

# COMPROMISE AND ATTRACTION EFFECTS

by

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Compromise and Attraction Effects

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## **Dedication**

Tezimi sevdiklerime ve Anadolu'da küçük kasabalarda büyük rüyalar kuran küçük kız ve erkek çocuklarına ithaf ediyorum.

# COMPROMISE AND ATTRACTION EFFECTS

Rüştü Duran

Economics, MA Thesis, 2011

Özgür Kıbrıs

Compromise Effect, Attraction Effect, Experimental Economics, Behavioral  
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The Compromise Effect denotes the tendency to choose the intermediate object rather than the extreme object in a choice set. The Attraction Effect denotes the tendency to choose the object which has a worse alternative according to the desirable attributes in the choice set. Despite the validity and importance of this phenomenon it is neglected to incorporate both the Compromise and Attraction Effects in formal choice models and to test whether such models outperform the standard value maximization model. Employing a survey on USB's in this article, we suggest that (1) both the Compromise and Attraction Effects are valid (2) The violation of WARP is possible, (3) none of the models outperform others while there are cases that standard value maximization outperforms others.

# UZLAŐIM VE CAZİBE ETKİLERİ

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Economics, MA Thesis, 2011

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Uzlaşım Etkisi, Cazibe Etkisi, Deneysel Ekonomi, Davranışsal Pazarlama

Uzlaşım etkisi, uç özellikler taşıyan objelerdense orta özellikleri taşıyan objeleri seçmeye eğilimi ifade eder. Cazibe etkisiyse kendinden her yönüyle kötü bir alternatifi bulunan objeyi seçmeye yönelik eğilimi ifade eder. Bu iki etkinin de önemi ve geçerliliğine karşın, bunlar formel seçim modelleriyle ilişkilendirip, standart değer maksimizasyonu modeline üstün gelip gelmediği test edilmemiştir. Flash bellekler üzerine bir anket düzenleyerek, (1) bu iki etkinin geçerliliğini, (2) WARP'ı ihlale sebep olabileceklerini ve (3) hiç bir seçim modelinin her durumda standart değer maksimizasyonuna üstün gelmediğini gösterdik.

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# 1 Introduction

## 1.1 Compromise and Attraction Effects

Suppose you are at a restaurant, and looking at the menu. The tastes of the meals are in the same order as the prices as Figure 1: Deli Cious is the most delicious one, Ave Rage is the fairly tasteful one and Dis Taste Ful is the most tasteless one. The prices related to these meals are also as shown in the menu. Which one would be your choice? I am sure that one encounters this kind of choice schemes many times in daily life, Kivetz, Netzer and Srinivasan (2004) show that most people choose the one which is not that tasteless and expensive. Using survey data they prove statistically the existence of this tendency. This tendency also is one of the subjects of this study and discussed in details later on.

Now think about another scenario with the same meals but different prices as shown in Figure 2. In this case, the fairly tasteful one is also the most expensive one. Which one would be your choice? Marketing research has shown that people tend to choose the most delicious one for this particular case.

These two hypothetical cases are related to two phenomena in economics Compromise and Attraction effects, which have drawn the attention of economists and marketing experts. Assuming an environment where objects differ only in two attributes, we can roughly say that the Compromise Effect is about the inclination of people choosing the object which is not extreme in terms of either attribute. The Attraction Effect implies if an object has an alternative which is worse than another according to the both attributes, an inclination of people choosing that better object. In our example these the two attributes are affordability and taste (the second attribute).

To have a better insight, look at Figure 3. The left side of Figure 3 represents the Menu de Compromise while the right side represents Menu de Attraction. In the figure, choice sets consist of three objects, and those objects differ only in these attributes. As the value of the attributes increase, they become more valuable. Because of these effects above, yellow ones are more likely to be chosen: Firstly, look at the graph of the Compromise Effect, left side of Figure 3. The yellow one here is Ave Rage because the compromise effect implies the one which is not extreme

tends to be chosen. Secondly, look at the graph of the Attraction Effect, right side of Figure 3. The yellow one here is Deli Cious because it is better than Ave Rage in every attribute.

## **1.2 The Aim of this Study**

Our aim is twofold. First, after observing the choices of the subjects with an experiment, we try to check the existence of these effects. Second, we calibrate different models using statistical tools and compare them in terms of goodness of fit. These models are probability functions which assign a probability of being chosen to each element in a choice set for each player.

There are of course people who do not exhibit these effects in their choice. Additionally, it is possible to observe that one of these effects in the choices of some individuals, while it seems the other effect has not a significant role in their decisions. Our aim here is, specifically, detecting the general tendency, not the individual tendencies. The Model section clarifies what general tendency means in our context in detail. But in the nutshell, we measure the general tendency as the marginal increase in the percent of people choosing one object when these effects are in question.

There are some models which try to explain this general tendency. These models, using some data about the choices of people from the choice sets, give us the extent of these effects for any case, for the population in general. This is, one of such models would say that when these alternatives considered, some percent of people would choose the first alternative, some other percent of people would choose the second alternative... Next, among the models which claim to explain these effects, we choose the most explaining one for some widely-used criteria. The details about the data and the models can be found in Data Analysis part.

## **1.3 Literature Review**

Compromise and Attraction effects have drawn the attention of researchers from different disciplines such as economics, political science and marketing. While there are many applied studies which try to detect and measure these effects, there are also theoretical studies which supply frameworks accounting for only one of them or both of them. Those studies study different domains and choices, such as among

political parties or among investment portfolios.

One example of empirical studies on the Compromise Effect is about investment portfolio choices which are studied by Benartzi and Thaler (2002). Their study is on a two-step survey. First, subjects choose an investment decision from a set which has many alternatives. Second, they are asked whether or not they want to switch another investment portfolio which is the mean of all participants. The result is that a significant amount of participants choose to switch to the mean portfolio. They discuss that the related context effect, it is Compromise effect here, may be the reason to this behavior. There are other studies on a wide range of domains and cases. For instance, Simonson and Nowlis(2000) on the other hand evaluate the Compromise Effect as a form of consideration set effects using ice- cream experiment, and also Lehmann and Pan(1994) conducted an experiment on mouthwashes.

Compromise Effect and Attraction Effects is demonstrated first by Simonson. Simonson (1989), defines them in a two-step experimentation. Consider a case in which agents are indifferent in two objects which differ only in two attributes. Introduction of an object which is the best one in one attribute and the worst one in the other attribute makes the object which is now the median according to either attributes more attractive to the agents. This is his definition of the Compromise Effect. For the Attraction Effect the object introduced is the median according to one attribute while the worst according to other attribute. The introduction of such object makes the object, which Pareto dominates the introduced object, more attractive to the agents.

On the other hand, Simonson and Tversky (1992) come with another definition for Compromise Effect which is more suitable to run experiments. For this reason we use their definition of Compromise Effect. Applying the same logic as theirs we defined the Attraction Effect. Definitions can be found in Model part.

It is possible to find applied studies on the Attraction Effect in many contexts. One interesting example is studied by Pan, O'Curry and Pitts (1995) on decisions from political parties. Because of the nature of these effects it is hard to create a real world choice setting to prove their existence. For this reason most of the empirical studies are created using hypothetical choice sets. Pan, O'Curry and Pitts have found real world data which is suitable to observe the existence of the

Attraction Effect. Their study indicates that the Attraction Effect is valid in this real world context as well. Beside this example there are other studies concerning the Attraction Effect such as Dhar and Simonson (2003), which is the effect of no-choice option on the Attraction Effect and another study is created by Simonson (1989) to verify the existence of these effects.

In addition to these empirical evidence supporting these effects, however there are attempts to explain these effects in a theoretical framework. Clippel and Eliaz (2010) analyze the decision making process such that objects differ only in two attributes. They model an intra-personal bargaining problem among different selves. They apply to this intra-personal bargaining problem the fallback bargaining. Brams and Kilgour (1998) defined this rule as a bargaining procedure under which bargaining starts with parties revealing their preference ranking over all alternatives in the choice set. When these parties are the inner selves of an agent such that each self cares only one attribute, Clippel and Eliaz (2010) show that the fallback bargaining outcomes consistently exhibit both Attraction and Compromise Effects. In the existence of  $k$  alternatives their procedure is as follows:

1- If there is an alternative which is ranked as the first according to two criteria then choose that alternative. Else pass to the next step.

2- If there is an alternative which is ranked as the first or the second according to two criteria then choose that alternative. Else pass to the next step.

...

$k$ -If there is an alternative which is ranked as the first or the second... or the  $k$ th according to two criteria then choose that alternative.

Let us check if it works for Figure 3. For the graph on the left side there is not an alternative which is ranked as the first according to two criteria. On the other hand the yellow one is ranked as the second according to those criteria while others ranked as whether the first and the third. So we stop at the second step and choose the yellow one. For the graph on the right side there is not an alternative which is ranked as the first according to two criteria. However, the yellow one is ranked as the first or the second so we stop at the second step and choose the yellow one. The graph on the left was representing the Compromise Effect while the right one was for the Attraction Effect and their outcomes are coincided with the fallback bargaining

procedure. The same procedure, under the name of Unanimity Compromise is studied and is shown that it is the only bargaining rule which satisfies some basic properties by Kibris, Sertel (2006) The same rule under the name of “Kant-Rawls Social Compromise” is previously proposed by Sertel and Hurwitz (1997)

Apart from these studies, there is another study by Kivetz, Netzer and Srinivasan (2004) which should be touched upon because it constitutes the base for our study; we use the same framework as theirs. In an environment in which the alternatives differ only in two desirable attributes, they verify the existence of the Compromise Effect. After verifying the existence, they calibrate and compare different models for capturing this effect. These models assign probability of being chosen to each object in a choice set by each agent. And all these models are convex in nature.

