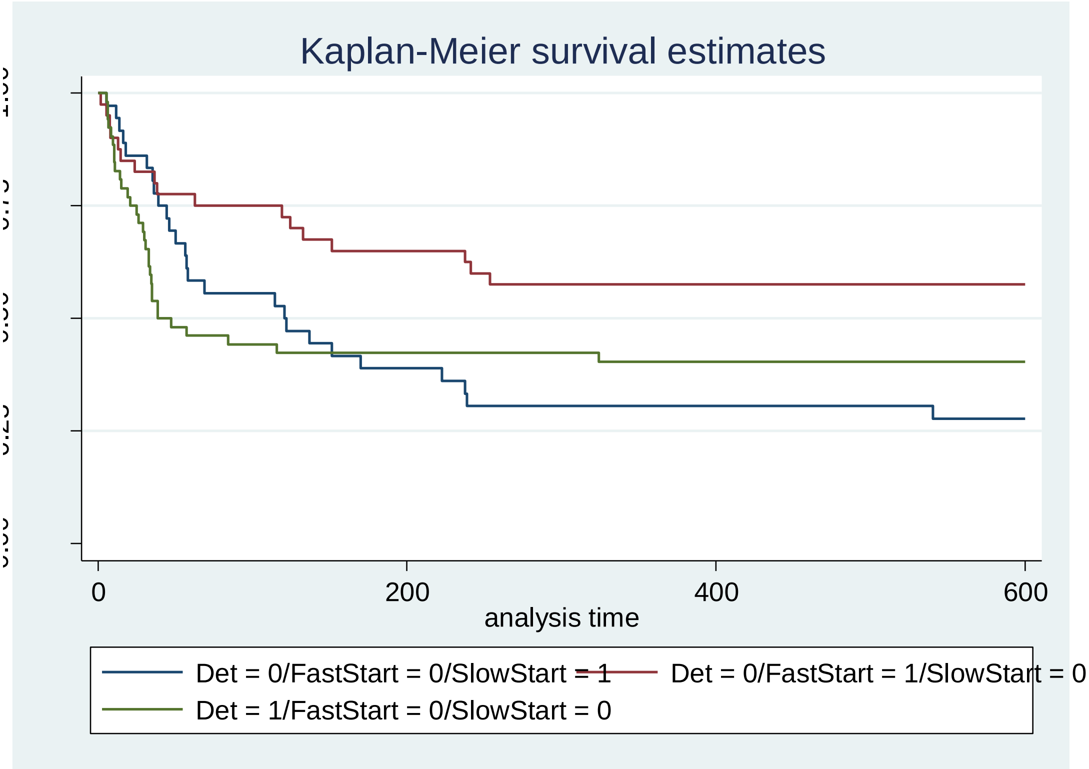

Figure 7: Kaplan-Meier curves for different treatment groups of Study 2

The three lines for Deterministic, Fast Start and Slow Start conditions appear to be different visually; however, to be able to interpret it confidently, we conduct a log-rank test of equality and get a Pr>chi2 result which is equal to 0.0620. This almost significant value implies that they are statistically different from each other when we compare them cumulatively. Yet, we make the pairwise comparisons to have a more robust comparison (Table 40).

Table 40: Pairwise comparisons of log-rank test for equality for Study 2

Comparison	***Pr>chi2***
Fast Start-Slow Start	0.0154
Slow Start-Deterministic	0.9378
Fast Start-Deterministic	0.0573

These results suggest that survival estimates for Fast Start queues are significantly different from Slow Start and Deterministic queues; however, they are not different between Slow Start and Deterministic queues.

Next, we conduct a Cox Proportional hazards analysis to be able to see coefficients of variables in detail. For this analysis, we consider the same model as in Study 1, but we exclude Queue Length variable from the analysis as it is not relevant for Study 2.

$$h(t) = h_0(t)\exp\left(\beta_1 FastStart + \beta_2 SlowStart + \beta_3 Decision2forsubject \right.$$
$$\left. + \beta_4 Decision3forsubject + \beta_5 EconandEng\right)$$

Table 41: First Cox model for Study 2

```
Cox regression -- Breslow method for ties

No. of subjects =          128                   Number of obs   =        128
No. of failures =           74
Time at risk    =    37706.955
                                                 LR chi2(5)      =      15.52
Log likelihood  =   -324.35235                   Prob > chi2     =     0.0084
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	.6727039	.2157782	-1.24	0.216	.3587488	1.261414
SlowStart	1.319815	.3765972	0.97	0.331	.7544495	2.30885
Decision2forsubject	.7887103	.2259451	-0.83	0.407	.4498526	1.382817
Decision3forsubject	.5153329	.1609971	-2.12	0.034	.2793578	.9506375
EconandEng	.5642894	.1495596	-2.16	0.031	.3356594	.9486476

Table 42: Test for proportional hazards assumption

```
. estat phtest, detail

      Test of proportional-hazards assumption

      Time:  Time
```

	rho	chi2	df	Prob>chi2
FastStart	0.15438	1.57	1	0.2106
SlowStart	0.34446	8.00	1	0.0047
Decision2f~t	0.03211	0.07	1	0.7870
Decision3f~t	-0.00388	0.00	1	0.9761
EconandEng	0.01203	0.01	1	0.9152
global test		9.39	5	0.0945

This model does not ensure proportional hazard ratio assumption (Table 42) because of Slow Start variable. Therefore, we interact Slow Start variable with t to be able to capture its variance over time.

This significant model (Table 43) implies that last decisions of subjects (*Decision3forsubject*) and subjects' major (*EconandEng*) have a significant effect on subjects' time spent in queues. They survive longer in their last queues and also, subject majoring Economics or Engineering survive longer compared to other subjects. In this analysis, main independent variables are not significant, meaning that they are not sufficient to explain subjects' time spent in queues.

Table 43: Second Cox model for Study 2

```
Cox regression -- Breslow method for ties

No. of subjects =          128                    Number of obs   =       128
No. of failures =           74
Time at risk    =    37706.955
                                                  LR chi2(6)      =     23.20
Log likelihood  =    -320.5099                    Prob > chi2     =    0.0007
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
main						
FastStart	.6925235	.2235898	-1.14	0.255	.3678015	1.303934
SlowStart	.753724	.2778049	-0.77	0.443	.3659987	1.552191
Decision2forsubject	.7811788	.2254135	-0.86	0.392	.443743	1.375211
Decision3forsubject	.5276736	.1661764	-2.03	0.042	.2846444	.978201
EconandEng	.5300681	.1419791	-2.37	0.018	.3135716	.8960382
tvc						
SlowStart	1.007857	.0031195	2.53	0.011	1.001761	1.013989

Note: variables in tvc equation interacted with _t

Additionally, a significant interaction of Slow Start variables with time means that subjects' quitting risk increases linearly with time in a Slow Start queue.

6.3. STUDY 3

In this study, we keep the design of the Study 1 the same together with the service times but service time ordering is changed. In the Study 1, service times were monotonically ordered, meaning that a long Fast (Slow) start queue has first 5 service times which are shorter (longer) than the announced mean. In Study 3, we change the order of the service times to remove this monotonicity and we reorder them in a way that alternates fast and slow service times (Table 44). We label this treatment as "On-Off" service times, since in the Fast Start condition, we see 2 fast, 2 slow, 2 fast, 2 slow and finally 1 fast and 1 slow service time. In the Slow Start condition, only the order of first 3 service times is reversed and all other service times are the same.

Table 44: Service times of Study 3

Fast Start	5, 15, 90, 65, 3, 5, 110, 164, 2, 141
Slow Start	90, 5, 15, 65, 3, 5, 110, 164, 2, 141

The purpose of this study is to see whether the late switch from fast to slow service times (after 5 customers in Study 1) drove the results or the first couple of fast service times have the same effect on people's decisions. Moreover after the 3rd service, progress effect is the same in the two queues, but bother faster than deterministic.

In this study, we only use long queues to economize the required number of subjects and we chose long queues over short queues as increased number of people in the queue and average service time per person that is equal to 1 minute allows easier manipulations. So in this study, we are not able to test hypotheses H_1, H_2 and H_3. Also, to decrease different order groups, we ordered the three queues as always starting with the deterministic one, and we randomize the order of Slow Start-Fast Start later on, constituting a total of 2 different order groups. The number of people in these different groups is summarized in Table 45.

Table 45: The number of people in different order groups in Study 3

Group No	Queue Order	Number of People
1	Det-Fast-Slow	26
2	Det-Slow-Fast	23

Study 3 is conducted with the participation of 49 subjects, 55% of the subjects being females, 53% of the subjects being risk averse over wait and 27% of the subjects being Economics and Engineering students. The average payment was 12 TRY.

The descriptive analyses for subjects joining and quitting behaviors are provided in Table 46.

Table 46: Descriptive statistics of Study 3

JOIN?	Det	FastStart	SlowStart
No	10	27	28
Yes	39	22	21
Joining Rate	0.80	0.45	0.43
QUIT?	**Det**	**FastStart**	**SlowStart**
No	10	13	13
Yes	29	9	8
Quitting Rate	0.74	0.41	0.38

6.3.1. Join

The β values that are investigated in Chapter 5 imply the bounded rationality of subjects and domination of randomness in people's joining decisions. However, we conduct logit analyses separately for Study 3 to see the effects of Randomness on people's joining decisions with the presence of our control variables.

The Hausman test and likelihood test of rho=0 imply a population averaged model for this analysis (Table 47).

Table 47: First model for Join decisions of Study 3

GEE population-averaged model		Number of obs	=	147
Group variable:	OverallSub~o	Number of groups	=	49
Link:	logit	Obs per group: min	=	3
Family:	binomial	avg	=	3.0
Correlation:	exchangeable	max	=	3
		Wald chi2(5)	=	16.59
Scale parameter:	1	Prob > chi2	=	0.0054

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-1.495308	.4580475	-3.26	0.001	-2.393065	-.5975512
Decision3forsubject	-.2512434	.4101285	-0.61	0.540	-1.05508	.5525937
EconandEng	.4349343	.4244948	1.02	0.306	-.3970602	1.266929
Gender	.2145405	.3741818	0.57	0.566	-.5188423	.9479232
Wait_RiskAverse	.0464606	.3558378	0.13	0.896	-.6509687	.7438899
_cons	1.113674	.4647662	2.40	0.017	.2027487	2.024599

In this significant model, we do not see the effects of gender and people’s risk preferences on their joining behavior. So, we exclude them from our analysis since they are control variables.

