Study of Auction Theory in eBay Data

Introduction:

Auction theory is an important area of study both in theory and in practice. In terms of theoretical significance, auction theory is a very important subdivision of game theory and offers insights into a broad range of other theoretical results. In practice, auction theory is applicable to numerous economic situations. These real life applications can take on scopes ranging from private silent auctions of art pieces to Federal Communications Commission's simultaneous multiple round auctions to distribute spectrum licenses. This paper aims to study some basic properties of auction theories using data extracted from the eBay website. The main thesis of this study is that the sample data collected from eBay shows deviations from the theoretical predictions of bidding behaviors in a second-price auction.

Theoretical Model and Prediction:

There are many types of auctions. One important type is second-price sealed auction. In such auctions, bidders are not aware of other bidders' bids; the highest bidder wins the object and pays the second highest bidding price. Each bidder has his own valuation of the object and he is aware of his own valuation. If only one bidder wins the object, the payoff utility to this sole winner is the difference between his valuation of the object and price he pays for the object (the second highest bid). If K bidders have the highest bid, all of them become winners of the object and the payoff utility to each of them is one Kth of the difference between his valuation of the object and the second highest bid. The auction theory predicts that in a second price auction, the optimal strategy is to bid one's own valuation.

EBay has an auction system that is essentially a second-price auction. Hence it is expected that bidders should bid their own valuations of the item of interest. In particular, the bidders' valuation of the object should be close to but should never exceed the market value of that object.

Data:

The merchandise chosen for this study is Nike dunks shoes. There is no particular criterion in terms of design, category or model for the selection of the commodity. The reason for this choice is as follow:

1. Nike dunks shoes have prices that are relatively consistent with time. There is normally no significant increase or decrease in the value of shoes in time unless the condition of the shoes changes drastically or there is open sale of some particular models.
2. Information of Nike dunks shoes, most importantly their market value and popularity, is readily available online. There are many websites, other than eBay and the Nike official website, that offer Nike dunks shoes for sale. And the items can be found in various conditions (both new and pre-owned).

3. There are a large number of sellers who offer Nike dunks shoes on the eBay website. This results in an abundance of auction items at all time, facilitating the collection of data.
4. Nike dunks shoes are a typical and ordinary item in the consumption bucket for an average consumer. Therefore, it is expected that the consumption behavior for this item should be rational and consistent.

The comprehensive list of data from 60 successful auctions of Nike dunks shoes are collected and recorded. The information contains name of item, condition of item (new/pre-owned), market price, starting price, winning bid amount, shipping fee, duration of auction, number of bidders and number of bids.

Methodology:

- A user account is created on the eBay website. 139 on-going auctions of Nike dunks shoes are added to the watch list over a month in order to track the bidding activities on these items.
- The market prices of the items are determined by searching for identical item on eBay under the buy-it-now option. If an identical item cannot be found, then a similar item that belongs to the same category and series is used. If no similar item is found on eBay, then the item is searched on Google and the lowest price of the item on other websites that offer Nike dunks shoes for sale is used.
- All data are collected and recorded manually.

Assumptions:

Several assumptions on the participants of the auction as well as the auction system itself are made in order to test the theoretical prediction.