Some questions arise. First, even though there are two important framework effects, this study is only on Compromise Effect. Maybe the same application could be executed on the Attraction Effect too. Second, all models they use were convex in nature. For this reason, any result in the favor of Compromise Effect was not an unforeseen result. To what extent these models can be successful in explaining both these effects at the same time? In this study, we answer these questions: Does the Attraction Effect also exist? Do these models also as explaining as before for both of the effects together.

## 2 Model

### 2.1 Compromise and Attraction Effects

The set of agents is  $N = \{i \in Z_{++} | n \in Z_{++}, i \leq n\}$

There are 8 sets of alternatives; each of them contains three objects. We call this kind of choice sets as trinary choice sets; Each agent choose only one object from trinary choice sets

$$1-s_1 = \{x_1, x_2, x_3\}$$

$$2-s_2 = \{x_2, x_3, x_4\}$$

$$3-s_3 = \{x_3, x_4, x_5\}$$

$$4-s_4 = \{x_4, x_5, x_6\}$$

$$5-s_5 = \{x_7, x_8, x_{10}\}$$

$$6-s_6 = \{x_8, x_9, x_{10}\}$$

$$7-s_7 = \{x_9, x_{10}, x_{12}\}$$

$$8-s_8 = \{x_{10}, x_{11}, x_{12}\}$$

$$\text{and } S = \cup_{i=1}^8 s_i$$

Additionally, there are two desirable attributes. The objects we consider differ only in these two attributes, say  $a_1$  and  $a_2$ . For any alternative, say  $x$ , the value of its attributes are shown as,  $a_1(x)$  and  $a_2(x)$ .

In the traditional framework, we mention about either a choice function or a choice correspondence. But in this framework we consider the choice function as a probability function defined on a given choice set. This probability function is also the measure of agent's tendency for any object. We call this measure as  $P(y > z | x, y, z)$ . It is the number of the people who choose  $y$  divided by the number of the people who choose either  $y$  or  $z$ , in the existence of  $x$  in the choice set. We call this probability as  $y$ 's relative probability to  $z$  in the set of  $\{x, y, z\}$ . For instance say that in a sample of 40 people; 5, 10, 25 people choose  $x, y, z$  respectively. Then  $P(y > z | x, y, z)$  is  $10 / (10 + 25) = 0.28571$

Using this notation, we can define both the Compromise and Attraction Effects:

**Definition 1 Compromise Effect:**  $\forall x, y, z, t \in S$  such that,  $a_1(x) > a_1(y) > a_1(z) > a_1(t)$  and,  $a_2(x) < a_2(y) < a_2(z) < a_2(t)$ , then  $P(y > z|x, y, z) > P(y > z|y, z, t)$

In words, assume a case that four objects are ordered reversely according to two attributes. There are two choice sets and the first one includes the first three objects and the second one includes the last three objects according to the first alternative. The Compromise Effect implies the second object's relative probability to the third object in the first set is larger than in the second set.

For instance, according to Figure 4, Compromise Effect implies that,  $P(x_2 > x_3|x_1, x_2, x_3) > P(x_2 > x_3|x_2, x_3, x_4)$

On the other hand, the literature does not contain a definition of the Attraction Effect for this setting. For this reason we create a new one.

**Definition 2 Attraction Effect:**  $\forall x, y, z, t \in S$  such that,  $a_1(y) > a_1(x) > a_1(z) > a_1(t)$  and,  $a_2(x) < a_2(y) < a_2(t) < a_2(z)$  then  $P(y > z|x, y, z) > P(y > z|y, z, t)$

In words, assume a case in which there are two incomparable objects and each has their own Pareto better alternatives, each of those Pareto better objects Pareto dominate only one other object. The Attraction Effect implies, the first Pareto better option's relative probability to the second Pareto better object is higher when the choice set includes the dominated object of the first Pareto better object.

For instance, according to Figure 4, Attraction Effect implies that,  $P(x_8 > x_{10}|x_7, x_8, x_{10}) > P(x_8 > x_{10}|x_8, x_9, x_{10})$

## 2.2 WARP

After introducing these effects, we show that these effects may cause irrational choices. In fact, regular violations of rationality are the important reasons why economists are curious about these effects.

Additionally, the literature does not contain a definition of WARP for this setting. For this reason we create a new one.

**Definition 3 WARP:**  $\forall x, y, z, t \in S$  for defined probabilities, if  $P(y > z|x, y, z) > P(z > y|x, y, z)$  then  $P(y > z|y, z, t) > P(z > y|y, z, t)$ .

In words, WARP implies the tendency for choosing some object does not change its direction when the choice set changes.

Considering this new version of WARP, in some cases Compromise and Attraction Effects may lead to its violations. Below are some samples.

**Example 1** For the Compromise Effect, using Figure 4, say that from the sets of  $\{1,2,3\}$  and  $\{2,3,4\}$  the number of the people who prefer these alternatives are  $(10,50,40)$  and  $(30,60,10)$  respectively. In this case the Compromise Effect emerges with  $P(x_2 > x_3|x_1, x_2, x_3) = 50/(50 + 40) > 30/(30 + 60) = P(x_2 > x_3|x_2, x_3, x_4)$ . On the other hand  $P(x_2 > x_3|x_1, x_2, x_3) = 50/(50 + 40) > 40/(50 + 40) = P(x_3 > x_2|x_1, x_2, x_3)$  but  $P(x_2 > x_3|x_2, x_3, x_4) = 30/(30 + 60) < 60/(30 + 60) = P(x_3 > x_2|x_2, x_3, x_4)$ . So there are choice profiles which exhibit Compromise Effect and thus result in violations of WARP.

**Example 2** For the Attraction Effect, again using Figure 4, say that from sets of  $\{7,8,10\}$  and  $\{8,10,9\}$  the number of the people who prefer these alternatives are  $(10,70,20)$  and  $(30,60,10)$  respectively. In this case the Attraction Effect emerges with  $P(x_8 > x_{10}|x_7, x_8, x_{10}) = 70/(70+20) > 30/(30+60) = P(x_8 > x_{10}|x_8, x_9, x_{10})$ . On the other hand  $P(x_8 > x_{10}|x_7, x_8, x_{10}) = 70/(70+20) > 20/(70+20) = P(x_{10} > x_8|x_7, x_8, x_{10})$ , but  $P(x_8 > x_{10}|x_8, x_9, x_{10}) = 30/(30+60) < 60/(30+60) = P(x_{10} > x_8|x_8, x_9, x_{10})$ . So there are choice profiles which have Attraction Effect in it and result in violations of WARP.

### 2.3 Models for Capturing the Effects

We see that both Attraction and Compromise Effects may create violations of WARP in Example 1 and Example 2. There are a few models which may account for the Compromise and Attraction Effects. Note that all these models have a probabilistic nature.

All models are using the concept of partworth. Partworth is how an agent values an attribute at marginal level. When collecting the data, 1st, 2nd and 5th questions

are used to construct a data set called partworth. Partworth is a three dimensional matrix and we denote it as  $P_{i,j,k}$ : The partworth of the level of attribute k of object j for consumer i. But how do we construct  $P_{i,j,k}$ ?

Where  $v_i(k)$  is the total valuation of agent i for k'th attribute. This is individual information gathered by surveys.

**Definition 4:**  $P_{i,j,k} = a_k(j) * v_i(k)$

**Example 3** Say we try to find  $P_{2,3,1}$ . Look at any of those survey papers in Appendix-1, because the questions are common for partworth it does not matter what we choose We take the 2nd person's survey paper. The specifications of object 3 ( It does not need to be listed in any questions. ) are say 4GB and \$35. Because  $k=1$ , we focus on GB attribute; but if it was  $k=2$ , then we had to focus on Dollar attribute. Assume that the point given by 2nd person to the 4 GB in Question 1 is 5 and "A'dan C'ye geçiş değeri" in Question 5 is 3. Then  $P_{2,3,1} = 5 * 3 = 15$ .

Note that we do not go deep into the nature of the models; because the models exist in the literature already, we are just interested the calibration and goodness of fit.

For some models below  $M_{i,j}^M$  is the deterministic component of utility of alternative j. for person i for model M.

Some other models  $M_{i,j}^{s,M}$  is the deterministic component of utility of object j in the choice set s for person i and for model M; s is any element of S, b is the logit scale parameter and  $c_k$  is the concavity parameter for attribute k,  $P_{i,\min,k}^s$  ( $P_{i,\max,k}^s$ ) is the minimum(maximum) partworth among  $j \in s$  for the person i and attribute k; and  $Pr_i(j|s)$  is the probability which the model assigns for j being chosen from the choice set s for i'th player.

### 2.3.1 VMM-Value Maximization Model

$$Pr_i^{VMM}(j|s) = \frac{\exp(b * M_{i,j}^{VMM})}{\sum_{h \in s} \exp(b * M_{i,h}^{VMM})}$$

where

$$M_{i,j}^{VMM} = \sum_k (P_{i,j,k})$$

b is the parameter to be calibrated.

### 2.3.2 Global Concavity Model

$$Pr_i^{GCM}(j|s) = \frac{\exp(b * M_{i,j}^{GCM})}{\sum_{h \in s} \exp(b * M_{i,h}^{GCM})}$$

where

$$M_{i,j}^{GCM} = \sum_k (P_{i,j,k})^{c_k}$$

b,  $c_k$  are the parameters to be calibrated.

### 2.3.3 CCM-Contextual Concavity Model

$$Pr_i^{CCM}(j|s) = \frac{\exp(b * M_{i,j}^{s,CCM})}{\sum_{h \in s} \exp(b * M_{i,h}^{s,CCM})}$$

where

b and  $c_k$  are the parameters of the model.