We rerun the model as a population averaged model, as implied by the statistical tests (Table 48).

Table 48: Second model for Join decicions of Study 3

```
GEE population-averaged model                   Number of obs      =       147
Group variable:              OverallSub~o       Number of groups   =        49
Link:                               logit       Obs per group: min =         3
Family:                          binomial                      avg =       3.0
Correlation:                 exchangeable                      max =         3
                                                Wald chi2(3)       =     16.41
Scale parameter:                        1       Prob > chi2        =    0.0009
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-1.491555	.4563093	-3.27	0.001	-2.385905	-.5972053
Decision3forsubject	-.250563	.4086115	-0.61	0.540	-1.051427	.5503007
EconandEng	.3627377	.4062734	0.89	0.372	-.4335435	1.159019
_cons	1.272241	.3665933	3.47	0.001	.5537317	1.990751

In this model, Randomness variable is significant with the negative coefficient indicating that subjects' joining probability is lower for the queues that have random service times, supporting the hypothesis H_4. In this analysis, we only include Decision3forsubject variable because all subjects first experience a deterministic queue and therefore, Randomness variable partially captures the order effect too. Economics and Engineering students' joining decisions do not differ significantly from other students.

6.3.2. Quit

Subjects' Quit decisions are manipulated with 2 independent variables in Study 3, as the different levels of randomness. In case of random service times, the queues might have a fast start or slow start condition with the service times that are presented in Table 44.

For Quit analyses, as we only use data from participants who join the queues, we have a total of 82 decisions from 46 subjects to be analyzed.

We run the logit analysis with our control variables as a random effects model since statistical tests imply so (Table 49).

Table 49: First model for Quit decisions of Study 3

```
Random-effects logistic regression              Number of obs      =        82
Group variable: OverallSubje~o                  Number of groups   =        46

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.8
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(6)       =      7.69
Log likelihood  = -44.955564                    Prob > chi2        =    0.2617
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-3.440758	1.391633	-2.47	0.013	-6.16831	-.7132069
SlowStart	-3.201047	1.344799	-2.38	0.017	-5.836805	-.5652887
Decision3forsubject	.7628334	1.078481	0.71	0.479	-1.35095	2.876617
EconandEng	.6734063	1.295462	0.52	0.603	-1.865653	3.212466
Gender	1.315083	1.252936	1.05	0.294	-1.140628	3.770793
Wait_RiskAverse	-1.294711	1.179553	-1.10	0.272	-3.606592	1.01717
_cons	1.978396	1.351898	1.46	0.143	-.6712756	4.628068
/lnsig2u	1.957474	.8689196			.2544229	3.660525
sigma_u	2.661093	1.156138			1.135657	6.235524
rho	.6827907	.1881972			.2816231	.9219886

```
Likelihood-ratio test of rho=0: chibar2(01) =     8.86 Prob >= chibar2 = 0.001
```

Since it is an insignificant model with our insignificant control variables gender and risk aversion over wait, we exclude them from this model and rerun it as a random effects model with 22 integration points as Quadrature Check results suggest (Table 50).

Table 50: Second model for Quit decisions of Study 3

```
Random-effects logistic regression              Number of obs      =        82
Group variable: OverallSubje~o                  Number of groups   =        46

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.8
                                                               max =         3

Integration method: mvaghermite                 Integration points =        22

                                                Wald chi2(4)       =      7.11
Log likelihood  = -46.180236                    Prob > chi2        =    0.1304
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-3.309208	1.391553	-2.38	0.017	-6.036603	-.581814
SlowStart	-3.143947	1.341907	-2.34	0.019	-5.774037	-.5138569
Decision3forsubject	.7215327	1.077185	0.67	0.503	-1.38971	2.832776
EconandEng	.1225644	1.220171	0.10	0.920	-2.268927	2.514055
_cons	2.136777	.9891969	2.16	0.031	.1979865	4.075567
/lnsig2u	2.034118	.8774257			.3143953	3.753841
sigma_u	2.765051	1.213063			1.170227	6.533354
rho	.6991536	.1845558			.2939135	.9284416

```
Likelihood-ratio test of rho=0: chibar2(01) =     9.17 Prob >= chibar2 = 0.001
```

In this model, our independent variables are highly significant; however, our model is not so significant.

Having significant variables but not having a significant model makes us think of the possibility of a masking effect and/or having too many variables to test. Therefore, we exclude all control variables from the analysis to be able to see the effects of our independent variables (Table 51).

Table 51: Third model for Quit decisions of Study 3

```
Random-effects logistic regression              Number of obs      =        82
Group variable: OverallSubje~o                  Number of groups   =        46

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.8
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(2)       =      6.99
Log likelihood  = -46.413332                    Prob > chi2        =    0.0303
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-3.009548	1.253209	-2.40	0.016	-5.465792	-.5533044
SlowStart	-2.790741	1.191737	-2.34	0.019	-5.126503	-.4549791
_cons	2.18292	.9290058	2.35	0.019	.3621025	4.003738
/lnsig2u	2.052491	.8720176			.3433681	3.761614
sigma_u	2.790569	1.216713			1.187303	6.558797
rho	.703004	.182068			.2999619	.9289563

```
Likelihood-ratio test of rho=0: chibar2(01) =     9.25 Prob >= chibar2 = 0.001
```

This finding suggests that in this study, people are less likely to quit random queues compared to deterministic queues. In this study, service times are the same as in Study 1 but reordered. Despite the lack of a monotonic sequence initially, seeing some fast service times early on that is enough to create an enduring progress effect results in higher patience in the queue. Also, in this study, the only difference between Fast start and Slow Start treatments is the order of first three service times. Therefore, not observing a significant difference between Fast start and Slow start treatments strengthen our result that underlines the effect of experiencing very fast service times on people’s patience.

6.3.3. Time spent in queue, t

Lastly for Study 3, we analyze t, time spent in queues. It is a continuous variable since it can take the values between 0 and 600 (in seconds), as each queue lasts 10 minutes.

The descriptive analyses for the variable t are provided in Table 52. The mean time spent in queues is approximately 293 seconds and roughly 56% of join decisions result in quitting the queue.

Table 52: Descriptive analyses of t for Study 3

		per subject			
Category	**total**	**mean**	**min**	**median**	**max**
(first) entry time		0	0	0	0
(first) exit time		293.086	8.143	114.988	600
failures	46	0.5609	0	1	1

Survival estimate of all subjects combined is provided in Figure 8. The shape resembles that observed in Study 1.

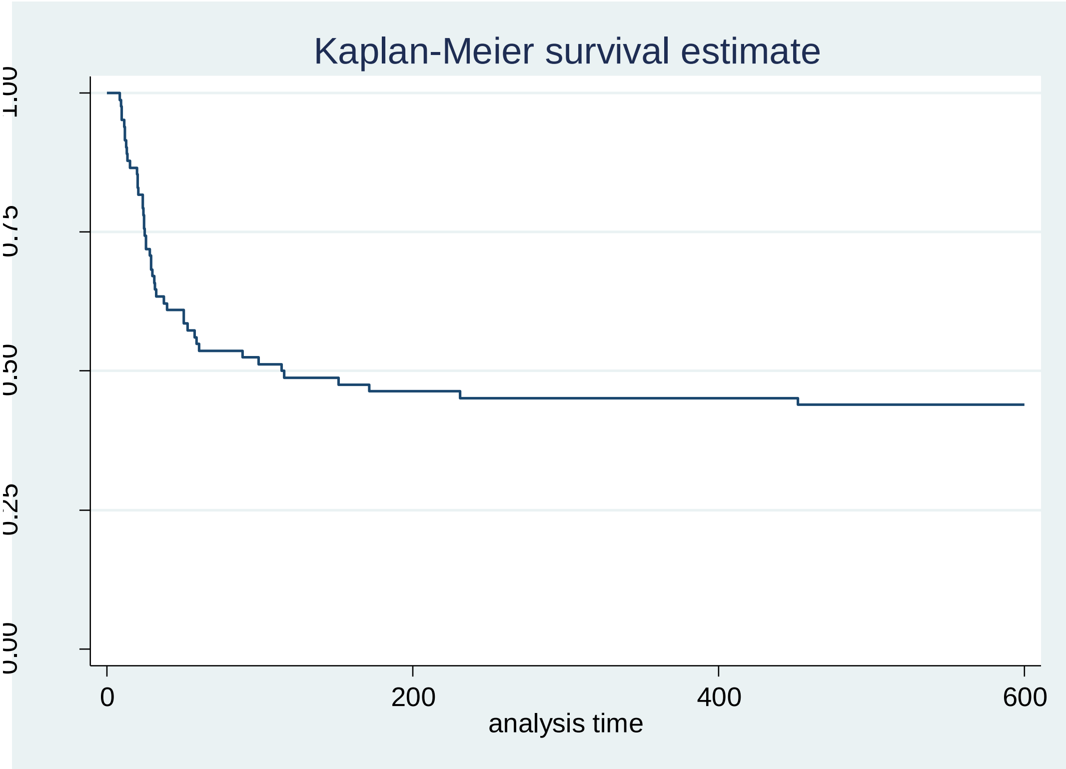

Figure 8: Kaplan-Meier curve for Study 3

Then, survival curves for different treatment groups, Deterministic, Fast start and Slow start queues, are separately estimated as shown in Figure 9.