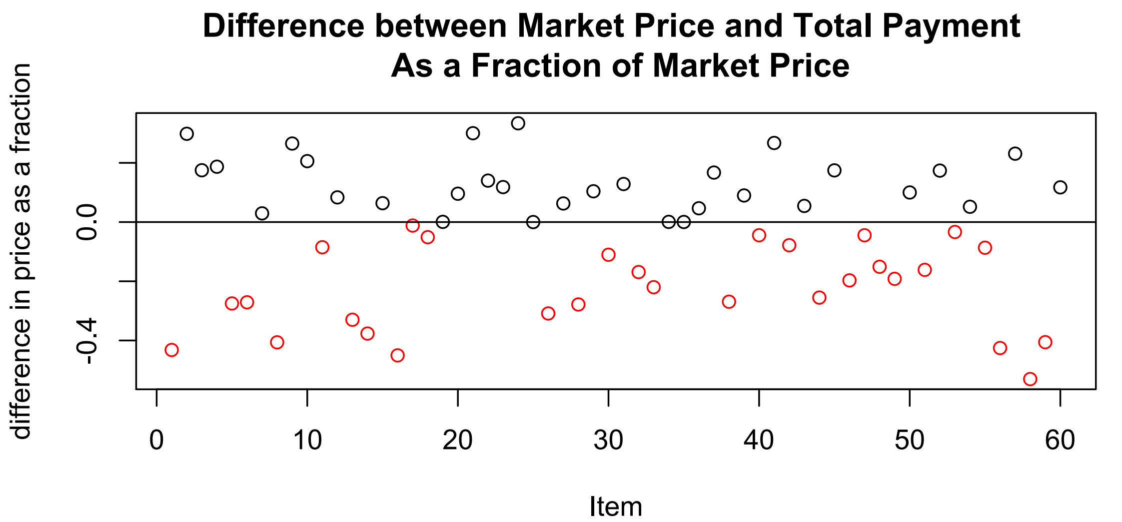
1. Bidders have perfect information of market price of the item and take this information into consideration when making bids.
2. The only utility for the winner of an auction comes from the difference between his valuation of the object and the payment for the object.
3. Bidders do not know other bidders' valuations of the object. Hence bidders do not change their valuations based on the other bidders' bids.
4. An eBay auction resembles a theoretical second-price sealed-bid auction closely.

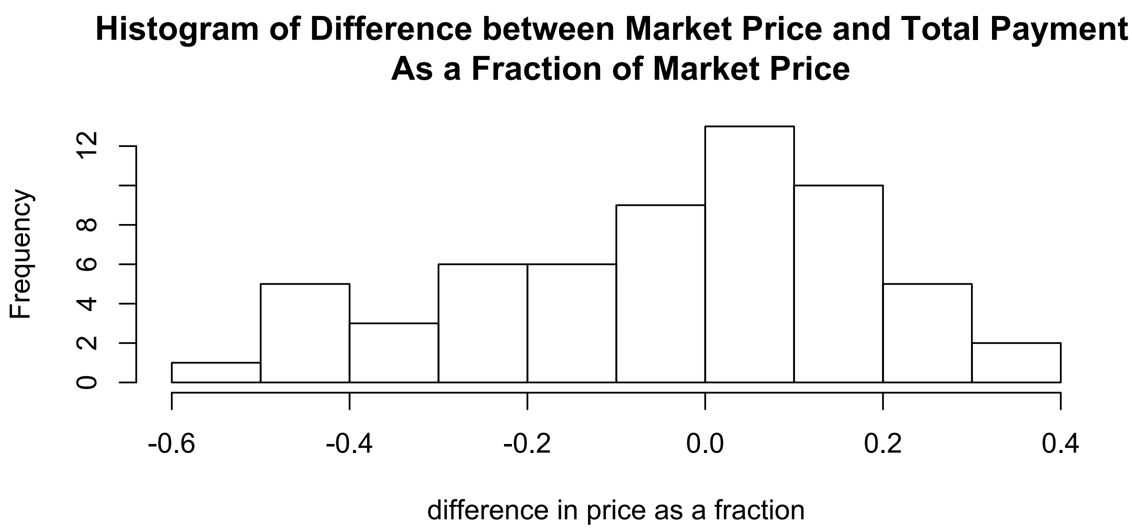
Analysis of data:

First take the shipping fee into consideration and calculate the total payment by the winner as the sum of the final bidding amount and the shipping fee. The argument to be tested in this case is that this total payment should be close to the market value and should never exceed the market value.

In order to visualize the relationship between the total payment and the market price, their differences are taken by subtracting the total payment from the market price. However, it must be noted that different items have different price ranges. This will most likely result in different variances in bidding. In order to make the data more consistent, the differences between the market price and the total payment are taken as a fraction of the market price.