### 2.3.4 NCCM-Normalized Contextual Concavity Model

$$Pr_i^{NCCM}(j|s) = \frac{\exp(b * M_{i,j}^{s,NCCM})}{\sum_{h \in s} \exp(b * M_{i,h}^{s,NCCM})}$$

where

$$M_{ij}^{s,NCCM} = \sum_k (P_{i,\max,k}^s - P_{i,\min,k}^s) x [(P_{i,j,k} - P_{i,\min,k}^s) / (P_{i,\max,k}^s - P_{i,\min,k}^s)]^{c_k}$$

### 3 Data Collection

For collecting data, a survey is used. For examples please see Appendix 1. There are 80 subjects who are sophomore students from Sabanci University and ITU(Istanbul Technical University) in Turkey. The objects of the survey are USB. The first reason we chose USB is because it is an object almost all people are familiar with. Second, it can easily be defined on two attributes because it is relatively a simple product in terms of technologic features.

Each subject is randomly classified into types of 1, 2, 3, or 4. Each subject is asked to make a choice from two different choice sets. The sets are assigned to the types according to the table below. For example, TYPE1 is asked to make a choice from the SET1 and SET5. These sets are the sets in Figure 4. The choices are observed using the 3rd and the 4th questions on the survey paper, at the Appendix-1

type/sets	SET1	SET2	SET3	SET4	SET5	SET6	SET7	SET8
TYPE1	✓	-	-	-	✓	-	-	-
TYPE2	-	✓	-	-	-	✓	-	-
TYPE3	-	-	✓	-	-	-	✓	-
TYPE4	-	-	-	✓	-	-	-	✓

There are five questions on each survey paper. The 3rd and the 4th questions are for observing the Compromise and Attraction Effects. The 1st, 2nd and the 5th questions are common among all types. These questions are used to supply required information for the competing models, which is discussed in Data Analysis part in detail.

## 4 Data Analysis

### 4.1 Testing the Existence of Compromise and Attraction Effects

After collecting the data, a table is constructed which shows what percent of subjects choose one object in the existence of other two objects. Using this data table we test the significance of the Compromise and Attraction Effects. The test is executed using a z-test. I now give an example of how we test the Compromise Effect.

The first row is the choice sets, the second row is the number of the subjects who made a choice from the related choice set, the first column is the different types of USB's, the numbers represent the percent of subjects who choose the related USB from the related choice set, '-' means the related USB is not included in the related choice set.

	SET 1	SET 2	SET 3	SET 4
USB	n=41	n=33	n=30	n=23
1	20	-	-	-
2	55	30	-	-
3	25	60	30	-
4	-	10	60	25
5	-	-	10	45
6	-	-	-	30

For instance testing  $P(x_2 > x_3 | x_1, x_2, x_3) > P(x_2 > x_3 | x_2, x_3, x_4)$ , the Compromise Effect between SET1 and SET2, is a work of testing the difference between proportions. We demonstrate this next.

We apply the procedure for testing the difference between proportions using z-test. Assume we have two samples and obtained two proportions  $p_1, p_2$  out of them and try to test the hypothesis of  $p_1 \geq p_2$  with the alternative hypothesis of  $p_2 > p_1$ . The procedure is as follows:

1. We find pooled sample proportion,  $p$ . The formula of  $p$  is

$$(p_1 x n_1 + p_2 x n_2) / (n_1 + n_2)$$

where  $n_1$  and  $n_2$  are the sizes of sample 1 and sample 2 respectively.

2. We compute the standard error, SE. The formula of SE is

$$\sqrt{p x (1 - p) x ((1/n_1) + (1/n_2))}$$

3. We find the test statistic,  $z$ . The  $z$ -statistic is computed as

$$(p_1 - p_2) / SE$$

4. We look at the normal distribution table and calculate the one sided  $p$ -value to finalize the test. If the  $p$  value is less than 0.01 then we reject the null hypothesis.

Now let us apply this procedure for the generic table above to test

$$P(x_2 > x_3 | x_1, x_2, x_3) > P(x_2 > x_3 | x_2, x_3, x_4)$$

**Example 4** The share of 2 relative to 3  $p_1 = 55 / (55 + 25) = 0.6875$  for SET 1 and  $p_2 = 30 / (60 + 30) = 0.33333$  for SET 2. The difference is  $p_1 - p_2 = 0.35417$ . The  $z$ -statistics can be obtained as follow:

1.  $p = (0.6875 x 41 x 0.80) + (0.33333 x 33 x 0.90) / (41 x 0.80 + 33 x 0.90) = 0.51920$

It is important here to note that our samples are not the  $n$ 's in the table, they are the subjects who play role in calculating  $p_1$  and  $p_2$

For example, for  $p_1$  we should look at the subjects who have chosen 2 or 3.

For this reason the sample size for  $p_1$  is  $41 * (0.55 + 0.25) = 41 * 0.80$

$$2. SE = \sqrt[2]{0.51920x(1 - 0.51920)x((1/(41x0.80)) + (1/(33x0.90)))} = 0.12655$$

$$3. z = 0.35417/SE = 2.7986 \approx 2.8$$

4.  $P(z < 2.8)$  corresponds at the normal distribution table to 0.9974. Any number which is greater than 0.01 would be enough to accept the null hypothesis. So we have a significant Compromise Effect in the object 2 relative to the object 3.

There are 9 hypotheses we test. These are, using Figure 4, for the Compromise Effect

1.  $P(x_2 > x_3 | x_1, x_2, x_3) > P(x_2 > x_3 | x_2, x_3, x_4)$ ,
2.  $P(x_3 > x_2 | x_2, x_3, x_4) > P(x_3 > x_2 | x_1, x_2, x_3)$ ,
3.  $P(x_3 > x_4 | x_2, x_3, x_4) > P(x_3 > x_4 | x_3, x_4, x_5)$ ,
4.  $P(x_4 > x_3 | x_3, x_4, x_5) > P(x_4 > x_3 | x_2, x_3, x_4)$ ,
5.  $P(x_4 > x_5 | x_3, x_4, x_5) > P(x_4 > x_5 | x_4, x_5, x_6)$ ,
6.  $P(x_5 > x_4 | x_4, x_5, x_6) > P(x_5 > x_4 | x_3, x_4, x_5)$

and for the Attraction Effect

1.  $P(x_8 > x_{10} | x_7, x_8, x_{10}) > P(x_8 > x_{10} | x_8, x_9, x_{10})$ ,
2.  $P(x_{10} > x_{12} | x_9, x_{10}, x_{12}) > P(x_{10} > x_{12} | x_{10}, x_{11}, x_{12})$ ,
3.  $P(x_{10} > x_8 | x_8, x_9, x_{10}) > P(x_{10} > x_8 | x_7, x_8, x_{10})$ ,
4.  $P(x_{12} > x_{10} | x_{10}, x_{11}, x_{12}) > P(x_{12} > x_{10} | x_9, x_{10}, x_{12})$ .

The number of the hypotheses large because we list each possible cases for Compromise and Attraction Effects. For instance for the SET 1 and SET 2 there are two possible ways which Compromise Effect may exhibit.  $P(x_2 > x_3 | x_1, x_2, x_3) >$

$P(x_2 > x_3|x_2, x_3, x_4)$  or  $P(x_3 > x_2|x_2, x_3, x_4) > P(x_3 > x_2|x_1, x_2, x_3)$ . So because there are 3 such possible case, for SET 2 and SET 3 , SET 3 and SET 4. For each of them we have two hypothesis testing and it makes 6 in total. The same logic for the Attraction Effect follows.

And note that each number is represented by a letter in the survey sheets and (1,2,3,4,5,6,7,8,9,10,11,12) are represented by (B, I, U, T, S, A, Y, S, D, O, R, I) respectively for Figure 4.

## 4.2 Calibrating the Models and Comparing Them

### 4.2.1 Calibration

These models are calibrated using maximum likelihood principle. In this principle, for each model we multiply the probabilities of each event and find the parameters which make this multiplication maximum.

If  $p^M$  is the set of parameters of model M, and  $Pr_i^{M(p^M)}(j_{is}, s)$  is the model's realized probability of j is being chosen by i, from set s with parameter set  $p^M$ . We used realized here which means we only take the realized choices into account. Then the Maximum Likelihood Estimated parameters for model M can be obtained by,

$$arg \max_{p^M} \prod_{i \in I} \prod_{s \in S} \prod_{j \in s} Pr_i^{M(p^M)}(j_{is}, s)$$

We use MATLAB when making the maximum likelihood estimation, for MATLAB code see Appendix 2.

### 4.2.2 Comparisons

When comparing different alternatives, we use 5 criteria. These are Aggregate-level Prediction 1, Aggregate-level Prediction 2, Individual Level Prediction, Bayesian Information Criterion, Akaike Information Criterion.

#### 4.2.2.1 Aggragate-level Prediction 1. (ALP1)

This criterion is based on mean absolute deviations(MAD).

