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Sniping Bargains: Late Bidding on Pairs of eBay Auctions

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Abstract

Internet auctions have resulted in much data that may shed light on buying and selling behavior. Furthermore, they have allowed for field experiments to explore these phenomena with more control and with greater depth. Finally, they have revealed new behavioral patterns worthy of exploration. One of these behaviors is late bidding, or sniping, which occurs when people place bids close to the auction's close to supposedly have a greater chance of winning at a lower price. This study investigated the monetary benefit a user may gain by delaying the decision of which auction to bid on until the last two minutes. It reviewed past data on DVD auctions to examine this effect.

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I. Background Information

Internet auctions have resulted in much data that may shed light on buying and selling behavior. Furthermore, they have allowed for field experiments to explore these phenomena with more control and with greater depth. Finally, they have revealed new behavioral patterns worthy of exploration. One of these behaviors is late bidding, or sniping, which occurs when people place bids close to the auction's close to supposedly have a greater chance of winning at a lower price. This study investigated the monetary benefit a user may gain by delaying the decision of which auction to bid on until the last two minutes. It reviewed past data on DVD auctions to examine this effect.

There has been much work done on eBay auctions in the past. eBay auctions use a proxy bidding system. Each bidder submits the maximum amount they are willing to pay for an item and the system automatically adjusts the appropriate increments whenever new bidders challenge the current price. Before proceeding, it will be useful to review some of the relevant literature describing buyer behavior on eBay.

Multiple Bidding (Ockenfels and Roth 2006)

Ockenfels and Roth, along with other researchers, have explored the phenomenon of multiple bidding. Instead of bidding once, many eBayers bid incrementally, placing multiple bids on the same auction. This is worthy to note, although this study is concerned with late bidding.

Late Bidding (Adapted Mostly from Bajari and Hortaçsu 2004)

Research has proven that late bidding is a common behavior (Bajari 462). Theoretically, late bidding should not be optimal because of eBay's proxy bidding system, which allows bidders to submit a private maximum reservation price for the item and subsequently places bids against competitors as they arrive. In 1961, William Vickrey observed that, in a second-price sealed-bid auction, bidding ones actual reservation price is a weakly dominant strategy because it has a larger chance of winning and the payoff is based on the second-highest bid, so there is no risk of being forced into a higher price (462). However, eBay data reveals late bidding behavior is still occurring. The question is why.

Ely and Hossain demonstrated that sniping produces a benefit, albeit a small one, by bidding on auctions for 20 different newly-released DVDs using 4 different valuation levels. (Ely and Hossain 2006)

Kamins et. al. conducted a field experiment investigating the value of sniping. It involved picking identical items (literally identical descriptions by identical sellers) for 190 coin auctions. They bid at different times, early or sniping, at the median price for previous auctions (averaging $10.50). They find no benefit to sniping but this is limited to these cheap coin lots, which may not be the best product to examine. Additionally, they only placed their bids at the median price. The benefit to sniping could stem from placing lower bids and winning at a higher frequency (Kamins et. al. 2006).

Gray and Reiley bid on 70 pairs of identical items from the same seller ending at the same time. These items included Playstation 2 games, DVDs, coin proof sets, Xbox games, die cast Hot Wheels cars, and Game Boy Advance games. They found a 2.54% price benefit to sniping, which was not statistically significant. This experiment seems very limited, since they only chose pairs of items from the same seller which means their sample was limited to sellers selling identical items at the same time. They also deliberately bid high enough to win every auction, relying on high values such as book values from pricing guides or the actual price of a new DVD in Walmart, in order to make their bids (Gray and Reiley 2004).

Ockenfels and Roth compared eBay auctions for computers and antiques with Amazon.com auctions for the same items (2003). They did so because Amazon.com auctions have a different ending rule which extends the length of the auction for ten minutes past the last bid, possibly removing a benefit from last-minute bidding. Ockenfels and Roth theorized that late bidding is a form of tacit collusion amongst bidders to attempt to have softer competition. While late bidding creates an inherent risk that the bid may not be transmitted, this risk implies cheaper prices to those bidders whose bids get submitted. Ockenfels and Roth's study revealed that last-minute bidding was much more prevalent on eBay than Amazon (and almost nonexistent on Amazon), suggesting that the idea of prohibiting competition is a huge factor driving this behavior. However other studies comparing hard endings with flexible endings do not produce the same results (Bajari 462-463).

Hasker, Gonzalez, and Sickles attempted to replicate the study to evaluate tacit collusion. They examined bids for computer monitors on eBay, reasoning that the winning price distributions from late bids should be more favorable to buyers than the distributions from early bids. They could not prove an inequality between these two distributions, contributing to additional evidence against the tacit collusion theory (Bajari 463). Bajari and Hortaçsu (2003) also examined a data set of eBay coin auctions and found that, based on regressions, early bidding is not correlated with increased final sales prices (463).

An alternative explanation to tacit collusion, also put forth by Ockenfels and Roth (2003), is bidder naïveté. The argument is that newer bidders make incremental bids in response to competitors because of a limited understanding of the proxy-bidding mechanism, so experienced bidders wait until the end in the hopes of limiting their bidding and securing a lower price. Ockenfels and Roth presented empirical evidence demonstrating that experienced bidders are less likely to make multiple bids. This research is bolstered by a controlled laboratory experiment understaken by Ariely, Ockenfels, and Roth (463), in which they conducted an eBay-type fixed-deadline auction with no probability of losing a bid in transmission. This should remove the benefits of tacit collusion, but there was still last minute bidding because it is a good response to naïve bidders.

Another explanation put forth in the research is that bidders hold private information about the item's true value, and by bidding early they signal this information to other bidders and increase the final price. Studies on eBay reveal that this factor could be encouraging late bidding. One study finds last minute bidding to be more prevalent in antiques auctions than in computer auctions, which makes sense based on this theory because antiques may contain more of this hidden information than commodities like computers (Bajari 463-464).