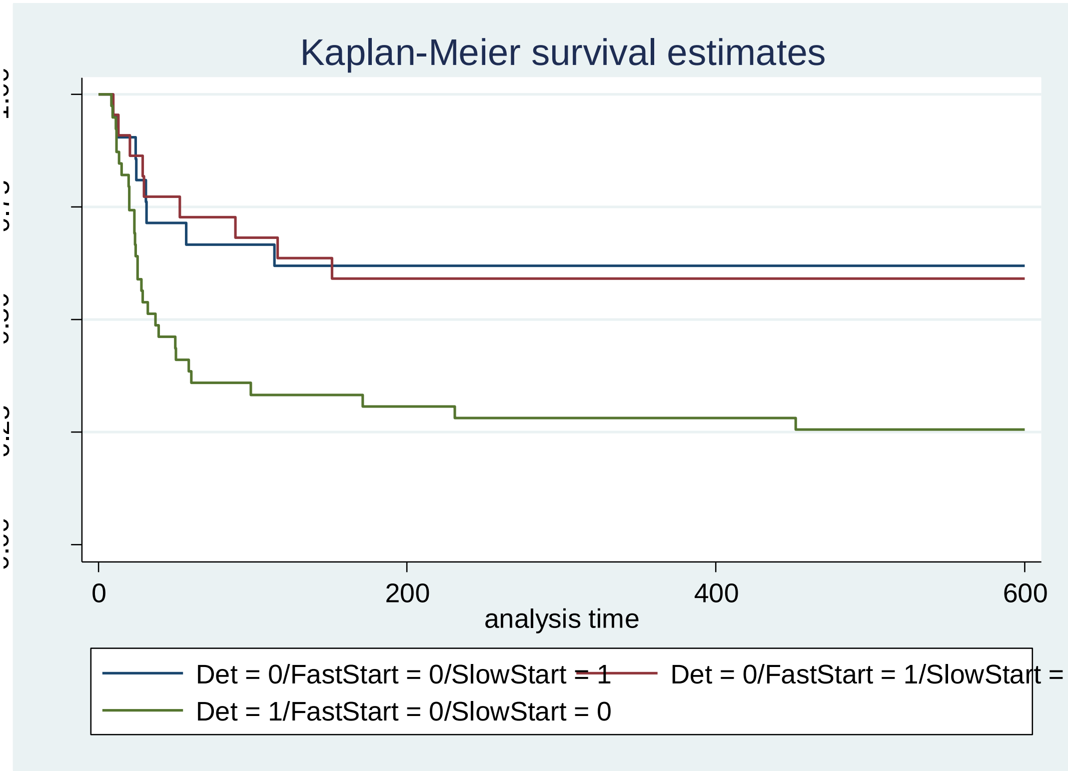

Figure 9: Kaplan Meier curves for different treatment groups of Study 3

Log-rank test for equality of survivor functions have Pr>chi2 result which equals to 0.0048, suggesting that the curves are significantly different from each other. However, it is a cumulative test to compare all the treatment groups. For robust interpretations, pairwise tests are conducted to see whether survival curves of treatment groups are significantly different from each other or not (Table 53).

Table 53: Pairwise comparisons of log-rank test for equality for Study 3

Comparison	***Pr>chi2***
Fast Start-Slow Start	0.9259
Slow Start-Deterministic	0.0109
Fast Start-Deterministic	0.0099

According to pairwise comparisons, subject behavior in Fast Start and Slow Start queues does not differ significantly from each other. However, subjects quitting decisions both in Fast Start and Slow Start queues differ significantly from Deterministic queues.

Next, we conduct a Cox Proportional hazards analysis to be able to see β values in detail. For this analysis, we consider the same model as in Study 1, but we exclude Queue Length and Decision2forsubject from the analysis as they are not relevant for the Study 3.

$$h(t) = h_0(t)\exp\left(\beta_1 FastStart + \beta_2 SlowStart + \beta_3 Decision3forsubject + \beta_4 EconandEng\right)$$

Table 54: First Cox model for Study 3

```
Cox regression -- no ties

No. of subjects =           82                     Number of obs   =         82
No. of failures =           46
Time at risk    =    24033.022
                                                   LR chi2(4)      =      11.28
Log likelihood  =   -181.11218                     Prob > chi2     =     0.0235
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	.3321071	.1502413	-2.44	0.015	.1368373	.8060309
SlowStart	.3084494	.1518769	-2.39	0.017	.1175066	.8096655
Decision3forsubject	1.376254	.6742283	0.65	0.514	.5268583	3.595035
EconandEng	1.273031	.4104376	0.75	0.454	.6767111	2.39483

In this significant model (Table 54) which satisfies the proportional hazards assumption, our control variables are not significant; and our independent variables are significant in the presence of them. Both Fast Start and Slow Start queues lead to lower hazard and longer survival times, compared to Deterministic queues. This finding suggests that experiencing some fast service times early on that create a progress effect in random queues compared to deterministic queues increase subjects' patience. Both the Fast Start and Slow Start sequence ensure such a progress effect, despite the small sequence difference of service times seen early on between these treatments.

6.4. STUDY 4

In this study, we aim to minimize the progress effect that is always present in our previous studies, in terms of number of people served in a given time relative to the deterministic queue. Table 55 summarizes the number of people served in our different studies with respect to time in multiples of 60 seconds.

Table 55: Progress in different studies in terms of number of people served

	Study 1		Study 2		Study 3	
Deterministic	**Fast Start**	**Slow Start**	**Fast Start**	**Slow Start**	**Fast Start**	**Slow Start**
1	5	0	3	0	2	0
2	6	1	5	1	3	3
3	6	1	6	2	4	4
4	6	2	6	2	6	6
5	7	2	6	2	7	7
6	7	3	7	3	7	7
7	8	3	8	3	7	7
8	8	3	8	4	9	9
9	9	4	9	5	9	9
10	10	10	10	10	10	10

This table should be read as follows: for example, when 3 people are served in a deterministic queue, 6 (1) people are served in the Fast (Slow) Start queue of the Study 1, 6 (2) people is served in the Fast (Slow) Start queue of the Study 2 and 4 (4) people are served in the Fast (Slow) Start queue of the Study 3. As it is observable from the table, deterministic queue always progress slower than the other queues until the 9th person in the queue generally.

So in this study, we change the service times in a way so that progress of all the queues are equalized after the 3rd service (Table 56) and we label this study as “Controlled Progress”.

Table 56 : Service times of Study 4

Fast Start	5, 90, 85, 60, 60, 60, 60, 60, 60, 60
Not so extreme Fast Start	20, 70, 90, 60, 60, 60, 60, 60, 60, 60

The Fast Start treatment provides a very short service time followed by two slower than the mean service times, finally continuing with the mean service time. The Not so extreme Fast Start is qualitatively the same, except that the first three service times are “not so extreme” relative to the mean service time, paralleling the difference between Study 1 and Study 2. With this design, we aim to see if a progress effect is present or not and also, to observe whether a very short service time like 5 seconds is sufficient to change people’s behavior in queues

By using only long queues, we randomize the order of the three queues that subjects experience. Also in this study, while presenting the experiment, we say to the participants that they will only experience three queues. By doing this, we aim to further minimize strategic choices on the part of the subjects, in anticipation of future queues. We have total of 6 different order groups and the number of subjects in each group is summarized in Table 57.

Table 57: The number of people in different order groups in Study 4

Group No	Queue Order	Number of People
1	Det-Fast-Slow	11
2	Det-Slow-Fast	8
3	Fast-Det-Slow	14
4	Fast-Slow-Det	16
5	Slow-Det-Fast	12
6	Slow-Fast-Det	12

A total of 73 subjects is participated in Study 4. 63% of the subjects are females, 51% of the subjects are risk averse over wait and 63% of the subjects are majoring Economics or Engineering. The average payment was 11 TRY.

The descriptive analyses for subjects joining and quitting behaviors are provided in Table 58. The statistical tests to compare these rates are provided in the following sections.

Table 58: Descriptive analyses for Study 4

JOIN?	**Det**	**FastStart**	**SlowStart**
No	33	27	41
Yes	40	46	32
Joining Rate	0.55	0.63	0.44
QUIT?	**Det**	**FastStart**	**SlowStart**
No	26	32	19
Yes	14	14	13
Quitting Rate	0.35	0.30	0.41

6.4.1. Join

The same procedure is followed for Join analyses as followed for Study 1, 2 and 3. Logit analyses are conducted for Study 4 to see the effect of Randomness on people's joining decisions with the presence of our control variables.

First, a population averaged model is conducted as suggested by statistical tests, with all of our control variables (Table 59).

Table 59: First model for Join decisions of Study 4

GEE population-averaged model		Number of obs =	219
Group variable:	OverallSub~o	Number of groups =	73
Link:	logit	Obs per group: min =	3
Family:	binomial	avg =	3.0
Correlation:	exchangeable	max =	3
		Wald chi2(6) =	5.55
Scale parameter:	1	Prob > chi2 =	0.4755

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-.1314227	.2970198	-0.44	0.658	-.7135708	.4507254
Decision2forsubject	-.2548581	.3427797	-0.74	0.457	-.9266939	.4169778
Decision3forsubject	-.585287	.3412744	-1.72	0.086	-1.254173	.0835985
EconandEng	.1032672	.2972367	0.35	0.728	-.479306	.6858404
Gender	.376101	.2935667	1.28	0.200	-.1992792	.9514811
Wait_RiskAverse	-.2745253	.2793664	-0.98	0.326	-.8220735	.2730228
_cons	.3641148	.4613137	0.79	0.430	-.5400434	1.268273

As the model significance is not sufficient, we cannot interpret this model.

As the next step, we exclude our gender and risk aversion control variables and rerun the analysis as a population averaged model (Table 60).

Table 60: Second model for Join decisions of Study 4

```
GEE population-averaged model                   Number of obs      =       219
Group variable:             OverallSub~o        Number of groups   =        73
Link:                              logit        Obs per group: min =         3
Family:                         binomial                       avg =       3.0
Correlation:                exchangeable                       max =         3
                                                Wald chi2(4)       =      3.01
Scale parameter:                       1        Prob > chi2        =    0.5559
```

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Randomness	-.1288304	.2932235	-0.44	0.660	-.7035379	.4458771
Decision2forsubject	-.2511108	.3386237	-0.74	0.458	-.914801	.4125795
Decision3forsubject	-.5774946	.3371325	-1.71	0.087	-1.238262	.0832729
EconandEng	-.0286953	.2869554	-0.10	0.920	-.5911176	.533727
_cons	.5377025	.3811893	1.41	0.158	-.2094148	1.28482

Since it is an insignificant model, we cannot interpret it.

This finding suggests that people’s joining decisions are not affected by randomness in Study 4.

6.4.2. Quit

Different levels of randomness are present in Study 4. A queue might have deterministic or random service times; and when it is random, there are two different sample paths as presented in Table 56.

For Quit analyses, only the data from participants who join the queues are possible to use; thus, we have a total of 118 decisions from 66 subjects to be analyzed.

We run the logit analysis with our control variables as a random effects model since statistical tests imply so (Table 61).

Table 61: First model for Quit decisions of Study 4

