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An Investigation of Internet Auction Markets: Evidence from eBay

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ABSTRACT

The purpose of this paper was to examine a market with different characteristics than a typical "financial" market using high frequency continuous transactions data. The market selected for this purpose was an Internet auction market for collectibles, specifically Ty Glory Bears™ sold on the eBay, Inc. web site. This market was chosen for its relatively high activity and homogeneity. The results indicated evidence of signaling related to seller's reputation and product information, seasonality based on day-of-the-week, and limited market depth.

INTRODUCTION

Financial economists have a long history of examining the behavior of markets. Traditionally, the focus has been on mainstream financial markets such as equities, bonds, and derivatives. However, there has also been an interest in examining other non-traditional markets. Gandar, et al (1988) and Gray and Gray (1997) are among the many researchers who explore the concept of efficiency in the NFL gambling markets. Other sports betting markets such as basketball (Brown and Sauer, 1993), baseball (Woodland and Woodland, 1994), and horseracing (Asch, et al, 1982; Thaler and Ziemba, 1988) have also been studied. Outside of the sports arena, Scott and Gulley (1995) and Papachristou and Karamanis (1998) both look at lottery markets. These investigations have led to mixed evidence on the efficiency of gambling markets.[1]

In addition to gambling markets, there has been a body of research into the area of collectibles markets. This has covered areas such as art (Bryan, 1985; Mok, et al, 1993; Matsumoto, et al, 1994; Pompe, 1996), stamps (Taylor, 1983; Cardell, et al, 1995), antique furniture (Graeser, 1993), coins (Dickie, et al, 1994), wine (Krasker, 1979), sports cards (O'Brien and Gramling, 1995) and comic books (Ang, et al, 1983). Most of these studies examine the return structure of the particular collectible market under investigation and consider its viability as an investment alternative based on its return as well as its correlation to more traditional financial investments (stocks, bonds, gold, etc.). However, there is limited evidence on the nature of these market based on high-frequency transaction data over a condensed period of time. There are three reasons for the lack of attention to this aspect of the collectibles market. First, the collectibles market has historically been extremely segmented by regional preferences. This makes it difficult to develop a meaningful database of transactions that aren't greatly influenced by regional biases. Second, often collectibles are distinctive making it difficult to separate market influences from product differences such as quality of condition from transaction to transaction. For example, a primary objective in Taylor's (1983) examination of the stamp market is developing a methodology to separate differences in quality from differences in price. Finally, there has not been a good source of high-frequency transaction data for a continuous time collectibles market.

This paper examines the auction of collectibles by using a continuous worldwide marketplace with a homogeneous product that eliminates the three problems described above. Because the auction is conducted via the Internet, participants can see all recently completed auctions to generate an expectation of a market price. One advantage of such an auction market is that with a worldwide market all participants are widely dispersed. That is, they likely share no community (e.g., geographic, union) with other participants. This reduces the likelihood of collusive behavior and, more importantly, eliminates the geographic premiums that are often apparent in collectible markets.

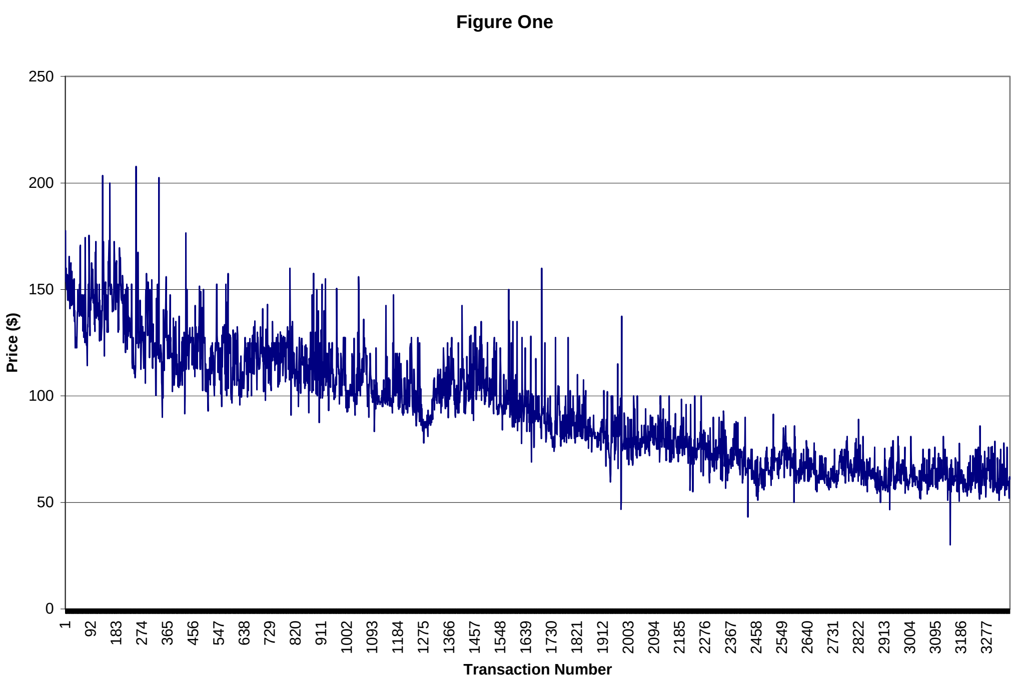
The wealth of data available through Internet auction markets has generated a growing body of interest (McDonald and Slawson, 2002; Houser and Wooders, 2001; Bajari and Hortacsu, 2002; Katkar and Lucking-Reiley, 2001; Melnik and Alm, 2002, and Roth and Ockenfels, 2000.) These papers tend to focus on using the Internet auction data to address theoretical related to auctions. For example, Roth and Ockenfels (2000) examine the rationale behind last-second bidding ("sniping") behavior using data from both eBay and Amazon auctions with computers and antiques. As an alternative, our focus is not on the explanation of auction activity, but on characteristics and activity of the market prices. Specifically, how do issues related to traditional financial markets such as seasonality, information signaling, and market depth reveal themselves in a non-traditional financial market?