Wang suggests that multiple auctions available for the same item contribute to last minute bidding (Wang 2003). Wang makes note of the fact that multiple auctions for the same item affect bidding behavior, so auctions should not be viewed as independent events. He suggests that even though last minute bidding is produced by multiple auctions, there still is no real benefit to sniping because the final prices end up being the same.

One other possible reason for late bidding is that bidders may not know their personal valuation of an item and, rather than search for it and incur added research costs, they simply wait until the end of the auction to make a decision (Bajari 464).

Alternatively, a seemingly unexamined area that may contribute to late bidding is the real cost of lock-in. By bidding early on an auction, a bidder is committing themselves to the auction and they must wait until they are outbid before pursuing another item. If this is a seven day auction, and they are outbid in the final minutes, the bidder has lost 7 days during which time they could have purchased an alternative item were they not locked into this auction. There is thus an economic value to being free to pursue other items instead of being locked into this uncertain contract.

Product Variation in Last Minute Bidding

The benefits from last minute bidding may vary from product to product. Schindler found that sellers use automatic extensions more often for art and cars, but not for computers, implying that the first two products might fuel more tacit collusion (Bajari 463). Other research has also demonstrated that the amount of late bidding and multiple bidding vary across different products (Borle et. al. 2006).

Forward Looking Bidding (adapted from Zeithammer 2006)

Robert Zeithammer has proposed a new model of equilibrium bidding assuming that the bidder knows the item will be available in future auctions. Rather than view the auction as an isolated event, many consumers bid on items such as DVDs in which the same item will be offered again soon after. The bidder is faced with a choice of winning now at a higher price but thereby sacrificing future surpluses that could be gained from bidding later. Assuming the bidder knows that there will be more auctions on the horizon, he should revise his bids downward with the hope of attaining this surplus. Zeithammer's model explores three scenarios in which bidders use different amounts of information:

1. Bidders do not pay attention to any future information at all.
2. Bidders only look at the frequency of future auctions available (eBay shows auctions for similar items ending soon). These bidders reduce their bids more when there are more auctions ending soon because they see the other opportunities.
3. Bidders can examine the near auctions in more depth to explore if the attributes of the product meet their needs. They will revise their bids downward if there are more desirable items coming up.

To test his theory, Zeithammer investigated different mp3 player brands and different DVD movies as different product types. His findings supported this model over a simpler one that ignored sequential auctions.

Zeithammer's work suggests that it is important to review other auctions when examining demand side strategies on eBay.

Anwar, McMillan, and Zheng conducted a study by examining eBay data for CPUs over a four month period and found that bidders do exhibit a cross-bidding strategy and when they do this leads to a lower price (Anwar et. al. 2006).

2. Introduction to this Study

This study will continue to look at auctions as a sequential set of opportunities as opposed to independent events. However, it combines these two approaches – late bidding and sequential auction strategies – to see if choosing between auctions leads to an economic benefit to sniping.

Research Worthy of Note in Designing Our Experiment

In designing the experiment, it is important to pay attention to total price. The total price paid includes sales price and shipping. Research has shown buyers tend to pay higher total prices if there is a lower ending sales price, possibly because of processing the two components in different mental accounts (Hossain and Morgan 2006). While the dataset on shipping prices was incomplete and the taxes are idiosyncratically administered, the experiment was run including and excluding what shipping prices were included in the data in order to see if there was an effect. Regressions were run with independent variables of whether or not the shipping or tax was included in order to ensure there were no significant differences in the results because of these variables.

Other important factors to note and control for in the experiment include seller feedback rating (much research has been done regarding its impact on auctions) and closing time of the auctions. Controls were included for these factors as well.

3. Methodology

This study analyzed a comprehensive dataset of DVD auctions on eBay which ended in October of 2002. This data includes each bidder's proxy bids (it lists the highest amount they are willing to pay, which is more than the item actually sold for in most cases). Pairs of auctions were chosen ending within 120 minutes of one another, assuming that buyers would choose between two auctions for the same DVD title. Within each pair, the price of the items 2 minutes before its end and the price 2 days before its end were noted, and the best deal was chosen in each scenario.

The proxy bid of the highest bidder (or the starting price if there was no highest bidder) was examined along with the auctions' bidding increment and shipping prices to determine:

1) How much a theoretical extra bidder would have to pay to win this auction.
2) If the theoretical bidder would bid if he held out for the 25th percentile or less (the individual price distributions for each movie title were used to compute these percentiles).

For each item pair, these choices were made at both the early and late times, and the amount paid was recorded. Moreover, whether the amount paid was in the 25th percentile or less was also recorded. Then, the differences in these amounts across the early and late condition were examined.

It was hypothesized that there would be statistically significant benefits to bidding late because the prices at that time more accurately reflect the final price, allowing the bidder to choose a better bargain.

The Data Set
This data set was furnished by eBay, and originally provided to Uri Simonsohn. It includes 35,888 different bids on 8,086 different items selling 54 different DVD titles. The data includes a wide variety of variables for each discrete bid. The relevant features for this study include:

- Item ID
- Movie title
- Used or new?
- Start price
- Proxy bid amount
- Bid increment
- Actual price at time of bid
- Start and end date and time
- Shipping price, when available
- Seller feedback rating
- Sold in eBay store or not?
- Shipping price included or not?
- Need to pay tax or not?

The Sorting Algorithm to Select Auction Pairs
The time each auction ended was standardized to the amount of minutes until November 30, 2002 at 11:59 PM. This data was then sorted first by movie, then by when the auction ended.

A sorting algorithm was developed to search for sets (thanks to much help from Vijay Nagappan). The difference between the end time of the auctions was examined to ensure that they ended within 120 minutes of each other. If more than one item could fit in the 120 minute span, the algorithm used a random number generator to decide which items became sets. The algorithm performed multiple sweeps and it paired remaining items into sets as well, even though they were more than 120 minutes apart. These extraneous sets were then removed.

4,238 items were placed in 2,119 pairs ending within 120 minutes of one another. 542 of the pairs were of two used items, 728 pairs were a mix of new and used items, and 849 pairs were of two new items.