```
Random-effects logistic regression              Number of obs      =       118
Group variable: OverallSubje~o                  Number of groups   =        66

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.8
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(7)       =      6.92
Log likelihood  = -67.645921                    Prob > chi2        =    0.4374
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-.6570738	.729703	-0.90	0.368	-2.087265	.7731177
SlowStart	.056653	.7671205	0.07	0.941	-1.446876	1.560182
Decision2forsubject	-2.379368	.9633793	-2.47	0.014	-4.267557	-.4911797
Decision3forsubject	-.8719422	.7217159	-1.21	0.227	-2.286479	.5425951
EconandEng	.5849715	.8762757	0.67	0.504	-1.132497	2.30244
Gender	1.488138	.9673109	1.54	0.124	-.4077562	3.384033
Wait_RiskAverse	.1130531	.7795431	0.15	0.885	-1.414823	1.64093
_cons	-1.190384	1.225875	-0.97	0.332	-3.593056	1.212287
/lnsig2u	1.473283	.8206022			-.1350678	3.081634
sigma_u	2.088908	.8570814			.934696	4.668402
rho	.5701432	.2011131			.2098358	.8688452

```
Likelihood-ratio test of rho=0: chibar2(01) =     6.62 Prob >= chibar2 = 0.005
```

Even if our control variable *Decision2forsubject* is significant, we cannot interpret it since the model is not significant. Therefore, we rerun the model without our gender and risk aversion control variables (Table 62).

Table 62: Second model for Quit decisions of Study 4

```
Random-effects logistic regression              Number of obs      =       118
Group variable: OverallSubje~o                  Number of groups   =        66

Random effects u_i ~ Gaussian                   Obs per group: min =         1
                                                               avg =       1.8
                                                               max =         3

Integration method: mvaghermite                 Integration points =        12

                                                Wald chi2(5)       =      5.95
Log likelihood  = -69.061687                    Prob > chi2        =    0.3113
```

Quit	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	-.6413992	.7287563	-0.88	0.379	-2.069735	.7869369
SlowStart	.1305311	.759204	0.17	0.863	-1.357481	1.618544
Decision2forsubject	-2.203568	.9389082	-2.35	0.019	-4.043795	-.3633422
Decision3forsubject	-.8659416	.7233162	-1.20	0.231	-2.283615	.5517322
EconandEng	.1213132	.8211163	0.15	0.883	-1.488045	1.730672
_cons	.076672	.8888973	0.09	0.931	-1.665535	1.818879
/lnsig2u	1.578831	.8012539			.0084018	3.149259
sigma_u	2.202109	.8822241			1.00421	4.828953
rho	.5957971	.1929603			.2346127	.876361

```
Likelihood-ratio test of rho=0: chibar2(01) =     7.70 Prob >= chibar2 = 0.003
```

We obtain again an insignificant model which prevents us from interpreting the results.

6.4.3. Time spent in queue, t

To analyze subjects' decisions further, time spent in queues, t variable is used. It is a continuous variable since it can take the values between 0 and 600 (in seconds), as each queue lasts 10 minutes.

We provide the descriptive analyses for the variable t in Table 63. The mean time spent in queues is approximately 413 seconds and roughly 35% of join decisions result in quitting the queue.

Table 63: Descriptive analyses of t for Study 4

		per subject			
Category	**total**	**mean**	**min**	**median**	**max**
(first) entry time		0	0	0	0
(first) exit time		412.9401	7.691	600	600
failures	41	0.3475	0	1	1

This quitting rate is also observable from survival estimate of subjects that is provided in Figure 10.

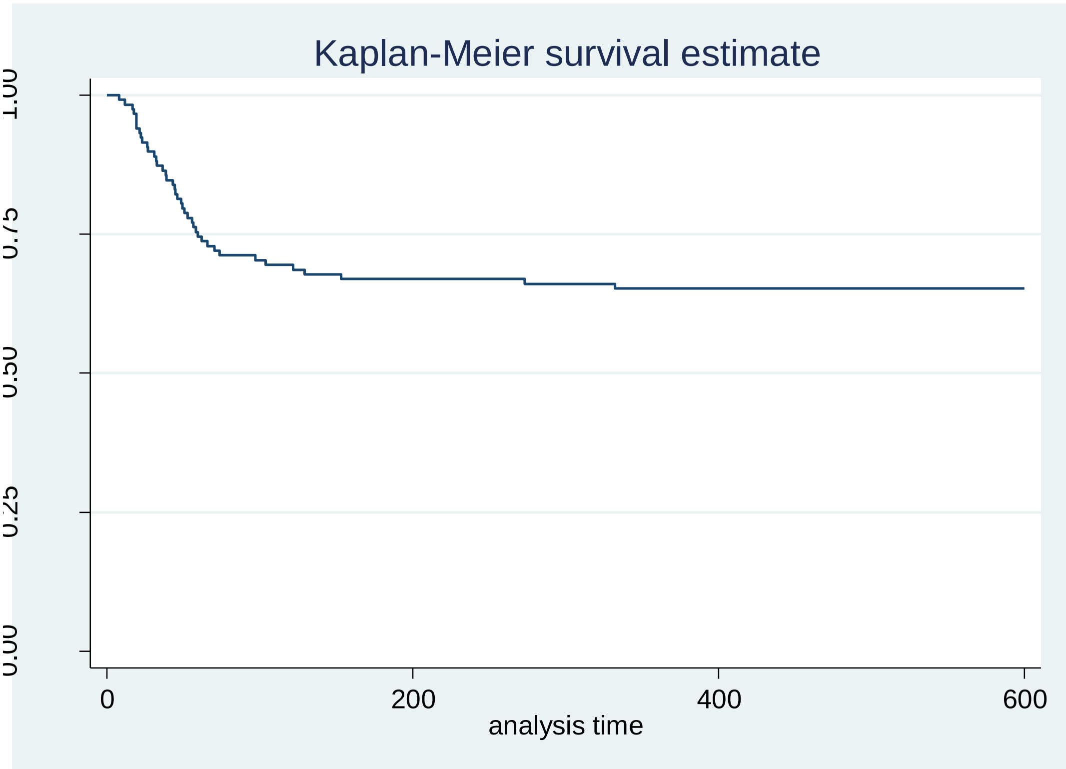

Figure 10: Kaplan Meier curve for Study 4

Then, to be able to compare survival estimates of different treatment groups, we plot them in Figure 11 separately.

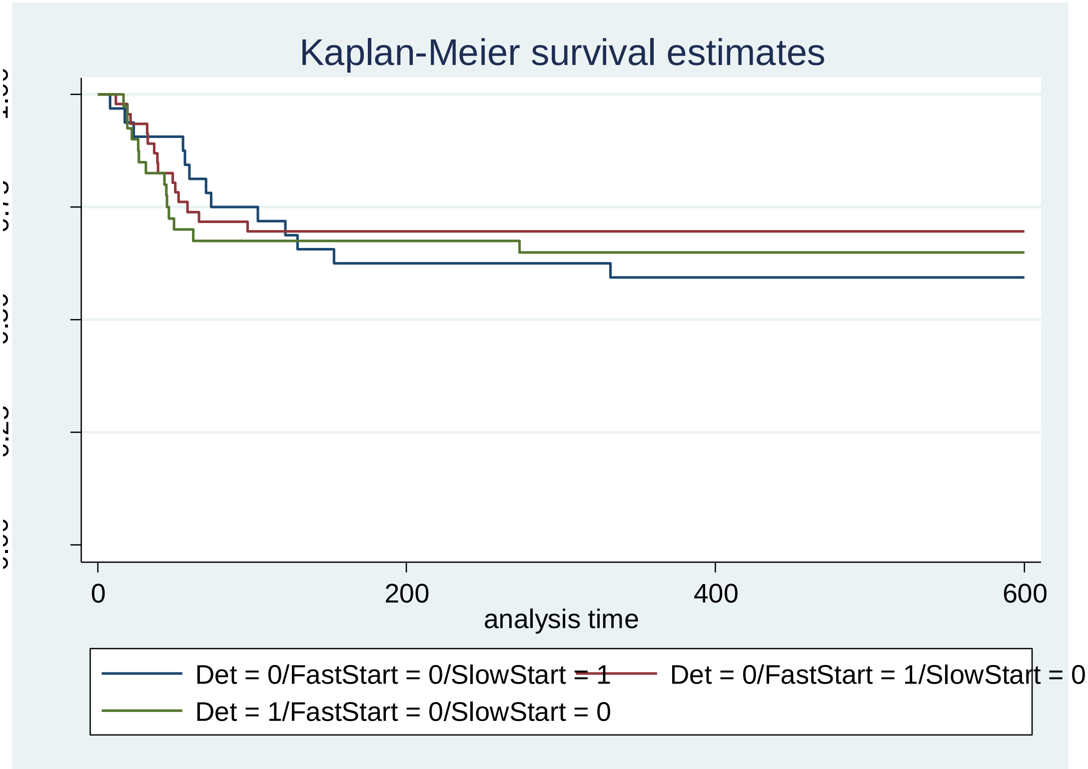

Figure 11: Kaplan Meier curves for different treatment groups of Study 4

As observable visually, there is no significant difference between these groups, which is also supported by log-rank test of equality for survivor functions with Pr>chi2 equals to 0.7885. However, pairwise test results are provided for integrity of analyses (Table 64).

Table 64: Pairwise comparisons of log-rank test for equality for Study 4

Comparison	***Pr>chi2***
Fast Start-Slow Start	0.5247
Slow Start-Deterministic	0.9213
Fast Start-Deterministic	0.5314

Lastly, we conduct Cox Proportional Hazards test to see the effects of our variables cumulatively (Table 65).