Where S is the set of the choice sets and s represents any element of that set, J is the set of the objects and j represents any element of that set, I is the set of the

subjects and  $i$  represents any element of that set,  $\Pr_i^M(j|s)$  is the probability that model assigns to  $j$  being chosen from the set  $s$  by subject  $i$ ,  $Rate(j|s)$  is the rate of the subjects who choose  $j$  from the set  $S$ ,  $(n|s)$  is the number of the subjects in the choice set  $s$ ,  $|S|$  is the number of the choice sets,  $|J|s|$  is the number of the objects in the choice set  $s$ , and  $\Pr^M$  is the probabilistic distribution which is described by model  $M$ , in the choice set  $s$  the formulation of *Aggregate-level Prediction 1* is:

$$ALP1^M(S, J, I, Pr^M) = \left( \sum_{s \in S} \left( \sum_{j \in J} \left( \left| \left( \sum_{i \in I} \Pr_i^M(j|s) \right) x(n|s)^{-1} - Rate(j|s) \right| \right) \right) x(|J|s|)^{-1} x(|S|)^{-1} \right)$$

and if  $|J|s|$  is equal for all  $s \in S$ , then we can write,

$$\left( \sum_{s \in S} \left( \sum_{j \in J} \left( \left| \left( \sum_{i \in I} \Pr_i^M(j|s) \right) x(n|s)^{-1} - Rate(j|s) \right| \right) \right) x(|J|s|)^{-1} x(|S|)^{-1} \right)$$

**Example 5** Assuming there are only three people, say after calibrating the model  $M$ , in choice set  $s_1$ , the probability of being chosen for person 1,2,3 and for objects  $x,y,z$  are  $(1/4, 1/2, 1/4)$ ;  $(1/6, 1/3, 1/2)$  and  $(3/8, 5/8, 0)$  respectively and  $n$  choice set  $s_2$ , the probability of being chosen for person 4,5,6 and for objects  $a,b,c$  are  $(1/8, 5/8, 1/4)$ ;  $(1/3, 1/2, 1/6)$  and  $(1/4, 1/2, 1/4)$  respectively. So our model predicts that  $x,y,z$  are chosen with probability  $((1/4 + 1/6 + 3/8)x(1/3), ((1/2) + (1/3) + (5/8))x(1/3), ((1/4) + (1/2) + (0))x(1/3)) = (0.26389; 0.48611; 0.25)$  respectively and  $a,b,c$  are chosen with probability  $((1/8) + (1/3) + (1/4))x(1/3), ((5/8) + (1/2) + (1/2))x(1/3), ((1/4) + (1/6) + (1/4))x(1/3)) = (0.23611; 0.54167; 0.22222)$  On the other hand our observations are such that  $x,y,z$  and  $a,b,c$  are chosen by  $(10, 15, 25)$  and  $(4, 5, 2)$  subjects respectively So MAD is  $((|0.26389 - 10/50| + |0.48611 - 15/50| + |0.25 - 25/50|) + (|0.23611 - 4/11| + |0.54167 - 5/11| + |0.22222 - 2/11|)) / (3 \times 2) = 0.12584$ . For this criterion the smaller is the better.

#### 4.2.2.2 Aggregate-level Prediction 2. (ALP2)

This criterion is based on mean squared deviations(MSD). The formula is almost the same, but the square is used instead of absolute value function; if  $|J|s|$  is equal for all  $s$ 's :

$$ALP2^M(S, J, I, Pr^M) = \left( \sum_{s \in S} \left( \sum_{j \in J} \left( \left( \sum_{i \in I} \Pr_i^M(j|s) \right) x(n|s)^{-1} - Rate(j|s) \right)^2 \right) \right) x(|J|s|)^{-1} x(|S|)^{-1}$$

For the example above it gives:

$$\left( \left( \left( (0.26389 - 10/50)^2 + (0.48611 - 15/50)^2 + (0.25 - 25/50)^2 \right) / 3 \right) + \left( \left( (0.23611 - 4/11)^2 + (0.54167 - 5/11)^2 + (0.22222 - 2/11)^2 \right) / 3 \right) \right) / 2 = 2.1117 \times 10^{-2}$$

For this criterion the smaller is the better.

Note that this criterion is not included in Kivetz, Netzer and Srinivasan's (2004) study. But as you see this criterion is very intuitive and resembles MAD.

#### 4.2.2.3 Individual Level Prediction

It is just the maximized value of the likelihood function we calculated when we are conducting Maximum Likelihood Parameter Estimation. The larger is the better.

#### 4.2.2.4 Bayesian Information Criterion (BIC)

BIC is a criterion used when comparing competing models. Intuitively, a model can be very explaining by adding more parameters and sample. So while we are evaluating a model we take into account the individual level of prediction and the number of parameters and sample size.

$$BIC^M = -2 * \ln(L^M) + px \ln(n)$$

where L is the maximized value of likelihood function. p is the number of parameters included. n is the size of the sampling.

For this criterion the less is the better.

#### 4.2.2.5 Akaike Information Criterion (AIC)

$$AIC^M = 2 * p - 2x \ln(L^M)$$

Note that we are not interested in sample size for AIC. For this criterion the less is the better.

## 5 The Results of our Experiment

### 5.1 Existence Results

Our results indicate that for 9 cases, these effects are significant.

The z values for the tests for the Compromise Effect:

1.  $P(x_2 > x_3|x_1, x_2, x_3) > P(x_2 > x_3|x_2, x_3, x_4) \rightarrow 0.2485$
2.  $P(x_3 > x_2|x_2, x_3, x_4) > P(x_3 > x_2|x_1, x_2, x_3) \rightarrow 1.8271$
3.  $P(x_3 > x_4|x_2, x_3, x_4) > P(x_3 > x_4|x_3, x_4, x_5) \rightarrow 1.4193$
4.  $P(x_4 > x_3|x_3, x_4, x_5) > P(x_4 > x_3|x_2, x_3, x_4) \rightarrow 1.5753$
5.  $P(x_4 > x_5|x_3, x_4, x_5) > P(x_4 > x_5|x_4, x_5, x_6) \rightarrow -0.3720$
6.  $P(x_5 > x_4|x_4, x_5, x_6) > P(x_5 > x_4|x_3, x_4, x_5) \rightarrow -0.3071$

and for the Attraction Effect

1.  $P(x_8 > x_{10}|x_7, x_8, x_{10}) > P(x_8 > x_{10}|x_8, x_9, x_{10}) \rightarrow 0.4041$
2.  $P(x_{10} > x_{12}|x_9, x_{10}, x_{12}) > P(x_{10} > x_{12}|x_{10}, x_{11}, x_{12}) \rightarrow 0.1718$
3.  $P(x_{10} > x_8|x_8, x_9, x_{10}) > P(x_{10} > x_8|x_7, x_8, x_{10}) \rightarrow 1.2168$
4.  $P(x_{12} > x_{10}|x_{10}, x_{11}, x_{12}) > P(x_{12} > x_{10}|x_9, x_{10}, x_{12}) \rightarrow 0.1945$

So for all cases, the existence of these effects cannot be rejected.

Additionally there is a violation of WARP.  $P(x_3 > x_4|x_2, x_3, x_4) > P(x_4 > x_3|x_2, x_3, x_4)$  but  $P(x_4 > x_3|x_3, x_4, x_5) > P(x_3 > x_4|x_3, x_4, x_5)$ . Because it is the case in Compromise Effect the implication is that Compromise Effect may cause violations of WARP. This results do not show that the choices from trinary choice sets in which the Attraction Effect prevails, WARP is not violated. The only thing it can be seen that it is not detected for this particular cases.

MODELS/PARAMETERS	$c_1$	$c_2$	b
VMM	-	-	1
GCM	0.45	0.35	0.6
CCM	0.45	0.25	0.35
NCCM	0.5	0.05	0.05

## 5.2 Comparison of the Models

We calibrated the parameters below using Maximum Likelihood Estimation

Because we use MATLAB, we had to choose sensitivity at the expense of speed. For this reason all of the results are at 0.05 sensitivity level.

MODEL/CRITERIA	LL	ALP1	ALP2	BIC	AIC
VMM	0	0.1605	0.6157	<b>60</b>	<b>2</b>
GCM	$1.0246 * e^{-54}$	<b>0.0717</b>	<b>0.1184</b>	180	6
CCM	<b><math>5.8060 * e^{-53}</math></b>	0.0914	0.1933	180	6
NCCM	$9.8024 * e^{-55}$	0.0831	0.1594	180	6

The table above represents the value of all criteria of each model. It indicates the CCM performs better according to LL on the other hand, GCM have better results of ALP1 and ALP2. And Lastly VMM performs better according to BIC and AIC due to its superiority of having less parameter. Additionally, the numerical results here is not alike with the study of Kivetzi Netzger and Srinivasan(2004), because we did not normalize them to 100 or 1000. Their results can be seen below.

The results of Kivetz, Netzger and Srinivasan (2004) can be found below. For parameters, the differences may stem from two different reasons. Firstly, while they calibrated these models for only Compromise effect we did it for both of these effects. The process of Maximum Likelihood Estimation is sensitive such changes which may bring about such inconsistencies.

On the other hand the results below, which belong to the same research, indicate two important results Firstly, NCCM outperformed other models but our model

MODELS/PARAMETERS	$c_1$	$c_2$	b
VMM	Not Calibrated(NC)	NC	NC
GCM	0.8	0.7	0.1
CCM	0.45	0.35	0.4
NCCM	0.05	0.15	0.05

does not have such a result. The second and the interesting result is that, when the Attraction Effect included, then these models are not as explaining as before. However, the loss in the prediction power does not reduce dramatically.

MODEL/CRITERIA	LL	ALP1	ALP2	BIC	AIC
VMM	960	11	NC	963	NC
GCM	965	10	NC	968	NC
CCM	938	6	NC	938	NC
NCCM	920	6	NC	927	NC

## 6 Comments and Further Questions

This study has shown the validity of Compromise and Attraction Effects. Additionally the possible violations of WARP are shown by survey data. Furthermore, the models which may capture these effects are compared and it is shown that none of them is superior to others. The concerns and future questions arisen with this study are as follows.

We observe that some people make decision according to the marginal expenditure. Especially, if the attributes are the size and the affordability, some agents finds the money they pay per size and choose the cheapest. Even though this behavior does not affect the validity of these effects for our setting and data set, in some cases this concern may outweigh these effects.