More descriptive data was generated on the sets including:

- Unique set ID linked to both items in each pair
- Difference in time between when the two items end
- Difference in seller feedback fating
- Difference in seller feedback rating / average of the two ratings (to standardize)
- Set type - whether the set was both used, both new, or mixed

The Lookup Table

The items in each set were compared to one another. A table was developed to search for the price at any time. Algorithms were developed to find the price for each item at 2 minutes and 2880 minutes (2 days). Whichever item had a cheaper price was the "choice" made at that time.

Once this choice was made, the proxy bid of the highest bidder on the item was combined with the increment (and in some cases the shipping price) to determine the amount one would have to pay to win the auction. That amount was recorded as an absolute value of price paid in each scenario.

The early condition was subtracted from the late condition in all of the analyses of differences between the scenarios. It was hypothesized that the results would be negative, indicating that the late condition was a better buy. Two effects, a price and a frequency effect, were examined using the amounts paid for the equivalent early and late scenarios.

A. Price Effect – The difference between the price paid in the early and late scenarios was examined as an absolute value.
B. Frequency Effect – If the amount to win was less than or equal to the 25th percentile value for that movie, it was recorded that the bidder would win this item at a bargain price. Then the frequency of winning across the early and late scenarios was compared.

There were some complications with the data. Bids which did not include the minutes until the end of the auction were excluded from the pricing table. This totaled 9,884, or 27.54%, of the 35,888 bids.

Controls
Each item pair's early and late scenario were used as controls for one another. After this process, regressions were used to see if there was a statistically significant correlation between the results and the movie title, the time of the auction, the seller's feedback rating, whether the items were old or new, what the composition of the set was in terms of old and new items, the amount of time between sets, and whether the item contained a shipping price, tax, or was sold in an eBay store.

4. Results

When shipping prices were excluded, the mean in the late condition was \$.016 greater than that of the early condition. When they were included, the mean in the late condition was \$.0035 less than that of the early condition. Neither of these relationships was statistically significant, indicating that there is no price effect.

When shipping prices were excluded, the mean chance of winning at the 25^{th} percentile or less in the late condition was .0019 lower than that of the early condition. When they were included, the mean chance of winning at the 25^{th} percentile or less in the late condition was .0024 lower than that of the early condition. Neither of these relationships was statistically significant, indicating that there is no frequency effect.

The statistical analysis of these effects is included in Appendix A. The effects were so small because most of the prices of the items did not change between 2 days and 2 minutes before the auctions ended.

5. Limitations

Of the 4,238 items, 2,926 (69.04%) items had the same price 2 minutes and 2 days before the auction ended. 914 (21.57%) items had greater prices 2 minutes before the auction ended and 398 (9.39%) had greater prices 2 days before the auction ended. 9.39% is quite a large number of items with prices heading in the downward direction as time goes on and it suggests that there may be some flaws in the data.

In addition, 27.54% of the bids were removed but the rest of the bids on any item were allowed to remain, so items were still included in the study even though their bidding history might have been altered. This may have resulted in inaccuracies in the pricing model.

Finally, sets were selected at random and controls were added later through a regression. Although the control regressions demonstrate that most of the control variables did not have any relationship with the difference between prices of items chosen in the early and late condition or the chance of the price being in the 25^{th} percentile or less, there were some variables that were significant (See Appendix B). Note that, while some variables were significant in these regressions, the R square values were extremely low, between .02 and .05, because the vast majority of items had no difference across the early and late condition.

The difference in the seller's feedback rating when compared to the average of the two ratings in a pair had a statistically significant slightly positive impact on the difference between the chance of winning at a price at or lower than the 25th percentile price (including shipping) in the early and late condition. This effect was slightly positive.

The movie title had a statistically significant effect on everything (including and excluding shipping prices), with different titles working in both directions.

In order to test the reason for this significance, the correlations of the individual regression coefficients for each movie title with the average price of that movie, standard deviation in that movie's price distribution, and number of items available for that movie title were examined. This was to explore the direction of any possible relationship between those variables and the regression coefficients.

Further, new simple linear regressions were run to map these variables on the p-values of those original regression coefficients. This was to test if the variable had a statistically significant relationship with the statistical significance of the regression coefficients. The correlation examined what the relationship was between each variable and the regression coefficient, while these regressions determined if that relationship mattered.

Finally, the coefficients of these latter regressions were used to examine how these variables were related to the significance of the movie coefficient. The coefficient here assessed in what way the variable impacted the statistical significance of the discrepancies whereas the coefficient from the original regression assessed in what way it impacted the actual values.

The results of this analysis are summarized in Appendix C. There was only one relationship that was almost statistically significant – the standard deviation of a movie's price distribution had a negative impact on the chance of winning at the 25th percentile price or less. The standard deviation of the movie's price distribution had a p-value of .057 if shipping prices were excluded, and .074 if they were included.

6. Discussion

This study found no economic benefits to late bidding. By controlling for each pair of items against themselves, and incorporating data on the hidden proxy bids to determine exactly how much a bidder would have to pay to win an item, this finding appears to be more robust than some of the other literature. However, the study's limitations may warrant further exploration with another historical dataset.

Despite the limitations to this study, there are some important insights that can be drawn from its analysis of item histories. First, the majority of items had the same prices 2 days and 2 minutes before the auction's close. This is important because it implies that waiting may not increase the amount of information available about the item's closing price.

Another interesting effect in this study was the fact that movie titles did make a difference, and this difference was not related to the average price. This suggests that differences in consumer tastes may be related to the manner in which they place bids, making late bidding an optimal strategy for some titles.

Although this finding was not significant, the fact that the standard deviation of movie prices had a negative impact on the chance of winning the title for a price at or lower than the 25th percentile is surprising because intuitively a larger spread might increase one's chances.

7. Future Research

Future research could examine larger sets of items and a more extreme time interval for early bidding (2 days was chosen in this study because some auctions only have a duration of 3 days). Further analyses were not conducted in this study because an endogenous ending rule was developed before the research began to protect against the follies of data mining.