Table 65: First Cox model for Study 4

```
Cox regression -- no ties

No. of subjects =          118                     Number of obs   =        118
No. of failures =           41
Time at risk    =    48726.933
                                                   LR chi2(5)      =       7.67
Log likelihood  =   -183.84762                     Prob > chi2     =     0.1756
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
FastStart	.5882388	.2407136	-1.30	0.195	.2637746	1.31182
SlowStart	.7992359	.3252736	-0.55	0.582	.3599585	1.774588
Decision2forsubject	.3384123	.1435408	-2.55	0.011	.1473672	.7771259
Decision3forsubject	.5475643	.2132166	-1.55	0.122	.2552613	1.174587
EconandEng	.9735155	.3174255	-0.08	0.934	.513806	1.844533

We test the assumption of proportional hazard and find out that a single hazard ratio is not sufficient for variables *SlowStart*, as its hazard changes over time (Table 66). Therefore, we conduct the analysis by interacting this variable with time.

Table 66: Test for proportional hazards assumption

```
. estat phtest, detail

      Test of proportional-hazards assumption

      Time:  Time
```

	rho	chi2	df	Prob>chi2
FastStart	0.05838	0.17	1	0.6821
SlowStart	0.32722	4.91	1	0.0267
Decision2f~t	0.25628	2.76	1	0.0965
Decision3f~t	0.25291	3.31	1	0.0690
EconandEng	-0.00092	0.00	1	0.9955
global test		9.09	5	0.1055

Table 67: Second Cox model for Study 4