Additionally, the Compromise and Attraction Effects are not the only framework effects. Endowment Effect, for instance is an important framework effect. People tend to overrate the value of the objects they have. Or sometimes some objects may behave as reference point and it may affect the decision of the agents. I think these both concerns, the marginal expenditure concern and the other framework effects concerns also should be incorporated the models we use and see whether or not they perform well.

Another concern is about the models we used. All the models we use have a convex nature. So combining all concerns the question is: Is it possible to find a better model to explain these effects? A model which has a weaker convex nature incorporated with other framework effects would help us to have better predictions.

The last concern we touch upon is the case dependence. Case dependence is the problem of generalization of basic principles. For instance the choice of the kind of the object may change the validity of the effect. Or the choice of the sizes. Say the object would be a spoon and the size is the perimeter of the spoon. Even though the normal-sized spoon we use is the extreme or Pareto worse one, the agents would choose that one. Or if the prices of the spoons were 100 dollar, 400 dollar, 500 dollar, most people would choose the 100 dollar spoon regardless from the size.

A study focusing on this problem would be a nice starting point to have a better understanding of the choices of people.

The practical implications of the Compromise and Attraction Effect are worth considering. Both of these models can be used product positioning. If producing an object has smaller marginal cost then the firms would create a positioning such that that object is the intermediate or the Pareto better object. This is particularly true for the objects which has not many attributes or have many attributes but the users able to evaluate only two of them. Sometimes, rather than producing three objects which is positioned according to these effects, firms may position their own product in a way that their product is the intermediate or Pareto better object of the market.



The menu for Cafe de Compromise is displayed on a white background with a red and yellow border. The title 'Cafe de Compromise' is centered at the top in a teal serif font. Below it, a horizontal line separates the title from the 'Daily Specials' section, which is also centered. Three items are listed in a cursive font, each with its price in a bold black font to the right.

Cafe de Compromise	
Daily Specials	
<i>Delli Cious</i>	<b>30.00</b>
<i>Ave Rage</i>	<b>20.00</b>
<i>Dis Taste Ful</i>	<b>10.00</b>

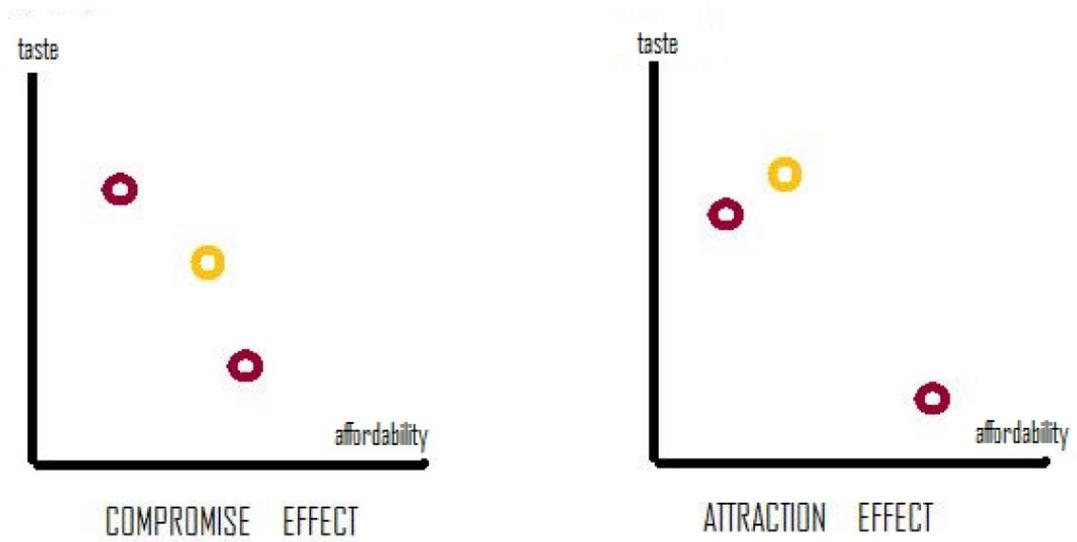
Figure 1: Menu of Cafe de Compromise.



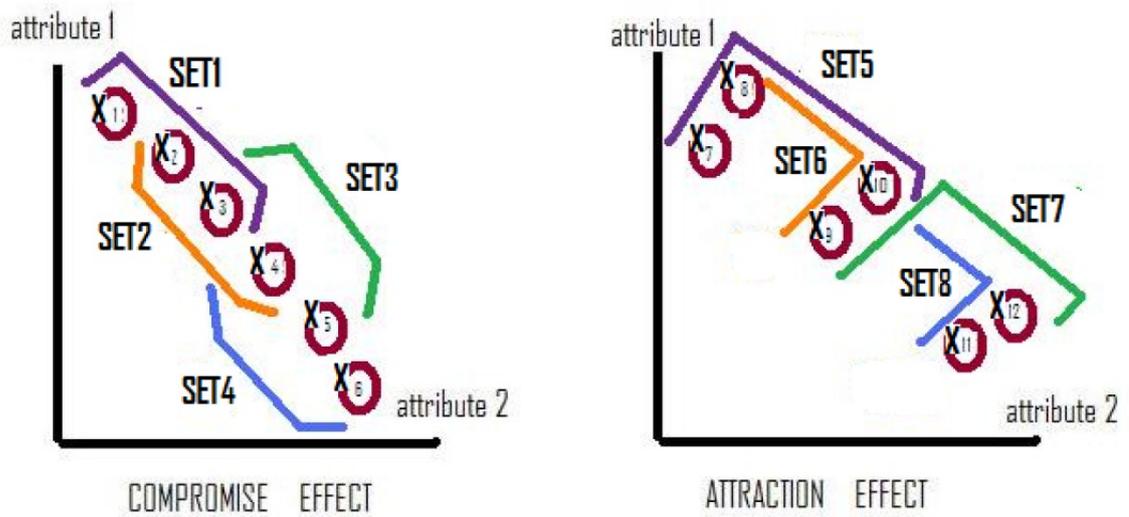
The menu for Cafe de Attraction is displayed on a white background with a red and yellow border. The title 'Cafe de Attraction' is centered at the top in a teal serif font. Below it, a horizontal line separates the title from the 'Daily Specials' section, which is also centered. Three items are listed in a cursive font, each with its price in a bold black font to the right.

Cafe de Attraction	
Daily Specials	
<i>Delli Cious</i>	<b>10.00</b>
<i>Ave Rage</i>	<b>15.00</b>
<i>Dis Taste Ful</i>	<b>5.00</b>

Figure 2: Menu of Cafe de Attraction.



**Figure 3:** Depiction of Compromise and Attraction Effects.



**Figure 4:** The Choice Sets Applied to Subjects.

## 7 Appendix 1: The Survey Sheets

OKUL NUMARAM:

1] Birazdan size bir kaç kısa sorunun sorulacağı bir deney yapacağız. Sorularda doğru veya yanlış cevap yok. Tek amacımız sizin seçimlerinizi gözlemlemek.

Soru 1- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece hafızaları farklı ama **diğer bütün yönleriyle aynı** (fiyat, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	J	K	L	M	N	O
Hafıza	1 GB	2 GB	4 GB	6 GB	8 GB	10 GB
Puanlama	..	..	..	..	..	..

Soru 2- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları farklı ama **diğer bütün yönleriyle aynı** (GB, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	P	Q	R	S	T	U
Fiyat	10TL	15TL	25TL	35TL	45TL	50TL
Puanlama	..	..	..	..	..	..

Soru 3- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
B = 10TL	1 GB	
I = 15TL	2 GB	_ USB belleğini seçerdim.
U = 25TL	4 GB	

Soru 4- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
Y = 15TL	1 GB	
S = 10TL	2 GB	_ USB belleğini seçerdim.
O = 25TL	6 GB	

Soru 5- Elinizde bir A USB'si var. Size bu A USB'sini satın almak yerine B veya C'den birini satın alabileceğiniz söyleniyor. A'dan B'ye ve A'dan C'ye geçmenin sizin için değerini iki değer toplamı 10 olacak şekilde belirleyin. Sizin için daha değerli olan geçiş daha çok puan almalı. (A,B,C GB ve fiyat dışında bütün yönleriyle aynıdır.)

Fiyat	Hafıza	Fiyat	Hafıza		
A 50TL	1GB	B 10TL	1 GB	A'dan B'ye geçiş değerim	..
		C 50TL	10 GB	A'dan C'ye geçiş değerim	..
					+
					10 Puan

OKUL NUMARAM:

2 Birazdan size bir kaç kısa sorunun sorulacağı bir deney yapacağız. Sorularda doğru veya yanlış cevap yok. Tek amacımız sizin seçimlerinizi gözlemlemek.

Soru 1- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece hafızaları farklı ama **diğer bütün yönleriyle aynı** (fiyat, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	J	K	L	M	N	O
Hafıza	1 GB	2 GB	4 GB	6 GB	8 GB	10 GB
Puanlama	..	..	..	..	..	..

Soru 2- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları farklı ama **diğer bütün yönleriyle aynı** (GB, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	P	Q	R	S	T	U
Fiyat	10TL	15TL	25TL	35TL	45TL	50TL
Puanlama	..	..	..	..	..	..

Soru 3- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
I = 15TL	2 GB	
U = 25TL	4 GB	_ USB belleğini seçerdim.
T = 35TL	6 GB	

Soru 4- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
S = 10TL	2 GB	
O = 25TL	6 GB	_ USB belleğini seçerdim.
D = 35TL	4 GB	

Soru 5- Elinizde bir A USB'si var. Size bu A USB'sini satın almak yerine B veya C'den birini satın alabileceğiniz söyleniyor. A'dan B'ye ve A'dan C'ye geçmenin sizin için değerini iki değer toplamı 10 olacak şekilde belirleyin. Sizin için daha değerli olan geçiş daha çok puan almalı. (A,B,C GB ve fiyat dışında bütün yönleriyle aynıdır.)