So far research has demonstrated that there is no economic benefit to sniping, and this study is consistent with the literature. However, one possible flaw in the research is the need for controls, a need which forces researchers to ignore non-commoditized products. Future research may be able to tackle this problem with a carefully constructed simulation experiment which forces artificial budget constraints and utility functions onto a community of people bidding on one-of-a-kind items. The person who maximizes his utility (as defined by the experiment) would win a monetary prize. This type of experiment may reveal economic benefits to late bidding.

Another facet of late bidding worthy of future research is the real economic cost of lock-in. By bidding early, bidders are locked into a contract which they do not know they will win. A study examining the relationship between time pressure in making a purchase decision and the amount of late bidding could demonstrate a time effect which may help explain late bidding.

Finally, there might be a number of psychological effects that contribute to the abundance of late bidding. In the future, it might be useful to measure utility instead of dollars when exploring the benefits of late bidding.

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9. Appendix A: T Tests for Differences Between Means in Early and Late Conditions

T Tests									
T Test	Mean1 (Late)	Standard Deviation 1	Mean2 (Early)	Standard Deviation 2	Difference Between Means (Late-Early)	DF	T Stat	P Value (One-Sided)	P Value (Two-Sided)
Prices in Early and Late Conditions (Excluding Shipping)	11.31851	2.9421388	11.3025	2.9702997	0.01603587	4237	0.2497	0.40142	0.8028
Prices in Early and Late Conditions (Including Shipping)	13.9567	3.4052137	13.9602	3.4355638	-0.0035064	4237	-0.047	0.48118	0.9624
Chance of Winning in 25th Percentile in Early and Late Condition (Excluding Shipping)	0.026899	0.1618088	0.02879	0.1672276	-0.0018877	4237	-0.528	0.29873	0.5975
Chance of Winning in 25th Percentile in Early and Late Condition (Including Shipping)	0.032091	0.1762615	0.03445	0.1824041	-0.0023596	4237	-0.606	0.27241	0.5448

10. Appendix B: Statistical Analysis to Control for Effects of Other Variables

Note: All prices are the prices it would take to win the auction chosen in the set. Each set has 2 data points, one for each item in the set (and each item has some unique characteristics).

Response Variable: Price Difference Between Early and Late Condition (Excluding Shipping Price)

Summary of Fit

RSquare	0.022971
RSquare Adj	0.007958
Root Mean Square Error	1.168153
Mean of Response	0.013485
Observations (or Sum Wgts)	4230

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	64	133.6243	2.08788	1.5301
Error	4165	5683.4781	1.36458	Prob > F
C. Total	4229	5817.1024		0.0044

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	4153	5683.4525	1.36852	641.4925
Pure Error	12	0.0256	0.00213	Prob > F
Total Error	4165	5683.4781		<.0001
				Max RSq
				1.0000

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.1740201	0.129869	1.34	0.1803
Mov[15 Minutes]	0.0024428	0.309804	0.01	0.9937
Mov[40 Days and 4]	0.0965037	0.106274	0.91	0.3639
Mov[A Knight Ta]	-0.709959	0.408886	-1.74	0.0826
Mov[Along Came]	-0.012337	0.273908	-0.05	0.9641
Mov[Americas Sw]	0.0551485	0.157562	0.35	0.7263
Mov[Angel Eyes]	-0.111922	0.47439	-0.24	0.8135
Mov[Big Fat Liar]	0.0389656	0.109168	0.36	0.7212
Mov[Blade 2]	0.0577103	0.119484	0.48	0.6291
Mov[Blow]	-0.008294	0.220777	-0.04	0.9700
Mov[Boiler Room]	-0.934392	0.470972	-1.98	0.0473
Mov[Bridget Jon]	0.5100302	0.365267	1.40	0.1627
Mov[Cast Away]	0.0549663	0.191938	0.29	0.7746
Mov[Changing Lane]	-0.046599	0.098858	-0.47	0.6374
Mov[Count of Mont]	0.1875203	0.095437	1.96	0.0495
Mov[Evolution]	0.0015737	0.813742	0.00	0.9985
Mov[Fight Club]	0.3482919	0.260096	1.34	0.1806
Mov[Frailty]	-0.030207	0.408838	-0.07	0.9411
Mov[Grease]	-0.046991	0.151063	-0.31	0.7558
Mov[Hard Day's Ni]	0.3485895	0.290324	1.20	0.2299
Mov[Heartbreake]	0.0767483	0.575343	0.13	0.8939
Mov[High Crimes]	0.053435	0.129528	0.41	0.6800
Mov[How the Gri]	0.2848356	0.207129	1.38	0.1692
Mov[Independenc]	0.0402731	0.309883	0.13	0.8966
Mov[Jurassic Pa]	0.061672	0.290382	0.21	0.8318
Mov[Lara Croft:]	0.1328232	0.178463	0.74	0.4568
Mov[Lord of the R]	0.0177946	0.063542	0.28	0.7795
Mov[Memento]	0.338778	0.187638	1.81	0.0711
Mov[Monsters inc.]	0.0957052	0.072429	1.32	0.1865
Mov[Moulin Roug]	-0.02692	0.365501	-0.07	0.9413
Mov[Murder by Num]	0.0461485	0.274453	0.17	0.8665
Mov[O Brother]	0.2405006	0.290218	0.83	0.4073
Mov[Panic Room]	0.0228009	0.080443	0.28	0.7769