```
Cox regression -- no ties

No. of subjects =          118                  Number of obs   =        118
No. of failures =           41
Time at risk    =    48726.933
                                                LR chi2(6)      =      12.20
Log likelihood  =   -181.58233                  Prob > chi2     =     0.0577
```

_t	Haz. Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
main						
FastStart	.5891718	.2406371	-1.30	0.195	.2645959	1.3119
SlowStart	.3683199	.2183852	-1.68	0.092	.1152201	1.177394
Decision2forsubject	.3417818	.1448412	-2.53	0.011	.1489445	.784284
Decision3forsubject	.5439448	.2111246	-1.57	0.117	.2541984	1.163957
EconandEng	.9934128	.3240654	-0.02	0.984	.5241501	1.882798
tvc						
SlowStart	1.01219	.0069135	1.77	0.076	.9987298	1.025831

Note: variables in tvc equation interacted with _t

This result suggests that there is no effect of Fast Start queues and subjects’ major on people’s time spent in queues. On the other hand Not so extreme Fast Start queues (referred as Slow Start in the analysis) are pertaining to lower risk and longer survival times, but the risk increases overtime.

Decision2forsubject and Decision3forsubject result in significantly longer survival times, implying that people spent more time as they progress in the experiment.

6.5. SUMMARY OF RESULTS

In this section, the results from all the studies are summarized and discussed.

6.5.1. Queue Length

We are only able to test our hypotheses about queue length in Study1, as in Study 2, 3 and 4 we only use long queues. Our result on this variable from Study 1appear robust and are also consistent with earlier empirical (outside the laboratory, in real operational contexts) observations from the literature.

Our first two hypotheses are about joining and quitting rates for the same expected waiting time but with different queue lengths.

For conducting logit analyses for Join decision, we combine the data from all of our 4 studies. Combining these is acceptable since the difference between these studies comes from the service time sequences observed after joining the queue, and before joining, queues look similar. Additionally, in our first analysis (Table 68) we control for different studies and do not find any significant effect. In the Table 69, logit analysis for Join decision of all studies is provided.

Table 68: First model for Join decision of All Studies

GEE population-averaged model		Number of obs =	948
Group variable:	Overallsub~o	Number of groups =	316
Link:	logit	Obs per group: min =	3
Family:	binomial	avg =	3.0
Correlation:	exchangeable	max =	3
		Wald chi2(8) =	23.69
Scale parameter:	1	Prob > chi2 =	0.0026

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	.094531	.2232097	0.42	0.672	-.342952	.5320141
Randomness	-.3572557	.1432068	-2.49	0.013	-.6379358	-.0765756
Decision2forsubject	-.5031842	.1747105	-2.88	0.004	-.8456105	-.160758
Decision3forsubject	-.5452744	.1751884	-3.11	0.002	-.8886374	-.2019114
EconandEng	-.08883	.1565823	-0.57	0.571	-.3957256	.2180656
Study1	.2281138	.2181628	1.05	0.296	-.1994774	.6557049
Study2	.1376955	.2046793	0.67	0.501	-.2634685	.5388595
Study3	.0534542	.2319825	0.23	0.818	-.4012231	.5081315
_cons	.7084736	.3208179	2.21	0.027	.079682	1.337265

Table 69: Second model for Join Decision of All Studies

GEE population-averaged model		Number of obs =	948
Group variable:	Overallsub~o	Number of groups =	316
Link:	logit	Obs per group: min =	3
Family:	binomial	avg =	3.0
Correlation:	exchangeable	max =	3
		Wald chi2(5) =	22.49
Scale parameter:	1	Prob > chi2 =	0.0004

Decision	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
QueueLength_Code	-.0272522	.175477	-0.16	0.877	-.3711808	.3166765
Randomness	-.3541995	.1428813	-2.48	0.013	-.6342416	-.0741574
Decision2forsubject	-.5165428	.1741409	-2.97	0.003	-.8578528	-.1752329
Decision3forsubject	-.5585869	.1746312	-3.20	0.001	-.9008577	-.2163161
EconandEng	-.1221185	.1505527	-0.81	0.417	-.4171964	.1729594
_cons	.9541439	.2173471	4.39	0.000	.5281515	1.380136

.

This analysis (Table 69) suggests that there is no significant effect of queue length on people's joining decisions.

In our analysis of bounded rationality (Chapter 5), we observe a lower β value for short queues compared to the β value of long queues. We cannot state anything about the significance of this comparison since confidence intervals are mostly overlapping and standard error is relatively higher for short queues. However, we observe some directional relationships between these β values, implying that people seem to be more boundedly rational in long queues than they are in short queues. While making this analysis, we keep in mind that as our queue length variables is a between subject variable, comparing the β values of long and short queues is comparing two different groups' bounded rationality, even in the presence of random assignment of subjects to the different treatment groups.

We observe a significant effect of queue length on people's reneging decisions, for the same expected waiting time, supporting our hypothesis H_2. This finding indicates that long queues decreases subjects' patience and result in quitting, even if the expected waiting time is the same. While making this conclusion, one might also consider the fact that in long queues, average service time per person is shorter than the average service time per person in short queues, as we try to control for the total time each queue takes. So this result is present despite the faster progress (in terms of number of people served) in the long queue when compared with the short queue. Table 70 summarizes the progress in long and short queues for a deterministic queue. For a rigorous comparison, we chose to concentrate on completion percentage which means the ratio of number of served people to the initial queue length. These percentages are equalized for long and short queues frequently. Moreover, when there is a difference, completion percentages in long queue are ahead of the short queue. So, we think that this significant difference between reneging rates from long and short queues comes from subjects' concentration solely on queue length and not so much the faster speed of the long queue.

Table 70: Comparisons of long and short queues

	Number of served people		Completion percentage	
Multiples of 60 seconds	Long Queue	Short Queue	Long Queue	Short Queue
60	1	0	0.1	0
120	2	1	**0.2**	**0.2**
180	3	1	0.3	0.2
240	4	2	**0.4**	**0.4**
300	5	2	0.5	0.4
360	6	3	**0.6**	**0.6**
420	7	3	0.7	0.6
480	8	4	**0.8**	**0.8**
540	9	4	0.9	0.8
600	10	5	**1**	**1**

Subjects' time spent in long and short queues are also analyzed, as an extension of their quitting decisions analysis. The survival estimates of long and short queues are different visually (Figure 12) and also significantly, according to the log-rank test of equality result that yields in Pr>chi2 that equals to 0.0002.

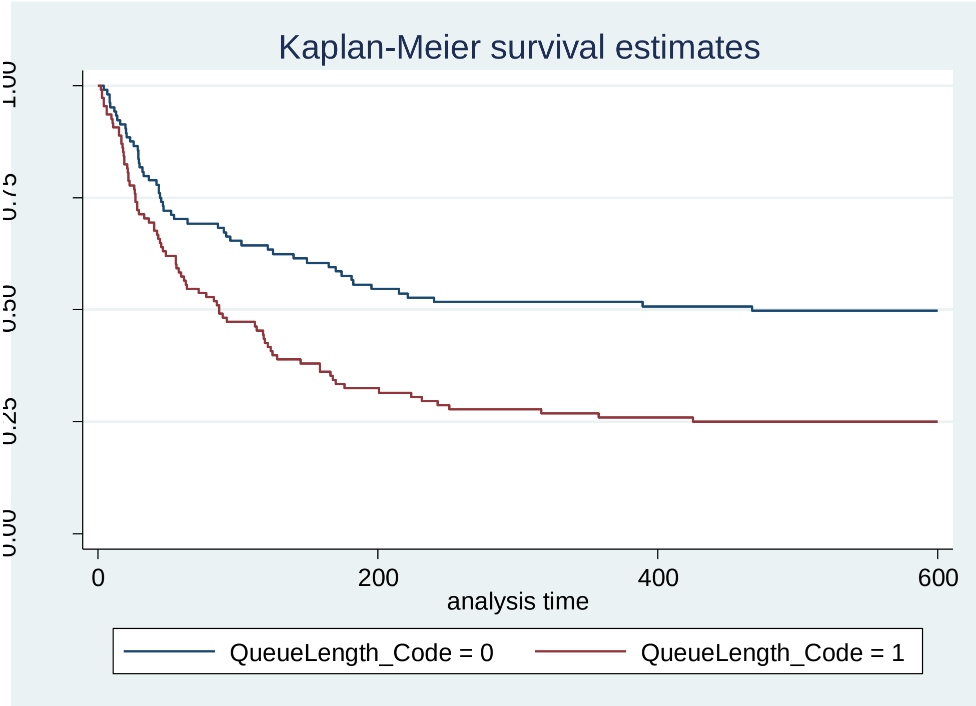

Figure 12: Kaplan Meier curves for long and short queues

This analysis, together with the results of Cox model that are provided in the section 6.1.3. imply that subjects survive shorter in long queues and support our hypothesis H_3 .

6.5.2. Encountered service times

In this section, our hypotheses about encountered service times are summarized. The service times from all of the studies are presented in Table 71 to facilitate interpretation of the results.

Table 71: Service times in seconds for different studies

	STUDY 1		STUDY 2		STUDY 3		STUDY 4	
	Fast Start	Slow Start	Fast Start	Slow Start	Fast Start	Slow Start	Fast Start	Slow Start
Service time 1	3	90	15	82	5	90	5	20
Service time 2	2	110	10	98	15	5	90	70
Service time 3	5	141	25	121	90	15	85	90
Service time 4	5	164	15	144	65	65	60	60
Service time 5	15	65	25	65	3	3	60	60
Service time 6	65	15	65	25	5	5	60	60
Service time 7	164	5	144	15	110	110	60	60
Service time 8	141	5	121	25	164	164	60	60
Service time 9	110	2	98	10	2	2	60	60
Service time 10	90	3	82	15	141	141	60	60

First, we investigate the effect of randomness on people's joining decisions. We hypothesize that "Joining rates for deterministic queues are greater than joining rates for random queues, where the expected waiting times are the same" and are able to test this hypothesis in all the studies, since the randomness is always present.

In Study 1, 2 and 4 we do not observe any significance of randomness. However in Study 3 the results suggest that randomness has an effect on participants' joining decisions; joining rates are greater for long queues compared to short queues. Since the difference in these studies comes from service time sequences that are only observable after joining, we do not expect any differences in people's joining behaviors. The observed significance of randomness on joining in Study 3 might be related to the fact that in this study, since we do not randomize the order of subjects in terms of their randomness, subjects always experience a deterministic queue initially. Therefore, the significance of randomness might also be attributed to queue order, even if we controlled for decision numbers. When we conduct Join decision analysis by comparing all data from all the studies (Table 69), we observe a significant effect of randomness on people's joining decisions; people's joining probability is lower for random queues, compared to deterministic queues. Additionally, the analysis of bounded rationality that is provided in the Chapter 5 characterize that subjects have an increased level of bounded rationality when the service times are random that led them to decide randomly while joining.

In addition to the analysis of the effect of randomness on people's joining decisions, we also analyze subjects' quitting decisions as well. For quit decisions, we take into consideration the two levels of randomness; fast start and slow start queues. In these analyses, we use the deterministic service times queue as a benchmark.

Our first analyses in section 6.1 show that people are less likely to quit fast start queues and survive longer in these queues, compared to deterministic queues, supporting our hypothesis $H_{5.2}$ and $H_{6.2}$. However, our hypothesis $H_{5.1}$ which indicates that people are more likely to quit slow start queues compared to deterministic queue, for the same expected waiting time, is not supported. And in parallel with it, we cannot say significantly that people survive shorter in slow start queues compared to deterministic queues. Our hypothesis $H_{6.1}$ is not supported.

When comparing the results for fast start and slow start queues, we discern that the effect of service time sequence might be driven by the values of service times relative to the announced mean, as well as the sense of progress that a fast start queue gives in terms of number of people served (or remaining people symmetrically) while a slow start queue does not. In Study 1, service time sequence is 3, 2, 5, 5, 15, 65, 164, 141, 110 and 90 seconds for a fast start and the reverse of it for a slow start queue. In this sequence, first five service times constitutes fast service times and have a mean of 6 seconds, which is one tenth of the announced mean. On the other hand, the mean of last five service times is 114 seconds, which is not even twice of the announced mean.

Additionally, in Study 1, subjects experience very fast service times in the fast start treatment, like less than 10 seconds and as short as 2-3 seconds for some, and then service times become very long. We think that here there might be an endowed progress effect associated with the extremely short service times, especially when seen early in the queue because practically, subjects see the person disappear from the queue in 2 to 5 seconds. Also, if subjects focus on the number of people in the queue, a fast start queue will always be progressing faster than the deterministic benchmark until the 8^{th} service, constituting a progress effect.

To make the results from Study 1 more robust, we conduct Study 2 with different service times, keeping the sequence the same, that is first five service times are faster than the mean. The aim of this study is to see whether the results of the Study 1 is driven by the extremeness of service times, or faster than the mean service times generally give the same effect. The new service times are still faster or slower than the mean, but not as extreme as in Study 1 (The average of the five fast service times is 30% of the announced mean). Also, very short service times like 2-5 seconds are excluded to prevent the creation of an endowed progress like effect. In this study, despite the progress effect that is still present and monotonic sequences, we do not find the same effects as in Study 1. It appears that the lack of extreme service times reduces subjects' perception of fast progress initially, making the fast start queue not significantly different from the deterministic queue. However, we find an almost significant effect of slow start treatment on people's quitting decision which is a reverse effect of what we find in Study 1.