Fiyat	Hafıza	Fiyat	Hafıza		
A 50TL	1GB	B 10TL	1 GB	A'dan B'ye geçiş değerim	..
		C 50TL	10 GB	A'dan C'ye geçiş değerim	..
					+
					10 Puan

OKUL NUMARAM:

3 Birazdan size bir kaç kısa sorunun sorulacağı bir deney yapacağız. Sorularda doğru veya yanlış cevap yok. Tek amacımız sizin seçimlerinizi gözlemlemek.

Soru 1- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece hafızaları farklı ama **diğer bütün yönleriyle aynı** (fiyat, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	J	K	L	M	N	O
Hafıza	1 GB	2 GB	4 GB	6 GB	8 GB	10 GB
Puanlama	..	..	..	..	..	..

Soru 2- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları farklı ama **diğer bütün yönleriyle aynı** (GB, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	P	Q	R	S	T	U
Fiyat	10TL	15TL	25TL	35TL	45TL	50TL
Puanlama	..	..	..	..	..	..

Soru 3- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
U = 25TL	4 GB	
T = 35TL	6 GB	_ USB belleğini seçerdim.
Ş = 45TL	8 GB	

Soru 4- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
İ = 45TL	10 GB	
O = 25TL	6 GB	_ USB belleğini seçerdim.
D = 35TL	4 GB	

Soru 5- Elinizde bir A USB'si var. Size bu A USB'sini satın almak yerine B veya C'den birini satın alabileceğiniz söyleniyor. A'dan B'ye ve A'dan C'ye geçmenin sizin için değerini iki değer toplamı 10 olacak şekilde belirleyin. Sizin için daha değerli olan geçiş daha çok puan almalı. (A,B,C GB ve fiyat dışında bütün yönleriyle aynıdır.)

Fiyat	Hafıza	Fiyat	Hafıza		
A 50TL	1GB	B 10TL	1 GB	A'dan B'ye geçiş değerim	..
		C 50TL	10 GB	A'dan C'ye geçiş değerim	..
					+ _____
					10 Puan

OKUL NUMARAM:

4) Birazdan size bir kaç kısa sorunun sorulacağı bir deney yapacağız. Sorularda doğru veya yanlış cevap yok. Tek amacımız sizin seçimlerinizi gözlemlemek.

Soru 1- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece hafızaları farklı ama **diğer bütün yönleriyle aynı** (fiyat, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	J	K	L	M	N	O
Hafıza	1 GB	2 GB	4 GB	6 GB	8 GB	10 GB
Puanlama	..	..	..	..	..	..

Soru 2- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları farklı ama **diğer bütün yönleriyle aynı** (GB, görünüş, kalite vs.) olan altı ürün sunuluyor. Daha çok istediğiniz daha fazla puan alacak şekilde USB bellekleri 1,2,3,4,5,6,7,8,9,10 sayılarından istediklerinizi kullanarak puanlayınız.

	P	Q	R	S	T	U
Fiyat	10TL	15TL	25TL	35TL	45TL	50TL
Puanlama	..	..	..	..	..	..

Soru 3- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
A = 50TL	10 GB	
T = 35TL	6 GB	_ USB belleğini seçerdim.
Ş = 45TL	8 GB	

Soru 4- Bir USB belleğe ihtiyacınız var. Dükkana girdiğinizde size sadece fiyatları ve hafızaları farklı diğer bütün yönleriyle aynı (görünüş, kalite vs.) olan üç ürün sunuluyor. Hangisini satın alırdınız?

Fiyat	Hafıza	
İ = 45TL	10 GB	
O = 25TL	6 GB	_ USB belleğini seçerdim.
R = 50TL	8 GB	

Soru 5- Elinizde bir A USB'si var. Size bu A USB'sini satın almak yerine B veya C'den birini satın alabileceğiniz söyleniyor. A'dan B'ye ve A'dan C'ye geçmenin sizin için değerini iki değer toplamı 10 olacak şekilde belirleyin. Sizin için daha değerli olan geçiş daha çok puan almalı. (A,B,C GB ve fiyat dışında bütün yönleriyle aynıdır.)

Fiyat	Hafıza	Fiyat	Hafıza		
A 50TL	1GB	B 10TL	1 GB	A'dan B'ye geçiş değerim	..
		C 50TL	10 GB	A'dan C'ye geçiş değerim	..
					+
					10 Puan

## 8 Appendix 2: The MATLAB Code

```

xlsread ('F.xls');
F=ans; % open the matrix which shows that which person is a member of which group.
xlsread ('U.xls');
U=ans; % open the matrix which shows that what is the rank of the alternatives among
      % other alternatives for each attribute.
xlsread ('exK1K2.xls');
K1K2=ans; % open the matrix which shows the answer to fifth question for each person.
xlsread ('exK1.xls');
K1=ans;% open the matrix which shows the answer to first question for each person.
xlsread ('exK2.xls');
K2=ans;% open the matrix which shows the answer to second question for each person.
xlsread ('C1C2.xls');
C1C2=ans;;% open the matrix which shows the answers to the third and forth questions
for each person.
xlsread ('FU.xls');
FU=ans;;% open the matrix which shows that which alternatives are included in each
choice set.
xlsread ('exS.xls');
S=ans;;;% open the matrix which shows the answers to the third and forth questions
      % for each person in another way

```

```

%-----CALIBRATION-----

```

```

sens=20; %sensitivity
e=exp(1) ; % define number e

```

```

for i=1:sens
    c1(i)=i/sens; % we produce numbers between 0 and 1 for each parameter.
                % We may increase the sensitivity and
                % the the scale but it will increase complexity. 0 and 1
                % is not arbitrary, I have taken them from previous
                % work.
end

```

```

c2=c1 ; % c1 c2 and b are the parameters to be calibrated.
b=c2 ;

```

```

%-----

```

```

% Now we produce partworth values and

```

```

for i=1:size(K1,1)
    for j=1:size(U,2)
        for k=1:2
            if k==1

```

```

        PIJK(i,j,k)=K1(i,U(k,j))* K1K2(i,1) ; %parthworh values

    else

        PIJK(i,j,k)=K2(i,U(k,j))* K1K2(i,2);
    end
end
end
end

%-----

PIKSMIN=1000*ones(size(K1,1),2,8); %startup values for P i,min,s
PIKSMAX=-1000*zeros(size(K1,1),2,8); %startup values for P,i,max,s

%-----

for i=1:size(K1,1)
    for k=1:2
        for s=1:8
            if S(i,s)~=0 % if choice set s is asked to the subject i.

                for j=1:12
                    if FU(s,j)==1 % if choice set s includes good j.
                        if PIJK(i,j,k)< PIKSMIN(i,k,s)
                            PIKSMIN(i,k,s)=PIJK(i,j,k);
                        end

                        if PIJK(i,j,k)> PIKSMAX(i,k,s)
                            PIKSMAX(i,k,s)=PIJK(i,j,k);
                        end
                    end
                end
            end
        end
    end
end

%-----

CCMMIJS=zeros(size(K1,1),12,8,sens,sens);
% startup value for MIJS for CCM.
CCMEBEMIJS=zeros(size(K1,1),12,8,sens,sens,sens);
% startup value for e to the power MIJS for CCM.
CCMPAYDA=zeros(size(K1,1),12,sens,sens,sens);
% startup value for the denominator of the probability function for CCM
CCMPROP=zeros(size(K1,1),12,8,sens,sens,sens);
% startup value for probability function for CCM.