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mov[Pearl Harbo]	0.1449198	0.119323	1.21	0.2246
Mov[Planet of t]	0.2883771	0.121138	2.38	0.0173
Mov[Pulp Fiction]	0.0027967	0.111888	0.02	0.9801
Mov[Reservoir Dog]	-0.576749	0.138632	-4.16	<.0001
Mov[Rookie]	0.0626791	0.07479	0.84	0.4020
Mov[Rush Hour 2]	-0.07445	0.1819	-0.41	0.6823
Mov[Scary Movie]	-0.793773	0.248781	-3.19	0.0014
Mov[Scream 3]	-0.039679	0.575938	-0.07	0.9451
Mov[Shrek]	0.5852858	0.156333	3.74	0.0002
Mov[Swordfish]	0.0366721	0.238216	0.15	0.8777
Mov[The Family]	-0.061082	0.334306	-0.18	0.8550
Mov[The Green M]	-0.215903	0.207045	-1.04	0.2971
Mov[The Hurrica]	0.0253753	0.813408	0.03	0.9751
Mov[The Matrix]	-0.051717	0.16785	-0.31	0.7580
Mov[The Mexican]	-0.01429	0.248131	-0.06	0.9541
Mov[The Mummy R]	-0.312298	0.229577	-1.36	0.1738
Mov[The Princes]	0.0329551	0.260593	0.13	0.8994
Mov[The Score]	-0.189537	0.366324	-0.52	0.6049
Mov[The Sixth S]	-0.084562	0.174533	-0.48	0.6281
Mov[True Romance]	0.0508576	0.174649	0.29	0.7709
Mov[Van Wilder (u]	-0.089926	0.169112	-0.53	0.5949
Set Type[Mix]	-0.012126	0.02669	-0.45	0.6496
Set Type[New]	-0.038173	0.043466	-0.88	0.3799
New?[0]	0.0030694	0.03083	0.10	0.9207
Store?[0]	-0.000704	0.045026	-0.02	0.9875
Ship?[0]	-0.022094	0.021819	-1.01	0.3113
Tax?[0]	-0.091575	0.047945	-1.91	0.0562
Min Til 11/30	-0.000002	0.000001	-1.24	0.2162
Min Apart	-0.001261	0.00052	-2.42	0.0154
Seller Rating	0.0000025	0.000009	0.27	0.7863
Seller Rating Difference	-0.000003	0.000008	-0.33	0.7446
Seller Rating Difference / Avg	0.1195031	0.066266	1.80	0.0714

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Mov	53	53	108.70740	1.5031	0.0109
Set Type	2	2	1.75931	0.6446	0.5249
New?	1	1	0.01353	0.0099	0.9207
Store?	1	1	0.00033	0.0002	0.9875
Ship?	1	1	1.39927	1.0254	0.3113
Tax?	1	1	4.97817	3.6481	0.0562
Min Til 11/30	1	1	2.08756	1.5298	0.2162
Min Apart	1	1	8.01278	5.8720	0.0154
Seller Rating	1	1	0.10027	0.0735	0.7863
Seller Rating Difference	1	1	0.14487	0.1062	0.7446
Seller Rating Difference / Avg	1	1	4.43785	3.2522	0.0714

Response Variable: Price Difference Between Early and Late Condition (Including Shipping Price Where Available)

Summary of Fit

RSquare	0.02747
RSquare Adj	0.012526
Root Mean Square Error	1.545301
Mean of Response	-0.00609
Observations (or Sum Wgts)	4230

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	64	280.930	4.38953	1.8382
Error	4165	9945.831	2.38795	Prob > F
C. Total	4229	10226.760		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	4153	9894.5649	2.38251	0.5577
Pure Error	12	51.2656	4.27213	Prob > F
Total Error	4165	9945.8305		0.9563
				Max RSq
				0.9950

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	0.0801492	0.171798	0.47	0.6409
Mov[15 Minutes]	0.0054201	0.409827	0.01	0.9894
Mov[40 Days and 4]	0.0398859	0.140585	0.28	0.7766
Mov[A Knight Ta]	-2.632842	0.540898	-4.87	<.0001
Mov[Along Came]	-0.019732	0.362341	-0.05	0.9566
Mov[Americas Sw]	0.04908	0.208433	0.24	0.8139
Mov[Angel Eyes]	-0.178649	0.627551	-0.28	0.7759
Mov[Big Fat Liar]	0.0614237	0.144414	0.43	0.6706
Mov[Blade 2]	-0.094363	0.15806	-0.60	0.5505
Mov[Blow]	-0.020924	0.292056	-0.07	0.9429
Mov[Boiler Room]	0.713306	0.62303	1.14	0.2523
Mov[Bridget Jon]	1.4881128	0.483197	3.08	0.0021
Mov[Cast Away]	0.0623394	0.253906	0.25	0.8061
Mov[Changing Lane]	0.0280162	0.130775	0.21	0.8304
Mov[Count of Mont]	0.1740014	0.12625	1.38	0.1682
Mov[Evolution]	0.0332528	1.076465	0.03	0.9754
Mov[Fight Club]	0.3523844	0.34407	1.02	0.3058
Mov[Frailty]	-0.080872	0.540835	-0.15	0.8811
Mov[Grease]	-0.130902	0.199835	-0.66	0.5125
Mov[Hard Day's Ni]	-0.03782	0.384058	-0.10	0.9216
Mov[Heartbreake]	0.0387909	0.761097	0.05	0.9594
Mov[High Crimes]	0.0584435	0.171348	0.34	0.7331
Mov[How the Gri]	0.3272417	0.274002	1.19	0.2324
Mov[Independenc]	0.0527668	0.409932	0.13	0.8976
Mov[Jurassic Pa]	-0.008987	0.384135	-0.02	0.9813
Mov[Lara Croft:]	-0.228348	0.236081	-0.97	0.3335
Mov[Lord of the R]	-0.000242	0.084057	-0.00	0.9977
Mov[Memento]	0.7832267	0.248218	3.16	0.0016
Mov[Monsters inc.]	0.0009293	0.095814	0.01	0.9923
Mov[Moulin Roug]	0.6793915	0.483507	1.41	0.1601
Mov[Murder by Num]	0.0537391	0.363062	0.15	0.8823
Mov[O Brother]	0.4212972	0.383917	1.10	0.2725
Mov[Panic Room]	-0.0026	0.106415	-0.02	0.9805
Mov[Pearl Harbo]	0.2848505	0.157847	1.80	0.0712
Mov[Planet of t]	0.4339924	0.160248	2.71	0.0068
Mov[Pulp Fiction]	0.0529601	0.148012	0.36	0.7205
Mov[Reservoir Dog]	-0.504104	0.183391	-2.75	0.0060
Mov[Rookie]	0.0050671	0.098937	0.05	0.9592