The result can be seen in the plot below:





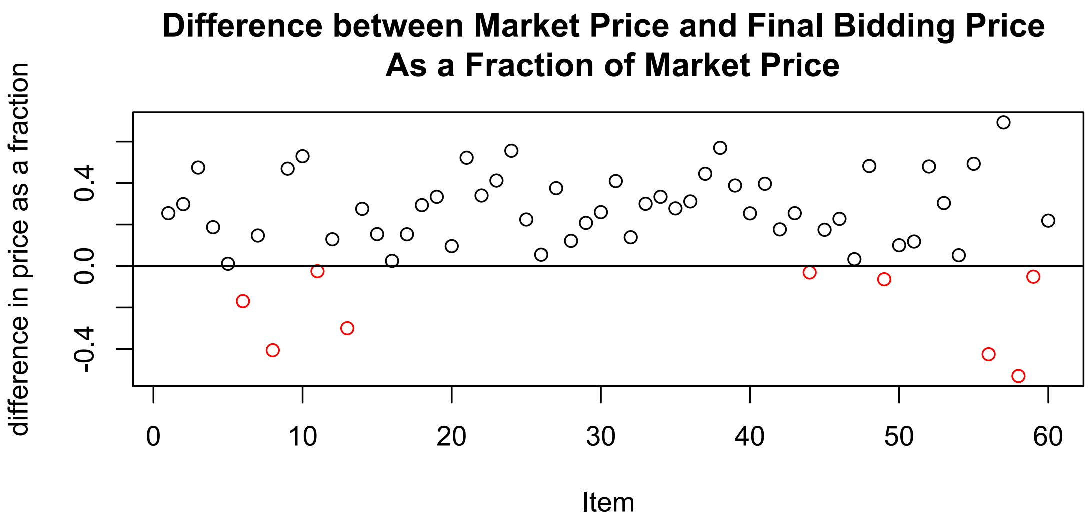
Theoretically, all the points in the first graph should be above the line at 0.0 since the bidders are expected to make bids such that the total payment amount is their own valuation of the object, which should not exceed the market price of the object. If the payment exceeds the market price, the bidder should simply purchase the item elsewhere and would have not participated in the auction in the first place. Yet there are quite a number of points (colored red) that are below the zero line. These are incidences of over-bidding. The second graph shows the rough distribution of the differences obtained. It can be seen that the sample data tend to concentrate around value zero, but there is a significant left tail below zero. Also the percentage of over-bidding behavior in the sample is 48.3%. All these results indicate significant over-bidding behavior in the sample data.