```

```
CCMMLE=ones(sens,sens,sens);
% startup value for maximim likelihood function for CCM.

%-----

GCMMIJS=zeros(size(K1,1),12,8,sens,sens);
GCMEBEMIJS=zeros(size(K1,1),12,8,sens,sens,sens);
GCMPAYDA=zeros(size(K1,1),12,sens,sens,sens);
GCMPROP=zeros(size(K1,1),12,8,sens,sens,sens);
GCMMLE=ones(sens,sens,sens);

%-----

VMMMIJS=zeros(size(K1,1),12,8);
VMMEBEMIJS=zeros(size(K1,1),12,8,sens);
VMMPAYDA=zeros(size(K1,1),12,sens);
VMMPROP=zeros(size(K1,1),12,8,sens);
VMMMLE=ones(1,sens);

%-----

NCCMMIJS=zeros(size(K1,1),12,8,sens,sens);
NCCMEBEMIJS=zeros(size(K1,1),12,8,sens,sens,sens);
NCCMPAYDA=zeros(size(K1,1),12,sens,sens,sens);
NCCMPROP=zeros(size(K1,1),12,8,sens,sens,sens);
NCCMMLE=ones(sens,sens,sens);

%-----

POPULATION=zeros(1,8); % startup value for the matrix which shows
%how many people answered for each choice set.

%-----

PAYRATE=zeros(12,8);
%start up value for the number of the people choosing an alternative from that choice set ↵

RATE=zeros(12,8);
%start up value for the rate of the people choosing an alternative from that choice set

%-----

counter1=size(K1,1)*2*3*sens*sens*sens;
counter2=counter1;
%counters to track the process.

%-----
```

```

% We now calculate the values which is used in the formule of
% each model.ap

for i=1:size(K1,1)

    for s=1:8
        if S(i,s)~=0 % if choice set s is asked to the subject i.

            POPULATION(s)=POPULATION(s)+1 ;
            PAYRATE(S(i,s),s)=PAYRATE(S(i,s),s)+1;

            for j=1:12

                RATE(j,s)=PAYRATE(j,s)/POPULATION(s);

                if FU(s,j)==1 % if choice set s includes good j.

                    for cone=1:sens
                        for ctwo=1:sens
                            for be=1:sens

                                %-----

CCMMIJS(i,j,s,cone,ctwo)= ((PIJK(i,j,1)-PIKSMIN(i,1,s))^c1(cone))+((PIJK(i,j,2)-PIKSMIN
(i,2,s))^c2(ctwo));
CCMEBEMIJS(i,j,s,cone,ctwo,be)= e^(b(be)*CCMMIJS(i,j,s,cone,ctwo));
CCMPAYDA(i,s,cone,ctwo,be)=CCMPAYDA(i,s,cone,ctwo,be)+CCMEBEMIJS(i,j,s,cone,ctwo,be);

                                %-----

GCMMIJS(i,j,s,cone,ctwo)=(PIJK(i,j,1)^c1(cone)+(PIJK(i,j,2)^c2(ctwo));
GCMEBEMIJS(i,j,s,cone,ctwo,be)= e^(b(be)*GCMMIJS(i,j,s,cone,ctwo));
GCM PAYDA(i,s,cone,ctwo,be)=GCM PAYDA(i,s,cone,ctwo,be)+GCMEBEMIJS(i,j,s,cone,ctwo,be);

                                %-----

VMMMIJS(i,j,s)=PIJK(i,j,1)+PIJK(i,j,2);
VMMEBEMIJS(i,j,s,be)= e^(b(be)*VMMMIJS(i,j,s));
VMMPAYDA(i,s,be)=(VMMPAYDA(i,s,be)+VMMEBEMIJS(i,j,s,be));

                                %-----

NCCMMIJS(i,j,s,cone,ctwo)= (((PIKSMAX(i,1,s)-PIKSMIN(i,1,s))^(1-c1(cone))) * ((PIJK(i,
j,1)-PIKSMIN(i,1,s))^c1(cone))) + (((PIKSMAX(i,2,s)-PIKSMIN(i,2,s))^(1-c2(ctwo))) *
((PIJK(i,j,2)-PIKSMIN(i,2,s))^c2(ctwo)));
NCCMEBEMIJS(i,j,s,cone,ctwo,be)= e^(b(be)*NCCMMIJS(i,j,s,cone,ctwo));
NCCMPAYDA(i,s,cone,ctwo,be)=NCCMPAYDA(i,s,cone,ctwo,be)+NCCMEBEMIJS(i,j,s,cone,ctwo,
be);

                                %-----

```

```
counter1=counter1-1
```

```
%-----
```

```
end
```

```
end
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
VMMPAYDA=VMMPAYDA/(sens*sens); %'t was overcounted
```

```
%-----
```

```
% Now we find the probability values for each model and for each
% parameter set.
```

```
for i=1:size(K1,1)
```

```
for s=1:8
```

```
if S(i,s)~=0 % if choice set s is asked to the subject i.
```

```
for j=1:12
```

```
if FU(s,j)==1 % if choice set s includes good j.
```

```
for cone=1:sens
```

```
for ctwo=1:sens
```

```
for be=1:sens
```

```
CCMPROP(i,j,s,cone,ctwo,be)= CCMEBEMIJS(i,j,s,cone,ctwo,be)/CCMPAYDA(i,s,cone,ctwo,be);
```

```
%-----
```

```
GCMPROP(i,j,s,cone,ctwo,be)= GCMEBEMIJS(i,j,s,cone,ctwo,be)/GCMPAYDA(i,s,cone,ctwo,be);
```

```
%-----
```

```
VMMPROP(i,j,s,be)= VMMEBEMIJS(i,j,s,be)/VMMPAYDA(i,s,be);
```

```
%-----
```

```
NCCMPROP(i,j,s,cone,ctwo,be)= NCCMEBEMIJS(i,j,s,cone,ctwo,be)/NCCMPAYDA(i,s,cone,ctwo,be);
```

```
be);
```

```
%-----
```

```
counter2=counter2-1
```

```
%-----
```

```
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
end
```

```
%-----
```

```
% We calculate likelihood values for each parameter set.
```

```
for i=1:size(K1,1)
```

```
for s=1:8
```

```
if S(i,s)~=0
```

```
for cone=1:sens
```

```
for ctwo=1:sens
```

```
for be=1:sens
```

```
CCMMLE(cone,ctwo,be)=CCMMLE(cone,ctwo,be)* CCMPROP(i,S(i,s),s,
cone,ctwo,be);
```

```
%-----
```

```
GCMMLE(cone,ctwo,be)=GCMMLE(cone,ctwo,be)* GCMPROP(i,S(i,s),s,
cone,ctwo,be);
```

```
%-----
```

```
VMMMLE(be)=VMMMLE(be)* VMMPROP(i,S(i,s),s,be);
```

```
%-----
```

```
NCCMMLE(cone,ctwo,be)=NCCMMLE(cone,ctwo,be)* NCCMPROP(i,S(i,
s),s,cone,ctwo,be);
```

```
%-----
```

```
end
```

```
end
```

```
        end
    end
end

%-----

CCMMLC1=-1; %startup values for each parameter for CCM.
CCMMLC2=-1;
CCMMLB=-1;
CCMcounter=0;%this is the counter for the number of parameter sets at which
%likelihood value is maximized.

CCMLL=max(max(max(CCMMLE))) % the maximized likelihood value of CCM.

%-----

GCMMLC1=-1;
GCMMLC2=-1;
GCMMLB=-1;
GCMcounter=0;

GCMLL=max(max(max(GCMMLE)))

%-----

VMMMLB=-1;
VMMcounter=0;

VMMLL=max(max(max(VMMMLE)))

%-----

NCCMMLC1=-1;
NCCMMLC2=-1;
NCCMMLB=-1;
NCCMcounter=0;

NCCMLL=max(max(max(NCCMMLE)))

%-----

%now we find the parameters of maximized likelihood value.

for cone=1:sens
for ctwo=1:sens
for be=1:sens

%-----
```

```
if CCMMLE (cone,ctwo,be)==CCMLL
    CCMLLC1=cone
    CCMLLC2=ctwo
    CCMLLB=be
    CCMcounter=CCMcounter+1
end

%-----

if GCMMLLE (cone,ctwo,be)==GCMLL
    GCMMLC1=cone
    GCMMLC2=ctwo
    GCMMLB=be
    GCMcounter=GCMcounter+1
end

%-----

if VMMMLE (be)==VMMLL
    VMMLB=be
    VMMcounter=VMMcounter+1
end

%-----

if NCCMMLE (cone,ctwo,be)==NCCMLL
    NCCMLLC1=cone
    NCCMLLC2=ctwo
    NCCMLLB=be
    NCCMcounter=NCCMcounter+1
end

%-----

end
end
end

CALIBPARAMETERSVMM=VMMLB;%calibrated parameters
CALIBPARAMETERSGCM=[GCMMLC1 GCMMLC2 GCMMLB];
CALIBPARAMETERSCCM=[CCMLLC1 CCMLLC2 CCMLLB];
CALIBPARAMETERSNCCM=[NCCMLLC1 NCCMLLC2 NCCMLLB];

LL=[VMMLL GCMLL CCMLL NCCMLL]; %maximized likelihood value
```

```
%-----  
  
    % The probabilities after calibration for each model.  
  
for i=1:size(K1,1)  
    for s=1:8  
        if S(i,s)~=0  
            for j=1:12  
  
                PROPCCM(i,j,s)= CCMPROP(i,j,s,CCMMLC1,CCMMLC2,CCMMLB);  
  
                %-----  
  
                PROPGCM(i,j,s)= GCMPROP(i,j,s,GCMMLC1,GCMMLC2,GCMMLB);  
  
                %-----  
  
                PROPVMM(i,j,s)= VMMPROP(i,j,s,VMMMLB);  
  
                %-----  
  
                PROPNCCM(i,j,s)= NCCMPROP(i,j,s,NCCMMLC1,NCCMMLC2,NCCMMLB);  
  
                %-----  
  
            end  
  
        end  
    end  
end  
  
%-----  
  
    %we now calculate ALP1 and ALP values for each model.  
  
CALIBRATECCM=sum (PROPCCM,1) * (1/3);  
  
CALIBRATEGCM=sum (PROPGCM,1) * (1/3);  
  
CALIBRATEVMM=sum (PROPVMM,1) * (1/3);  
  
CALIBRATENCCM=sum (PROPCCM,1) * (1/3);  
  
  
ALP1CCM=0;  
ALP1GCM=0;  
ALP1VMM=0;  
ALP1NCCM=0;  
  
ALP2CCM=0;  
ALP2GCM=0;  
ALP2VMM=0;  
ALP2NCCM=0;
```

```

for s=1:8
    for j=1:12

        ALP1CCM=(ALP1CCM+abs(CALIBRATECCM(1,j,s)-RATE(j,s)))/24;

        ALP1GCM=(ALP1GCM+abs(CALIBRATEGCM(1,j,s)-RATE(j,s)))/24;

        ALP1VMM=(ALP1VMM+abs(CALIBRATEVMM(1,j,s)-RATE(j,s)))/24;

        ALP1NCCM=(ALP1NCCM+abs(CALIBRATENCCM(1,j,s)-RATE(j,s)))/24;

        ALP2CCM=(ALP2CCM+(CALIBRATECCM(1,j,s)-RATE(j,s)).^2)/24;

        ALP2GCM=(ALP2GCM+(CALIBRATEGCM(1,j,s)-RATE(j,s)).^2)/24;

        ALP2VMM=(ALP2VMM+(CALIBRATEVMM(1,j,s)-RATE(j,s)).^2)/24;

        ALP2NCCM=(ALP2NCCM+(CALIBRATENCCM(1,j,s)-RATE(j,s)).^2)/24;

    end
end

ALP1=[ALP1VMM ALP1GCM ALP1CCM ALP1NCCM];
ALP2=[ALP2VMM ALP2GCM ALP2CCM ALP2NCCM];

%-----

%Bayesian Information Criteron

BICCCM= (-2*CCMLL)+3*(size(K1,1)) ; % sample s'ze 12 m' 24 mu
BICGCM= (-2*GCMLL)+3*(size(K1,1)) ;
BICVMM= (-2*VMMLL)+(size(K1,1)) ;
BICNCCM= (-2*NCCMLL)+3*(size(K1,1)) ;

BIC=[BICVMM BICGCM BICCCM BICNCCM];
%-----

%Akeike Information Criteron

AICCCM= (-2*CCMLL)+3*2;
AICGCM= (-2*GCMLL)+3*2 ;
AICVMM= (-2*VMMLL)+2 ;
AICNCCM= (-2*NCCMLL)+3*2 ;