In Study 3, we use the same service times as in Study 1 but in a mixed order. The purpose of this study is to investigate if the results of Study 1 are originated from the late switch from fast to slow service times in a fast start queue, or if it is sufficient to observe a couple of fast service times initially for the same effect. The results from this study suggests that the effect of observing some fast service times is persistent compared to deterministic queue, leading to longer survival times. Survival curves of fast start and slow start queues are not significantly different from each other, implying that the small progress related differences in the beginning do not affect subjects' patience.

Finally, in Study 4 the aim is to minimize the progress effect in the queues. Thus, the progresses of all the three queues are equalized after 3rd service. We manipulate random service times; one queue has a 5 seconds service time followed by two slower than the mean service times and the other queue has a 20 seconds service time followed by slower yet closer to the mean service times. When we compare these two random queues, we do not observe a significant difference in terms of patience which means that experiencing only one really fast service time does not affect people's quitting behavior. Also, an initial progress effect relative to the deterministic queue does not seem to be enough to mitigate a significant difference between deterministic and random queues when it is not an enduring effect. In a way, this is not surprising since in this treatment all service times become deterministic subsequent to the third service time.

In summary, while more experiments are needed to verify the robustness of these results, an effect of extremely fast service times is present on people's quitting decisions and time to abandon. However, this effect is coupled with an enduring progress effect compared to the deterministic queue. It is hard to distinguish these effects in our experimental setting since we keep the total waiting time of each queue the same and make our participants actually wait.

With Study 2, the extremeness of "faster than the announced mean" service times is reduced after which the effect of fast service times disappeared. This might be merely because of the service time values; or implicitly because of the –relative- disappearance of endowed progress effect. In Study 3, we test the effect of the monotonicity, which results again an endowed and enduring progress effect. Findings from this study suggest that progress matters, since we use the same service times as in Study 1 in different order. Lastly, in Study 4, the progress effect is aimed to be equalized among all the queues; but we keep the endowed progress effect with only one service time being 5 seconds in fast start conditions. We do not find any significant difference between fast start, slow start and random queues. The progresses in terms of number of people are summarized in Table 72 for different studies.

Table 72: Progress in terms of number of people served in different studies

		STUDY 1		STUDY 2		STUDY 3		STUDY 4	
Seconds	Deterministic	Fast Start	Slow Start	Fast Start	Slow Start	Fast Start	Slow Start	Fast Start	Not so extreme Fast Start
60	1	5	0	3	0	2	0	1	1
120	2	6	1	5	1	3	3	2	2
180	3	6	1	6	2	4	4	3	3
240	4	6	2	6	2	6	6	4	4
300	5	7	2	6	2	7	7	5	5
360	6	7	3	7	3	7	7	6	6
420	7	8	3	8	3	7	7	7	7
480	8	8	3	8	4	9	9	8	8
540	9	9	4	9	5	9	9	9	9
600	10	10	10	10	10	10	10	10	10

Consequently, more experiments are needed to clarify whether there is a distinct endowed progress like effect of very short service times or whether what we find is a combination of all the other effects. However, we observe a combined effect of extremely fast service and an enduring progress effect as a consequence, on people’s quitting decisions and time to abandon. The results further confirm that the effects we have identified, like progress, endowed progress, faster or slower than the mean service times, only affect patience if their presence is significant as demonstrated by the extreme service times in Studies 1 and 3, and monotonous sequences of Studies 1 and 2, or the random service time durations in Studies 1, 2 and 3.

Chapter 7

CONCLUSION

Queues are inevitable in many service settings. For service seekers, waiting, which is the essential part of queuing, is lost time forever, and mostly undesirable. On the other hand, making their customers wait result in unsatisfied customers and consequent gain loss for organizations. Therefore, queuing is important to be analyzed for both actors.

Queues mainly consist of three elements; customers, servers and queues. There is a rich literature on queues concentrating on different aspects of these models and the human part of the queuing systems is analyzed with different approaches. The Classical Queuing Theory models customer behavior in queues, like reneging, by assuming these are random variables with an assumed statistical distribution. In another stream of the literature, customers are modeled as rational agents under the framework of utility maximization, following Naor's work (1969). In this study, paralleling Naor's work, we investigate experimentally the effects of queue length and service time uncertainty on people's queue related decisions.

Our queue length manipulation does not suffice to explain people's joining decisions in individual studies. However, the Join decision analysis with the combination of all of the studies implies a significant effect of randomness on people's joining decisions. According to this, people are less likely to join random queues, compared to deterministic queues. Additionally, our analysis of bounded rationality in Chapter 5 shows directionally how customers are affected by different manipulations. For example, people become more boundedly rational while deciding to join to random queues compared to deterministic queues. Similarly, long queues have a negative effect on the level of bounded rationality. The effect of randomness on joining behavior is also observed in some of our studies (Study 3).

Our second group of analyses is centered on people's quitting decisions and time to quit. We found that people's probability to quit is higher in long queues compared to short queues, for the same expected waiting time. Also, survival estimates for long and short queues are significantly different from each other; implying that people survive longer in short queues.

Our findings from this study contribute also to understand the effects of waiting experience on people's quitting decisions. We found that people's patience increase in the queues where the first few service times are faster than the announced mean. The effect of fast service times is also causing a progress effect in terms of number of people. Therefore, our subsequent studies to test the robustness of this finding show that the effect of very fast service times early on disappears as service times become closer to the mean or when the progress effect is only short lived.

This work contributes to the Behavioral Operations Management area with a focus on experimental queuing. In our experiment, subjects actually wait and feel the annoyance of the wait. Therefore, our findings show that they do not stick to their initial decisions while waiting and even in the deterministic queue, the quitting rate is 63%. In the deterministic queue, all the characteristics are the same as disclosed in the announcement that subjects see before deciding to join. So, this quitting rate is explicable by considering the additional cost of the annoyance of waiting in the queue or by some choice related errors. These results highlight the importance of making subjects wait and experience queues in an experiment, as opposed to the prevalent approach which focuses on survey-like results where subjects are asked about preferences between different waiting situations without actually experiencing the wait.

This experiment has some limitations. In our current design, it is hard to distinguish between the effects of endowed progress and very fast service times as we keep the total waiting time in each queue same. Also, randomization of order of the three queues divides our total number of subjects into small and unequal groups which poses a problem while running statistical analyses. Using only two different orders in Study 3 prevents us from seeing clearly the effects of our experimental manipulations. Using a large enough number of subjects would strengthen our results in any case.

In future research, the effects of fast service times and endowed progress might be distinguished. Also, the effect of queue length might be tested with different lengths to strengthen this result. Different service time paths and different extremeness levels relative to the mean might also be a subject for further research.

Managerial implications of this study provide insight into how the queue must be designed for low reneging probabilities. Our findings in relation with queue length suggest that long queues increase subjects' quitting probabilities. Therefore, the designers of the queues might consider it. Also, we found that experiencing very fast service times compared to announced mean increases subjects' patience in the queue which might as well be helpful for new queue designs with low reneging rates. These results may be useful in designing delay announcements for service systems. The findings suggest that if reneging wants to be reduced, announcements should give customers a sense of fast progress.

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VITA

Büşra GENÇER was born in Bursa. In 2008, she graduated from Galatasaray High School. She received her B.S. degree in Industrial Engineering from Istanbul Technical University (ITU), Istanbul, Turkey, in 2012. She spent the academic year 2010-2011 at Grenoble Institute of Technology, Grenoble, France under the framework of Erasmus Exchange. She received her M.S. degree in Industrial Engineering from Koc University, Istanbul, Turkey in 2015, under the supervision of Prof. Zeynep Aksin and Prof. Evrim Didem Gunes. In Koc University, she assisted Operations Management courses both in graduate and undergraduate levels as a Research & Teaching Assistant. Her research interests are centered on behavioral operations management, with a specific focus on queuing and waiting situations.

APPENDIX A: THE SCRIPT OF PILOT STUDY PRESENTATION

Slide 1-2

Dear Participant,

Welcome.

From now on, please imagine that you're a tourist in a city. You're interested in visiting some touristic attractions.

For each attraction, you'll need to wait in a queue until it's your turn to start service. By saying service, I refer to visiting or enjoying the attraction. Attractions are visited by one person at a time. Therefore, the speed of your progress in the queue will be determined by the service time. Please note that each person participating in the experiment may encounter different number of attractions.

Your purpose is to maximize your earnings – that is maximize the points you'll gain through your decisions regarding joining or leaving queues.

Your total net points will be translated into cash and paid to you at the end of the experiment. You'll earn points by getting service. But you'll lose points while you're waiting in the queue. Each queue starts with a budget.

Slide 3

For each attraction, you can choose to;

- Not join; meaning that you don't join the queue at the beginning, OR
- Join and leave; which means you join the queue and quit before enjoying the attraction, OR

- Join and wait, meaning that you join the queue and wait until it is your turn to enjoy the attraction.

Slide 4

For different attractions, you may experience different types of queues, in terms of the reward of the queue and the service time of the queue.

Slide 5

For some queues, you may know the exact reward of the queue before joining. Let's consider an example. If it is stated that you can get 30 points if you enjoy the attraction, it means that you will get 30 points at the end of the queue with 100% probability. On the other hand, you may experience some queues where reward is probabilistic. For example, it can be stated that you can get a reward between 20 points and 40 points. If it is the case, it means that the minimum number of points you can get will be 20, and maximum number of points you can get will be 40. Also, all points between 20 and 40 have equal likelihood for you to gain as reward. Please note that you will only learn your reward from the queues at the very end of the experiment.

Slide 6