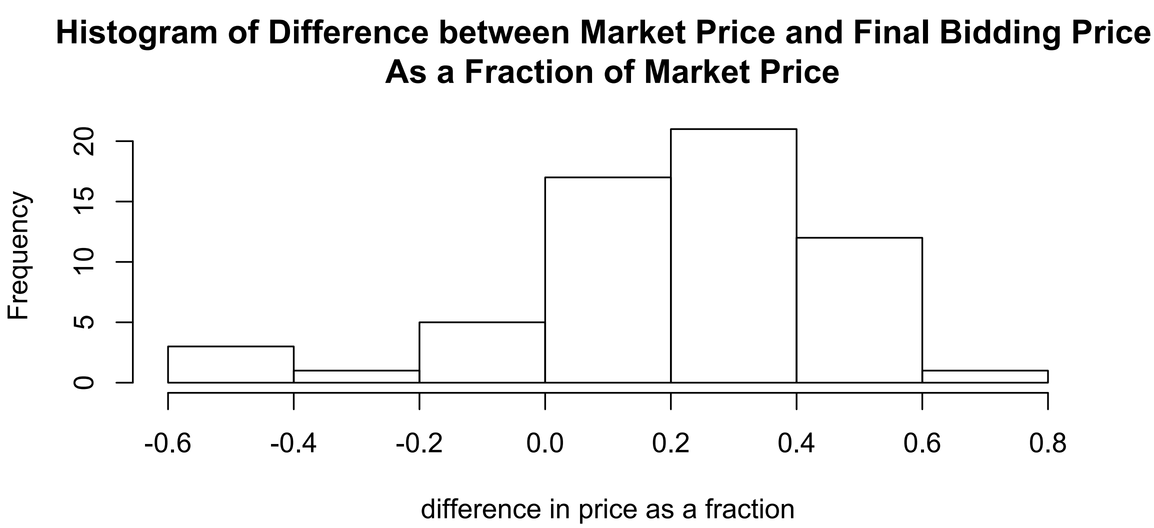
A proportion-test can be performed to test if the over-bidding in the sample is a real concern or can be explained away by chance variable. Set the criteria for randomness to be 5%. This means that if the over-bidding can be accounted for purely by chance or randomness, then the proportion of over-bidding in the sample data should be less than or equal to 5%. The null hypothesis can be expressed as the following: the proportion of over-bidding in the sample is less than or equal to 5%. The alternative hypothesis is that the proportion of over-bidding in the sample is larger than 5%. The result is shown below:

```
> prop.test(length(which(diff<0)),length(diff),
0.05,alternative=c('greater'))

	1-sample proportions test with continuity correction

data:  length(which(diff < 0)) out of length(diff), null
probability 0.05
X-squared = 228.1579, df = 1, p-value < 2.2e-16
alternative hypothesis: true p is greater than 0.05
95 percent confidence interval:
 0.3723439 1.0000000
sample estimates:
        p
0.4833333
```

The p-value is extremely small in this case, indicating that it is highly implausible that the over-bidding is simply by chance. Hence we reject the null hypothesis that the over-bidding in the sample is simply due to chance.

Now repeat the analysis without regard to the shipping fee. The rationale behind this choice is that it is possible that bidders do not consider the shipping cost as a part of the total value of the object even though they have to pay for it eventually. Hence by auction theory, it is expected that the final bidding amount is close to but never exceeds the market value of the item.
The differences between the market price and the final bidding amount are taken as a fraction of the market price. The result can be seen in the plot below:





Theoretically, all the points in the first graph should be above the line at 0.0 since the bidders are expected to make bids that are equal their own valuation of the object, which should not exceed the market price of the object. If the highest bid exceeds the market price at any point during the auction, the bidders should simply stop increasing bids and purchase the item. Yet there are several points (colored red) that are below the zero line. These are incidences of over-bidding. The second graph shows the rough distribution of the differences obtained. It can be seen that most of the differences in fraction concentrate on values above zero and below 0.4. There is a small left tail below zero. The percentage of over-bidding behavior in the sample in this case is 15%. The results indicate a significant decrease in the degree of over-bidding behavior in the sample data when the effect of shipping fee is taken away. But there is still some over-bidding present in the sample.

A proportion test can be performed to test if the over-bidding is a real concern or can be explained away by chance variable. Again, set the criteria for randomness to be 5%. This means that if the over-bidding can be accounted for purely by chance or randomness, then the proportion of over-bidding in the sample should be less than or equal to 5%. The null hypothesis in this case can be expressed as the following: the proportion of over-bidding is less than or equal to 5%. The alternative hypothesis is that the proportion of over-bidding is larger than 5%. The result is shown below:

```
> prop.test(length(which(diff2<0)),length(diff2),
0.05,alternative=c('greater'))

	1-sample proportions test with continuity correction

data:  length(which(diff2 < 0)) out of length(diff2), null
probability 0.05
X-squared = 10.614, df = 1, p-value = 0.0005612
alternative hypothesis: true p is greater than 0.05
95 percent confidence interval:
 0.08306296 1.00000000
sample estimates:
   p
0.15
```

The p-value is 0.0005612. This value is still very small. The test will fail on a 1% significance level. Therefore, there is still significant over-bidding in the sample data. We reject the null hypothesis that the over-bidding in the sample is simply due to chance.