```

```
AIC=[AICVMM AICGCM AICCCM AICNCCM];
```

```
%-----
```

```
%-----EXISTENCE-----
```

```
% we test the existence of the compromise and attraction effect.
```

```
% we test P1(2,3)>P4(2,3)      H1
```

```
%      P4(3,2)>P1(3,2)      H2
```

```
%      P2(3,4)>P5(3,4)      H3
```

```
%      P5(4,3)>P2(4,3)      H4
```

```
%      P3(4,5)>P6(4,5)      H5
```

```
%      P6(5,4)>P3(5,4)      H6
```

```
%                                     for the compromise effect
```

```
%we test P7(8,10)>P9(8,10)    H7
```

```
%      P9(10,12)>P11(10,12)  H8
```

```
%      P9(10,8) > P7(10,8)   H9
```

```
%      P11(12,10) > P9(12,10) H10
```

```
%                                     for attraction effect
```

```
%H1 H2.. are the tests/
```

```
P123=RATE(2,1)/(RATE(3,1)+RATE(2,1)); %these are the p's in the formula.
```

```
P423=RATE(2,2)/(RATE(3,2)+RATE(2,2));
```

```
P432=RATE(3,2)/(RATE(2,2)+RATE(3,2));
```

```
P132=RATE(3,1)/(RATE(2,1)+RATE(3,1));
```

```
P234=RATE(3,2)/(RATE(3,2)+RATE(4,2));
```

```
P534=RATE(3,3)/(RATE(3,3)+RATE(4,3));
```

```
P543=RATE(4,3)/(RATE(4,3)+RATE(3,3));
```

```
P243=RATE(4,2)/(RATE(4,2)+RATE(3,2));
```

```
P345=RATE(4,3)/(RATE(5,3)+RATE(4,3));
```

```
P645=RATE(4,4)/(RATE(5,4)+RATE(4,4));
```

```
P654=RATE(5,4)/(RATE(4,4)+RATE(5,4));
```

```
P354=RATE(5,3)/(RATE(4,3)+RATE(5,3));
```

```
P7810=RATE(8,5)/(RATE(8,5)+RATE(10,5));
```

```
P9810=RATE(8,6)/(RATE(8,6)+RATE(10,6));
```

```
P91012=RATE(10,7)/(RATE(10,7)+RATE(12,7));
```

```
P111012=RATE(10,8)/(RATE(10,8)+RATE(12,8));
```

```
P9108=RATE(10,6)/(RATE(10,6)+RATE(8,6));
```

```
P7108=RATE(10,5)/(RATE(10,5)+RATE(8,5));
```

```
P111210=RATE(12,8)/(RATE(12,8)+RATE(10,8));
```

```
P91210=RATE(12,7)/(RATE(12,7)+RATE(10,7));
```

```
%let us find pooled proportions
```

```
PoolH1=(P123*RATE(2,1)*POPULATION(1)+P423*RATE(2,2)*POPULATION(2))/(RATE(2,1) *  
*POPULATION(1)+RATE(2,2)*POPULATION(2));
```

```

PoolH2=(P432*RATE(3,2)*POPULATION(2)+P123*RATE(3,1)*POPULATION(1))/(RATE(3,2)
*POPULATION(2)+RATE(3,1)*POPULATION(1));
PoolH3=(P234*RATE(3,2)*POPULATION(2)+P534*RATE(3,3)*POPULATION(3))/(RATE(3,2)
*POPULATION(2)+RATE(3,3)*POPULATION(3));
PoolH4=(P543*RATE(4,3)*POPULATION(3)+P243*RATE(4,2)*POPULATION(2))/(RATE(4,3)
*POPULATION(3)+RATE(4,2)*POPULATION(2));
PoolH5=(P345*RATE(4,3)*POPULATION(3)+P645*RATE(4,4)*POPULATION(4))/(RATE(4,3)
*POPULATION(3)+RATE(4,4)*POPULATION(4));
PoolH6=(P654*RATE(5,4)*POPULATION(4)+P354*RATE(5,3)*POPULATION(3))/(RATE(5,4)
*POPULATION(4)+RATE(5,3)*POPULATION(3));
PoolH7=(P7810*RATE(8,5)*POPULATION(5)+P9810*RATE(8,6)*POPULATION(6))/(RATE(8,5)
*POPULATION(5)+RATE(8,6)*POPULATION(6));
PoolH8=(P91012*RATE(10,7)*POPULATION(7)+P111012*RATE(10,8)*POPULATION(8))/(RATE(10,7)
*POPULATION(7)+RATE(10,8)*POPULATION(8));
PoolH9=(P9108*RATE(10,6)*POPULATION(6)+P7108*RATE(10,5)*POPULATION(5))/(RATE(10,6)
*POPULATION(6)+RATE(10,5)*POPULATION(5));
PoolH10=(P111210*RATE(12,8)*POPULATION(8)+P91210*RATE(12,7)*POPULATION(7))/(RATE
(12,8)*POPULATION(8)+RATE(12,7)*POPULATION(7));

```

```
% now we calculate the standard error.
```

```

SEH1=sqrt(PoolH1*(1-PoolH1)*((RATE(2,1)*POPULATION(1))^-1+(RATE(2,2)*POPULATION(2))^-
1));
SEH2=sqrt(PoolH2*(1-PoolH2)*((RATE(3,2)*POPULATION(2))^-1+(RATE(3,1)*POPULATION(1))^-
1));
SEH3=sqrt(PoolH3*(1-PoolH3)*((RATE(3,2)*POPULATION(2))^-1+(RATE(3,3)*POPULATION(3))^-
1));
SEH4=sqrt(PoolH4*(1-PoolH4)*((RATE(4,3)*POPULATION(3))^-1+(RATE(4,2)*POPULATION(2))^-
1));
SEH5=sqrt(PoolH5*(1-PoolH5)*((RATE(4,3)*POPULATION(3))^-1+(RATE(4,4)*POPULATION(4))^-
1));
SEH6=sqrt(PoolH6*(1-PoolH6)*((RATE(5,4)*POPULATION(4))^-1+(RATE(5,3)*POPULATION(3))^-
1));
SEH7=sqrt(PoolH7*(1-PoolH7)*((RATE(8,5)*POPULATION(5))^-1+(RATE(8,6)*POPULATION(6))^-
1));
SEH8=sqrt(PoolH8*(1-PoolH8)*((RATE(10,7)*POPULATION(7))^-1+(RATE(10,8)*POPULATION(8))
^-1));
SEH9=sqrt(PoolH9*(1-PoolH9)*((RATE(10,6)*POPULATION(6))^-1+(RATE(10,5)*POPULATION(5))
^-1));
SEH10=sqrt(PoolH10*(1-PoolH10)*((RATE(12,8)*POPULATION(8))^-1+(RATE(12,7)*POPULATION
(7))^-1));

```

```
%now we compute the z=statistics for every test.
```

```

zH1= (P123-P423)/SEH1;
zH2= (P432-P123)/SEH2;
zH3= (P234-P534)/SEH3;
zH4= (P543-P243)/SEH4;
zH5= (P345-P645)/SEH5;

```

```
zH6= (P654-P354)/SEH6;
zH7= (P7810-P9810)/SEH7;
zH8= (P91012-P111012)/SEH8;
zH9= (P9108-P7108)/SEH9;
zH10= (P111210-P91210)/SEH10;

z=[sign(zH1+2.326) sign(zH2+2.326) sign(zH3+2.326) sign(zH4+2.326) sign(zH5+2.326)
sign(zH6+2.326) sign(zH7+2.326) sign(zH8+2.326) sign(zH9+2.326) sign(zH10+2.326)];

% according to the normal distribution table the ones which has a
%larger value than -2.326 will make us to accept the null hypothesis, the
%existence of these effect the positive numbers indicate the existence
%of these effects

%-----Violations of WARP-----

WARP23= sign(P123-P132)*sign(P423-P432);
WARP34= sign(P234-P243)*sign(P534-P543);
WARP45= sign(P345-P354)*sign(P645-P654);

WARP810=sign(P7810-P7108)*sign(P9810-P9108);
WARP1012=sign(P91012-P91210)*sign(P111012-P111210);

% negative signs indicate a violation.

WARP=[WARP23 WARP34 WARP45 WARP810 WARP1012];

%-----DISPLAY OF RESULTS-----

z

CALIBPARAMETERSVMM
CALIBPARAMETERSGCM
CALIBPARAMETERSCCM
CALIBPARAMETERSNCCM

LL

ALP1

ALP2

BIC
```

AIC

%-----

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