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mov[Rush Hour 2]	-0.412009	0.240628	-1.71	0.0869
Mov[Scary Movie]	-1.1912	0.329101	-3.62	0.0003
Mov[Scream 3]	-0.082492	0.761885	-0.11	0.9138
Mov[Shrek]	0.5786282	0.206806	2.80	0.0052
Mov[Swordfish]	0.0339672	0.315126	0.11	0.9142
Mov[The Family]	-0.093319	0.442239	-0.21	0.8329
Mov[The Green M]	-0.380967	0.273892	-1.39	0.1643
Mov[The Hurrica]	-0.019261	1.076024	-0.02	0.9857
Mov[The Matrix]	0.1377785	0.222042	0.62	0.5350
Mov[The Mexican]	-0.027806	0.328242	-0.08	0.9325
Mov[The Mummy R]	-0.338819	0.303697	-1.12	0.2646
Mov[The Princes]	-0.013691	0.344728	-0.04	0.9683
Mov[The Score]	-0.110351	0.484595	-0.23	0.8199
Mov[The Sixth S]	-0.268184	0.230882	-1.16	0.2455
Mov[True Romance]	-0.080064	0.231036	-0.35	0.7290
Mov[Van Wilder (u]	-0.059095	0.223712	-0.26	0.7917
Set Type[Mix]	-0.032901	0.035307	-0.93	0.3515
Set Type[New]	-0.050869	0.057499	-0.88	0.3764
New?[0]	0.0052903	0.040784	0.13	0.8968
Store?[0]	-0.025608	0.059563	-0.43	0.6673
Ship?[0]	-0.040178	0.028863	-1.39	0.1640
Tax?[0]	-0.11367	0.063424	-1.79	0.0732
Min Til 11/30	1.9061e-7	0.000002	0.10	0.9192
Min Apart	-0.001029	0.000688	-1.50	0.1350
Seller Rating	-9.9e-7	0.000012	-0.08	0.9356
Seller Rating Difference	0.0000012	0.000011	0.11	0.9144
Seller Rating Difference / Avg	0.1008505	0.087661	1.15	0.2500

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Mov	53	53	246.52796	1.9479	<.0001
Set Type	2	2	5.40964	1.1327	0.3223
New?	1	1	0.04018	0.0168	0.8968
Store?	1	1	0.44139	0.1848	0.6673
Ship?	1	1	4.62718	1.9377	0.1640
Tax?	1	1	7.67018	3.2120	0.0732
Min Til 11/30	1	1	0.02456	0.0103	0.9192
Min Apart	1	1	5.33771	2.2353	0.1350
Seller Rating	1	1	0.01561	0.0065	0.9356
Seller Rating Difference	1	1	0.02759	0.0116	0.9144
Seller Rating Difference / Avg	1	1	3.16060	1.3236	0.2500

Response Variable: 25th Percentile Bid in Late Condition – 25th Percentile in Early Condition (Excluding Shipping Price)

Summary of Fit

RSquare	0.037541
RSquare Adj	0.022752
Root Mean Square Error	0.060777
Mean of Response	-0.00189
Observations (or Sum Wgts)	4230

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	64	0.600086	0.009376	2.5384
Error	4165	15.384784	0.003694	Prob > F
C. Total	4229	15.984870		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	4153	15.384784	0.003704	.
Pure Error	12	0.000000	0.000000	Prob > F
Total Error	4165	15.384784		.
				Max RSq
				1.0000

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.002526	0.006757	-0.37	0.7086
Mov[15 Minutes]	0.0040711	0.016119	0.25	0.8006
Mov[40 Days and 4]	0.0000233	0.005529	0.00	0.9966
Mov[A Knight Ta]	-0.003578	0.021274	-0.17	0.8664
Mov[Along Came]	-0.000679	0.014251	-0.05	0.9620
Mov[Americas Sw]	-0.000414	0.008198	-0.05	0.9597
Mov[Angel Eyes]	0.0055285	0.024682	0.22	0.8228
Mov[Big Fat Liar]	-0.003927	0.00568	-0.69	0.4893
Mov[Blade 2]	0.0006725	0.006217	0.11	0.9139
Mov[Blow]	0.0019051	0.011487	0.17	0.8683
Mov[Boiler Room]	-0.000673	0.024504	-0.03	0.9781
Mov[Bridget Jon]	-0.000169	0.019004	-0.01	0.9929
Mov[Cast Away]	0.0022097	0.009986	0.22	0.8249
Mov[Changing Lane]	-0.001848	0.005143	-0.36	0.7193
Mov[Count of Mont]	-0.01133	0.004965	-2.28	0.0225
Mov[Evolution]	0.0089693	0.042337	0.21	0.8322
Mov[Fight Club]	0.000957	0.013532	0.07	0.9436
Mov[Frailty]	0.0061864	0.021271	0.29	0.7712
Mov[Grease]	-0.00086	0.00786	-0.11	0.9129
Mov[Hard Day's Ni]	-0.00268	0.015105	-0.18	0.8592
Mov[Heartbreake]	-0.000321	0.029934	-0.01	0.9915
Mov[High Crimes]	-0.000265	0.006739	-0.04	0.9687
Mov[How the Gri]	-0.063242	0.010777	-5.87	<.0001
Mov[Independenc]	-0.000943	0.016123	-0.06	0.9534
Mov[Jurassic Pa]	0.0002258	0.015108	0.01	0.9881
Mov[Lara Croft:]	0.004514	0.009285	0.49	0.6269
Mov[Lord of the R]	-0.000445	0.003306	-0.13	0.8928
Mov[Memento]	0.0484363	0.009762	4.96	<.0001
Mov[Monsters inc.]	-0.00272	0.003768	-0.72	0.4705
Mov[Moulin Roug]	0.0038774	0.019016	0.20	0.8384
Mov[Murder by Num]	-0.000133	0.014279	-0.01	0.9926
Mov[O Brother]	0.0019392	0.0151	0.13	0.8978
Mov[Panic Room]	-0.002146	0.004185	-0.51	0.6082
Mov[Pearl Harbo]	-0.016899	0.006208	-2.72	0.0065
Mov[Planet of t]	-0.01792	0.006303	-2.84	0.0045
Mov[Pulp Fiction]	0.0008166	0.005821	0.14	0.8885
Mov[Reservoir Dog]	0.0000239	0.007213	0.00	0.9974