Service time of the queue may also differ. For some queues, it can be mentioned that the queue has a constant service time. For example, if it is stated that the queue has a constant service time which is equal to 3 minutes, it means that everybody in the queue will spend 3 minutes in service with 100% probability.

On the other hand, it is also possible that a queue has a variable service time. For example, if it is stated that service times are exponentially distributed with an average of 2 min/service, it is possible to see a service time which is 2 minutes, but it is also possible to receive a service time which is more than 2 minutes, as well as a service time which is less than 2 minutes.

Slides of Experiment Screens

Now, you will see the process with screens used in the experiment. First, you will see a scenario about the attraction. Here, there is an example of it. In this scenario, you will see reward of the queue and service time of the queue, as well as cost of waiting per minute. For example in this one, reward of the queue is 40 points. Service time of the queue is constant. As it is stated that each person's visit length is same and it is 3 minutes. Cost of waiting per minute is 1 point. When you finish reading the scenario, you can click on OK. In the following screen, you will see your budget. In this example, it is 10 points. After that, you will see the queue for this attraction and decide whether to join the queue or not. If you don't want to join the queue, you click on NO. If you want to join the queue, you click on YES.

Now, the red person at the end of the queue is you. At the time you joined, first person at the queue starts getting service. The person who is getting service has a green box above his or her head. If you don't want to wait until the end of the queue and leave immediately, you can click on LEAVE NOW button.

Slide 7

What about your points? You know that you have 3 options when you see a queue for an attraction; not join, join and leave and join and wait.

Now, let's talk about your point calculation for each option.

In each option, you will get your budget as points.

If you choose to not join, that's all about your points. If you join the queue and wait in the queue, you will lose cost of waiting. The amount of this cost depends on how much time you spent in the queue.

If you leave the queue before getting service, it's all about your points.

If you stay in the queue until getting service, you get reward of the queue.

If you don't want to wait until the end of the queue and leave immediately, you can click on LEAVE NOW button.

Final

Dear Student, It's all about the instructions.

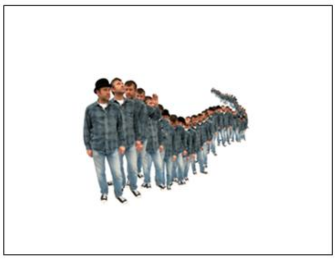
Please do not talk to each other during the session.

Using cell phones is not allowed. Please do not mention about the experiment outside of the lab. It is required for the sake of the study.

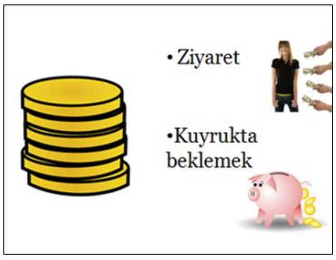
If you have any question, please raise your hand and wait for the experimenter to come to your desk. Also, when you see in your screen that experiment is over, please raise your hand and wait. Thank you.

APPENDIX B: SLIDES AND SCRIPT OF THE PRESENTATION

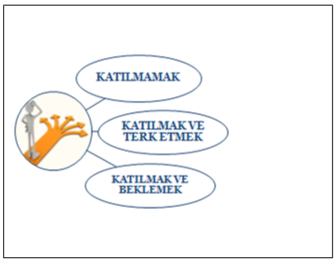
Sevgili Katılımcı,
Deneyimize hoş geldiniz.
Lütfen, şu andan itibaren, turist olarak bir gün boyunca bir şehri gezeceğinizi düşününüz. Takriben 45 dakika sürecek deney süresince, bu şehirdeki bazı turistik yerleri ziyaret edeceksiniz.



Her bir ziyareti tamamlamak için öncesinde kuyrukta beklemeniz gerekecek.



Amacınız, gün boyunca en çok puanı kazanmak. Kuyruklarda sonuna kadar bekleyip ziyaretinizi tamamladığınızda puan kazanacaksınız. Ancak, kuyrukta beklediğiniz her dakika için de puan kaybedeceksiniz. Her bir kuyruğa, bir bütçe ile başlayacaksınız.



Her ziyaret için;
Kuyruğa katılmamak
Kuyruğa katılıp bir süre bekledikten sonra kuyruğu terk etmek
Kuyruğa katılıp sonuna kadar beklemek ve ziyareti tamamlamak
Arasında bir seçim yapacaksınız.

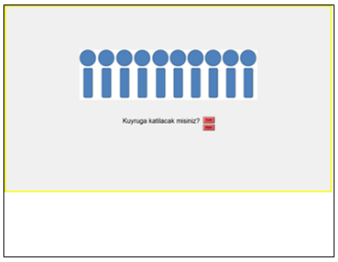
Bu deneyde, lütfen her bir kuyruğu kendi içinde değerlendirin ve kararınızı buna göre verin. Puan maksimizasyonu için diğer kuyrukları ve toplam süreyi düşünmeniz gerekmiyor. Her kuyruk için kuyruğa katılma, kuyruğa katılmama ya da kuyruğu terk etme kararlarını sadece o kuyruğu düşünerek verin.

ŞİMDİ, BU KARARLARI NASIL VERECEĞİNİZİ DENEY EKRANLARI ÜZERİNDEN GÖRELİM.

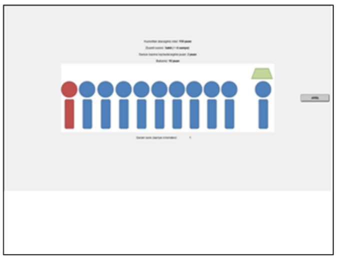
Şimdi, bu kararları nasıl vereceğinizi deney ekranları üzerinden hep beraber görelim.

Her bir ziyaret başında, o ziyaretle ilgili bazı açıklamalar okuyacaksınız. Şu anda, bunun bir örneğini görüyorsunuz. Bu açıklamalar sayesinde, ziyaret sonunda alacağınız puanı, kuyruktaki bekleme süresinin özelliklerini ve beklediğiniz birim zaman başına kaç puan kaybedeceğinizi öğreneceksiniz.

Bir sonraki ekranda, o kuyruk için verilen bütçeyi göreceksiniz. Bu örnekte bütçeniz 10 puan.



Şimdiki ekranda ise, yapacağınız ziyaret öncesinde beklemeniz gereken kuyruğu görüyorsunuz. Bu aşamada 2 seçenek arasında karar vermelisiniz. **"Evet"**e tıklayarak kuyruğa katılıp beklemeye başlayabilirsiniz, ya da **"Hayır"** a tıklayarak bu kuyruğa katılmamayı seçebilirsiniz. Kuyruğa katılıp katılmama kararınızı vermek için bir zaman kısıtlamanız bulunmuyor.



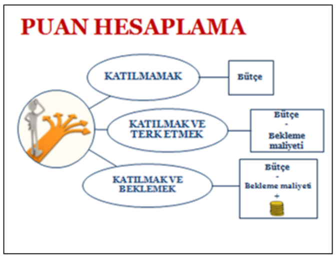
Eğer kuyruğa katılırsanız, kuyruğun sonundaki kırmızı kişi siz oluyorsunuz. Kuyruğa katıldığınız anda, sıranın en başındaki kişi ziyaretine başlıyor. Bir kişinin ziyarete başlayıp başlamadığını, kafasının üzerindeki yeşil kutucuk belirliyor.
Kuyrukla ilgili ödül, ziyaret süresi ve bekleme maliyeti bilgilerini hatırlamak istediğinizde, kuyruğun üst kısmındaki ilgili yere bakabilirsiniz.
Kuyruğa girdiğinizden beri geçen süreyi, kuyruğun hemen altındaki **"Geçen süre"** kısmından takip edebilirsiniz. Bu süreye bakacak olursanız, açıklamada da belirtildiği gibi, kuyruktaki herkesin ziyaret süresinin birbirinden farklı olduğunu göreceksiniz.
Kuyruğa girdiğiniz andan itibaren, tekrar iki seçenek arasında karar verebilirsiniz. Kuyruğun sonuna kadar bekleyip ziyareti tamamlayabileceğiniz gibi, **"Ayrıl"** tuşuna basarak, istediğiniz bir anda kuyruğu terk edebilirsiniz.

•Kuyruğa katılmadığınızda,

•Kuyruğa katılıp bir süre bekledikten sonra kuyruğu terk ettiğinizde,

•Kuyruğa katılıp sonuna kadar beklediğinizde,

sıradaki ekranda bununla ilgili bir açıklama göreceksiniz.



Her kuyruk için 3 seçenek arasında karar vermeniz gerektiğini artık biliyorsunuz.
Kuyruğa katılmamak
Kuyruğa katılıp bir süre bekledikten sonra kuyruğu terk etmek
Kuyruğa katılıp ve sonuna kadar beklemek
Şimdi, bu 3 seçenek için puanlarınız nasıl hesaplanacak bundan bahsedelim.
Her seçenekte, o kuyruk için size ayrılmış bütçeyi alacaksınız.
Eğer kuyruğa katılmamayı seçerseniz, o kuyruktan alacağınız bütün puan bütçeniz olacak.
Kuyruğa katıldığınızda, beklediğiniz süre boyunca puan kaybedeceksiniz. Kaybedeceğiniz bu puanın miktarı, kuyrukta ne kadar süre beklediğinize göre değişecek.
Eğer ziyareti tamamlamadan kuyruktan çıkarsanız, kuyruktan alacağınız bütün puan bu olacak.
Eğer kuyrukta sonuna kadar bekleyip ziyareti tamamlarsanız, kuyruğun ödülünü kazanacaksınız.
Kuyruklardan kazandığınız puanları ancak deney sonunda öğrenebileceksiniz. Deney boyunca kazandığınız toplam puan, yine deney sonunda nakit paraya çevrilerek size ödenecek.

Sevgili Katılımcı,
Deneyle ilgili tüm bilgiler bunlar.
Lütfen deney süresince birbirinizle konuşmayınız, cep telefonu kullanmayınız.
Eğer bir sorunuz olursa lütfen elinizi kaldırıp ilgilinin yanınıza gelmesini bekleyiniz.
Teşekkürler!

APPENDIX C: EXIT SURVEY OF FOCUS GROUP STUDY

Q1: Please indicate your gender.

☐ Female ☐ Male

Q2: Please indicate your nationality.

☐ Turkish ☐ Other (Please specify) ☐

Q3: Please indicate your date of birth. (DD/MM/YYYY)

_ _ / _ _ / _ _ _ _

Q4: Please indicate your current year of study.

- ☐ Freshman
- ☐ Sophomore
- ☐ Junior
- ☐ Senior
- ☐ Graduate student

Q5: Please indicate the college/school you attend. (You can select more than one if you are double majoring)

- ☐ College of Administrative Sciences and Economics
- ☐ College of Sciences
- ☐ College of Sciences and Humanities
- ☐ College of Engineering
- ☐ Law School
- ☐ School of Nursing

- ☐ Graduate School of Business
- ☐ Graduate School of Sciences & Engineering
- ☐ Graduate School of Social Sciences & Humanities
- ☐ Health Sciences Institute

Q6: Please specify your department.

……………………………………………………………………………………..

Q7: Did you join Queue 1 where the attraction was to see a sculpture?

☐ Yes *(Please go to **Q9**)*   ☐ No

Q8: Why did you not join the Queue 1? Please check all possible reason(s) that apply.

- ☐ I wasn’t interested in seeing a sculpture
- ☐ The queue seemed too long
- ☐ Not joining was the best option according to my reward-cost calculation
- ☐ I wanted to finish the experiment as soon as possible
- ☐ I don’t care about the payment; I’m here for extra credits
- ☐ I had some urgent needs
- ☐ Other reasons (Please specify)

*(Please go to **Q11**)*

Q9: Did you quit Queue 1 where the attraction was to see a sculpture?

☐ Yes   ☐ No *(Please go to **Q11**)*

Q10: Why did you quit Queue 1? Please check all possible reason(s) that apply.

- ☐ I got bored
- ☐ The queue did not move as fast as I expected
- ☐ I thought some people in front of me would quit the queue but they did not
- ☐ The queue seemed too long after joining
- ☐ Quitting was the best option according to my reward-cost calculation
- ☐ I forgot to check the time
- ☐ I wasn't interested in seeing a sculpture
- ☐ I wasn't aware of the time
- ☐ I had some urgent needs
- ☐ Other reasons

Q11: Did you join Queue 2 where the attraction was to visit a zoo?

☐ Yes *(Please go to **Q13**)* ☐ No

Q12: Why did you not join the Queue 2? Please check all possible reason(s) that apply.

- ☐ I wasn't interested in visiting a zoo
- ☐ The queue seemed too long
- ☐ Not joining was the best option according to my reward-cost calculation
- ☐ I wanted to finish the experiment as soon as possible
- ☐ I don't care about the payment; I'm here for extra credits
- ☐ I had some urgent needs
- ☐ Other reasons (Please specify)

*(Please go to **Q15**)*

Q13: Did you quit Queue 2 where the attraction was to see a sculpture?

☐ Yes ☐ No *(Please go to **Q15**)*

Q14: Why did you quit Queue 2? Please check all possible reason(s) that apply.

☐ I got bored

☐ The queue did not move as fast as I expected

☐ I thought some people in front of me would quit the queue but they did not

☐ The queue seemed too long after joining

☐ Quitting was the best option according to my reward-cost calculation

☐ I forgot to check the time

☐ I wasn't interested in visiting a zoo

☐ I wasn't aware of the time

☐ I had some urgent needs

☐ Other reasons

Q15: Did you join Queue 3 where the attraction was to enjoy a concert?

☐ Yes *(Please go to **Q17**)* ☐ No

Q16: Why did you not join the Queue 3? Please check all possible reason(s) that apply.

☐ I wasn't interested in enjoying a concert

☐ The queue seemed too long

☐ Not joining was the best option according to my reward-cost calculation

- ☐ I wanted to finish the experiment as soon as possible
- ☐ I don’t care about the payment; I’m here for extra credits
- ☐ I had some urgent needs
- ☐ Other reasons (Please specify)

*(Please go to **Q19**)*

Q17: Did you quit Queue 3 where the attraction was to see a sculpture?

☐ Yes ☐ No *(Please go to **Q19**)*

Q18: Why did you quit Queue 3? Please check all possible reason(s) that apply.

- ☐ I got bored
- ☐ The queue did not move as fast as I expected
- ☐ I thought some people in front of me would quit the queue but they did not
- ☐ The queue seemed too long after joining
- ☐ Quitting was the best option according to my reward-cost calculation
- ☐ I forgot to check the time
- ☐ I wasn’t interested in enjoying a concert
- ☐ I wasn’t aware of the time
- ☐ I had some urgent needs
- ☐ Other reasons

Q19: Please indicate to what extent you are interested in following activities.

	1 *(not interested)*	**2**	**3**	**4**	**5**	**6**	**7** *(very interested)*
Seeing a sculpture	○	○	○	○	○	○	○
Visiting a zoo	○	○	○	○	○	○	○
Seeing a concert	○	○	○	○	○	○	○

Q20: In the experiment, did you experience any queue(s) where reward was probabilistic?

☐ Yes ☐ No

Q21: In the experiment, did you experience any queue(s) where service time was variable?

☐ Yes ☐ No

Q22: Suppose it is stated that service time is constant and 2 minutes per person. People in front of you do not quit the queue. In such a queue, how long will you wait until it's your turn if there are 2 people in front of you?

☐ 2 min

☐ 1 min

☐ 4 min

☐ 8 min

Q23: Assume a case where reward is probabilistic based on a fair coin toss and you can get a reward of 20 points or 40 points. Which of the following values is possible for you to gain as reward?

- ☐ 25
- ☐ 30
- ☐ 40
- ☐ 45