Discussion:

The result from the sample shows deviations from the theoretical predictions about bidding behavior in a second-price auction. There are a number of factors that can account for this deviation. Some possible explanations are discussed below:

1. The assumption that bidders know the market value of the items might not hold in reality. There can be asymmetric information about the market value as different consumers put in different amount of effort researching on the true market value of the item they are bidding for. It is also possible that some bidders simply follow common sense and do not know the exact value of the item.
2. Some bidders experience winning mentality. Specifically, bidders get utility not only from the difference between their own valuation of the item and the payment for the item, but also from simply being the winner of an auction. This encourages over-bidding. This is especially true in the case where the item up for auction is popular and there are a great number of bidders participating in the auction.
3. The basic structure of the eBay auction is not a perfect second-price sealed-bid auction as required by the theory. During an eBay auction, people are able to bid multiple times whereas they are not supposed to in theory. This means that bidders' private valuation of the object is dynamic as the auction goes on instead of being static or fixed. This flexibility encourages bidders to increase their private valuation of the item over time when they see the bidding price keeps going up. Eventually the bidders adjust their bidding amount accordingly, resulting in over-bidding.

Conclusion:

The sample data collected for the purpose of this paper confirms the presence of over-bidding in eBay auctions, a violation of a fundamental result in auction theory. This violation is not surprising because the eBay auction system cannot imitate a second-price theoretical auction perfectly and the real bidders do not behave as expected due to a number of confounding factors. This paper only gives a preliminary result of the subject under study. There are limitations to the sample data as well as the data collection method. One important limitation is the fact that the eBay database is not accessible to the public, resulting in limited sample size and limited validity and rigorousness of conclusion. In addition, the estimated market values of auction objects are not perfectly accurate as most items are pre-owned and it is hard to determine quantitatively the exact value of the item. Moreover, in reality the level of rationality of consumers is bounded, and their bidding behavior can deviate significantly from theoretical rationality. Further studies should attempt to overcome these limitations and look into other types of auctions as well as other aspects of the auction theory such as revenue equivalence and so on.

R-Code:

```
ebay = read.csv("/Users/SeleneX/Desktop/eBay.csv")
names(ebay)

pay=ebay[,5]+ebay[,6]
diff=(ebay[,3]-pay)/ebay[,3]
percentage=length(which(diff<0))/length(diff)*100
above=diff[which(diff>=0)]
below=diff[which(diff<0)]
par(mfrow = c(2, 1))
plot(which(diff>=0),above,xlim=c(1,length(diff)),ylim=c(min
(diff),max(diff)),xlab='Item',ylab='difference in price as
a fraction',main='Difference between Market Price and Total
Payment \n As a Fraction of Market Price')
points(which(diff<0),below,col='red')
abline(h=0)
hist(diff,xlab='difference in price as a
fraction',main='Histogram of Difference between Market
Price and Total Payment \n As a Fraction of Market Price')
prop.test(length(which(diff<0)),length(diff),0.05,alternati
ve=c('greater'))

diff2=(ebay[,3]-ebay[,5])/ebay[,3]
percentage2=length(which(diff2<0))/length(diff2)*100
above2=diff2[which(diff2>=0)]
below2=diff2[which(diff2<0)]
par(mfrow = c(2, 1))
plot(which(diff2>=0),above2,xlim=c(1,length(diff2)),ylim=c(
min(diff2),max(diff2)),xlab='Item',ylab='difference in
price as a fraction',main='Difference between Market Price
and Final Bidding Price \n As a Fraction of Market Price')
points(which(diff2<0),below2,col='red')
abline(h=0)
hist(diff2,xlab='difference in price as a
fraction',main='Histogram of Difference between Market
Price and Final Bidding Price \n As a Fraction of Market
Price')
prop.test(length(which(diff2<0)),length(diff2),0.05,alterna
tive=c('greater'))
```