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mov[Rookie]	-0.002375	0.003891	-0.61	0.5416
Mov[Rush Hour 2]	0.0022688	0.009464	0.24	0.8105
Mov[Scary Movie]	0.0025873	0.012944	0.20	0.8416
Mov[Scream 3]	0.0059473	0.029965	0.20	0.8427
Mov[Shrek]	-0.033486	0.008134	-4.12	<.0001
Mov[Swordfish]	0.000698	0.012394	0.06	0.9551
Mov[The Family]	0.0045575	0.017393	0.26	0.7933
Mov[The Green M]	0.0035815	0.010772	0.33	0.7395
Mov[The Hurrica]	0.0008843	0.04232	0.02	0.9833
Mov[The Matrix]	0.0403147	0.008733	4.62	<.0001
Mov[The Mexican]	0.0030214	0.01291	0.23	0.8150
Mov[The Mummy R]	0.0028421	0.011944	0.24	0.8119
Mov[The Princes]	0.0008481	0.013558	0.06	0.9501
Mov[The Score]	0.0097808	0.019059	0.51	0.6079
Mov[The Sixth S]	0.0026285	0.009081	0.29	0.7722
Mov[True Romance]	0.0026656	0.009087	0.29	0.7693
Mov[Van Wilder (u]	0.0017883	0.008799	0.20	0.8390
Set Type[Mix]	0.0036414	0.001389	2.62	0.0088
Set Type[New]	0.0034955	0.002261	1.55	0.1223
Seller Rating	-8.322e-8	4.816e-7	-0.17	0.8628
Seller Rating Difference	-1.864e-7	4.29e-7	-0.43	0.6640
Seller Rating Difference / Avg	0.0029788	0.003448	0.86	0.3876
New?[0]	-0.000267	0.001604	-0.17	0.8676
Store?[0]	-0.004451	0.002343	-1.90	0.0575
Ship?[0]	0.002181	0.001135	1.92	0.0548
Tax?[0]	-0.001789	0.002494	-0.72	0.4733
Min Til 11/30	7.7482e-8	7.392e-8	1.05	0.2946
Min Apart	0.0000527	0.000027	1.95	0.0517

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Mov	53	53	0.45913964	2.3453	<.0001
Set Type	2	2	0.04571973	6.1887	0.0021
Seller Rating	1	1	0.00011030	0.0299	0.8628
Seller Rating Difference	1	1	0.00069705	0.1887	0.6640
Seller Rating Difference / Avg	1	1	0.00275742	0.7465	0.3876
New?	1	1	0.00010269	0.0278	0.8676
Store?	1	1	0.01333303	3.6095	0.0575
Ship?	1	1	0.01363438	3.6911	0.0548
Tax?	1	1	0.00190035	0.5145	0.4733
Min Til 11/30	1	1	0.00405837	1.0987	0.2946
Min Apart	1	1	0.01399628	3.7891	0.0517

Response Variable: 25th Percentile Bid in Late Condition – 25th Percentile in Early Condition (Including Shipping Price Where Available)

Summary of Fit

RSquare	0.045894
RSquare Adj	0.031233
Root Mean Square Error	0.07714
Mean of Response	-0.00236
Observations (or Sum Wgts)	4230

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	64	1.192153	0.018627	3.1303
Error	4165	24.784207	0.005951	Prob > F
C. Total	4229	25.976359		<.0001

Lack Of Fit

Source	DF	Sum of Squares	Mean Square	F Ratio
Lack Of Fit	4153	24.784207	0.005968	.
Pure Error	12	0.000000	0.000000	Prob > F
Total Error	4165	24.784207		.
				Max RSq
				1.0000

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-0.00998	0.008576	-1.16	0.2446
Mov[15 Minutes]	0.0058041	0.020458	0.28	0.7766
Mov[40 Days and 4]	0.0018372	0.007018	0.26	0.7935
Mov[A Knight Ta]	-0.005164	0.027001	-0.19	0.8483
Mov[Along Came]	-0.001602	0.018088	-0.09	0.9294
Mov[Americas Sw]	0.0022264	0.010405	0.21	0.8306
Mov[Angel Eyes]	0.0067205	0.031327	0.21	0.8301
Mov[Big Fat Liar]	-0.000523	0.007209	-0.07	0.9422
Mov[Blade 2]	0.0203126	0.00789	2.57	0.0101
Mov[Blow]	0.0009244	0.014579	0.06	0.9494
Mov[Boiler Room]	0.0020881	0.031101	0.07	0.9465
Mov[Bridget Jon]	-0.001311	0.024121	-0.05	0.9567
Mov[Cast Away]	0.0038295	0.012675	0.30	0.7626
Mov[Changing Lane]	0.0008755	0.006528	0.13	0.8933
Mov[Count of Mont]	-0.008545	0.006302	-1.36	0.1752
Mov[Evolution]	0.0110975	0.053736	0.21	0.8364
Mov[Fight Club]	0.0015237	0.017176	0.09	0.9293
Mov[Frailty]	0.0027392	0.026998	0.10	0.9192
Mov[Grease]	0.001043	0.009976	0.10	0.9167
Mov[Hard Day's Ni]	-0.000022	0.019172	-0.00	0.9991
Mov[Heartbreake]	0.0029864	0.037993	0.08	0.9374
Mov[High Crimes]	0.0017045	0.008554	0.20	0.8421
Mov[How the Gri]	-0.124637	0.013678	-9.11	<.0001
Mov[Independenc]	0.0027701	0.020463	0.14	0.8923
Mov[Jurassic Pa]	0.0002086	0.019176	0.01	0.9913
Mov[Lara Croft:]	0.0034854	0.011785	0.30	0.7674
Mov[Lord of the R]	0.0004061	0.004196	0.10	0.9229
Mov[Memento]	-0.000562	0.012391	-0.05	0.9639
Mov[Monsters inc.]	-0.001005	0.004783	-0.21	0.8336
Mov[Moulin Roug]	0.0045675	0.024136	0.19	0.8499
Mov[Murder by Num]	0.0006918	0.018124	0.04	0.9696
Mov[O Brother]	0.0020104	0.019165	0.10	0.9165
Mov[Panic Room]	0.000327	0.005312	0.06	0.9509
Mov[Pearl Harbo]	-0.016033	0.00788	-2.03	0.0419
Mov[Planet of t]	-0.036219	0.007999	-4.53	<.0001
Mov[Pulp Fiction]	0.0012567	0.007389	0.17	0.8650

Term	Estimate	Std Error	t Ratio	Prob>|t|
Mov[Reservoir Dog]	-0.02457	0.009155	-2.68	0.0073
Mov[Rookie]	0.0002968	0.004939	0.06	0.9521
Mov[Rush Hour 2]	0.0027	0.012012	0.22	0.8222
Mov[Scary Movie]	0.0922441	0.016428	5.61	<.0001
Mov[Scream 3]	0.0012138	0.038033	0.03	0.9745
Mov[Shrek]	-0.033043	0.010324	-3.20	0.0014
Mov[Swordfish]	0.0020536	0.015731	0.13	0.8961
Mov[The Family]	0.0028672	0.022076	0.13	0.8967
Mov[The Green M]	0.003465	0.013672	0.25	0.7999
Mov[The Hurrica]	-0.001419	0.053714	-0.03	0.9789
Mov[The Matrix]	0.0414021	0.011084	3.74	0.0002
Mov[The Mexican]	0.0032496	0.016386	0.20	0.8428
Mov[The Mummy R]	0.0055059	0.01516	0.36	0.7165
Mov[The Princes]	0.0026251	0.017209	0.15	0.8788
Mov[The Score]	0.0064331	0.024191	0.27	0.7903
Mov[The Sixth S]	0.0029669	0.011525	0.26	0.7969
Mov[True Romance]	0.0028375	0.011533	0.25	0.8057
Mov[Van Wilder (u]	0.0019489	0.011168	0.17	0.8615
Set Type[Mix]	0.0012204	0.001763	0.69	0.4887
Set Type[New]	0.0035069	0.00287	1.22	0.2219
Seller Rating	1.4412e-7	6.113e-7	0.24	0.8136
Seller Rating Difference	-2.032e-7	5.445e-7	-0.37	0.7090
Seller Rating Difference / Avg	0.0100845	0.004376	2.30	0.0212
New?[0]	-0.000197	0.002036	-0.10	0.9228
Store?[0]	-0.001318	0.002973	-0.44	0.6576
Ship?[0]	0.0014706	0.001441	1.02	0.3075
Tax?[0]	-0.000612	0.003166	-0.19	0.8467
Min Til 11/30	1.1458e-7	9.382e-8	1.22	0.2221
Min Apart	-0.000026	0.000034	-0.75	0.4534

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Mov	53	53	1.0952515	3.4728	<.0001
Set Type	2	2	0.0156195	1.3124	0.2693
Seller Rating	1	1	0.0003308	0.0556	0.8136
Seller Rating Difference	1	1	0.0008287	0.1393	0.7090
Seller Rating Difference / Avg	1	1	0.0316027	5.3108	0.0212
New?	1	1	0.0000559	0.0094	0.9228
Store?	1	1	0.0011692	0.1965	0.6576
Ship?	1	1	0.0061990	1.0417	0.3075
Tax?	1	1	0.0002223	0.0374	0.8467
Min Til 11/30	1	1	0.0088752	1.4915	0.2221
Min Apart	1	1	0.0033458	0.5623	0.4534

11. Appendix C: Statistical Analysis to See How Movie Variables Impact the Movie Regression Coefficients

Response Variable: P Value for Individual Movie Coefficients in Regression for Difference in Absolute Prices (Excluding Shipping)			
Movie Attributes	**Correlation Between Variable and Original Regression Coefficients**	**P Value for Regression of P Value**	**Coefficient of Regression of P Value**
Average Price Excluding Shipping	0.227142347	0.070182779	-0.043002764
Standard Deviation of Prices Excluding Shipping	0.12878064	0.691222831	-0.024944453
Number of Items	0.126989498	0.307059251	-0.000351636

Response Variable: P Value for Individual Movie Coefficients in Regression for Difference in Absolute Prices (Including Shipping)			
Movie Attributes	**Correlation Between Variable and Original Regression Coefficients**	**P Value for Regression of P Value**	**Coefficient of Regression of P Value**
Average Price Including Shipping	0.151683232	0.562707351	-0.014532537
Standard Deviation of Prices Including Shipping	0.076992554	0.100322405	-0.120686992
Number of Items	0.039357722	0.227452994	0.00044721

Response Variable: P Value for Individual Movie Coefficients in Regression for Difference in Bidding at 25th Percentile or Less (Excluding Shipping)			
Movie Attributes	**Correlation Between Variable and Original Regression Coefficients**	**P Value for Regression of P Value**	**Coefficient of Regression of P Value**
Average Price Excluding Shipping	-0.034418532	0.635489095	-0.01042958
Standard Deviation of Prices Excluding Shipping	0.130029667	0.056818872	-0.10731582
Number of Items	-0.130355694	0.115280007	-0.000491318

Response Variable: P Value for Individual Movie Coefficients in Regression for Difference in Bidding at 25th Percentile or Less (Including Shipping)			
Movie Attributes	**Correlation Between Variable and Original Regression Coefficients**	**P Value for Regression of P Value**	**Coefficient of Regression of P Value**
Average Price Including Shipping	-0.007183173	0.959287317	-0.001149912
Standard Deviation of Prices Including Shipping	-0.247533312	0.073933673	-0.117273865
Number of Items	-0.053346831	0.704405448	-0.000126734