DATA AND METHODOLOGY

The data for this study is collected from the Internet site managed by eBay, Inc. This is currently the largest Internet auction market with over 9 million auctions running at a given point in time and over 49 million registered participants. The eBay site can be found at http://www.ebay.com. The closing transaction price from 3359 individual auctions that ended between 12:00 AM PST July 5th and 12:00 PM PST August 4th, 1998 were recorded. The item being auctioned in all instances was one or more Glory Bear Beanie Babies™ produced by Ty, Inc. Figures 1-4 illustrate the pattern transaction data in a graphical format.

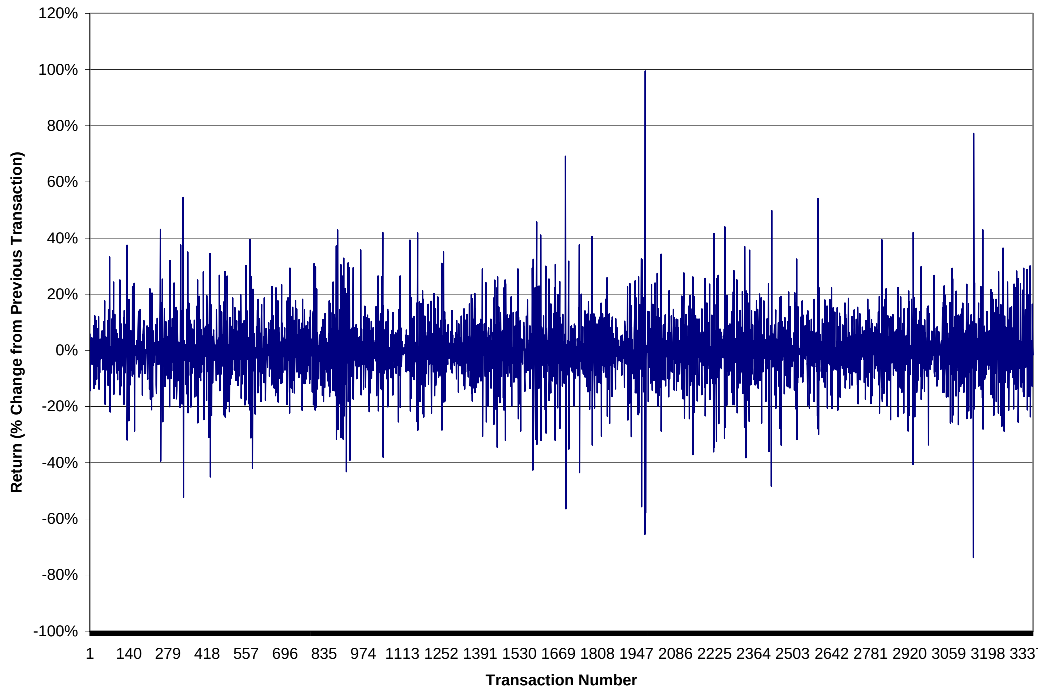
The following graphs plot the price (Figure One) and return (Figure Two) of Ty Glory Bear Beanie Babies™ with completed auctions on eBay between 12:00 AM PST July 5th and 12:00 PM PST August 4th, 1998. The return is defined as the percentage change in price from the previous transaction. Both graphs include all observations.

Figure 1: Ty Glory Bear Beanie Babies, eBay Auction , July 5th



The specific item being auctioned was carefully selected to meet two primary criteria. First, the item being auctioned had to be homogeneous in nature. Many items available in Internet auction markets do not meet this criterion. Older collectibles such as coins and trading cards can vary in value dramatically based on condition. At the time of this sample, the Glory Bear Beanie Baby™ was a new release, which helped insure that all auctions were for items that were in similar condition. By using a homogeneous item, we can determine that the price change is not due to changes in the nature of the item being sold. The second primary criterion for consideration in item selection is an active market. During the sample period, there was an average of 186.125 completed auctions for $20,202.06 in Glory Bear Beanie Babies™ each day. Such an active market allows for price discovery since current prices for recently completed transactions are readily available. Many items available on Internet auction markets have far less active markets.[2] Table One provides summary statistics for the sample of transactions used in this study.

Figure 2: Ty Glory Bear Beanie Babies, eBay Auction, August 4th



The following graphs plot the price (Figure Three) and return (Figure Four) of Ty Glory Bear Beanie Babies™ with completed auctions on eBay between 12:00 AM PST July 5th and 12:00 PM PST August 4th, 1998. The return is defined as the percentage change in price from the previous transaction. Both graphs exclude all observations in which the return is greater than ±20%.

Figure 3: Ty Glory Bear Beanie Babies, eBay Completed Auction, July 5th

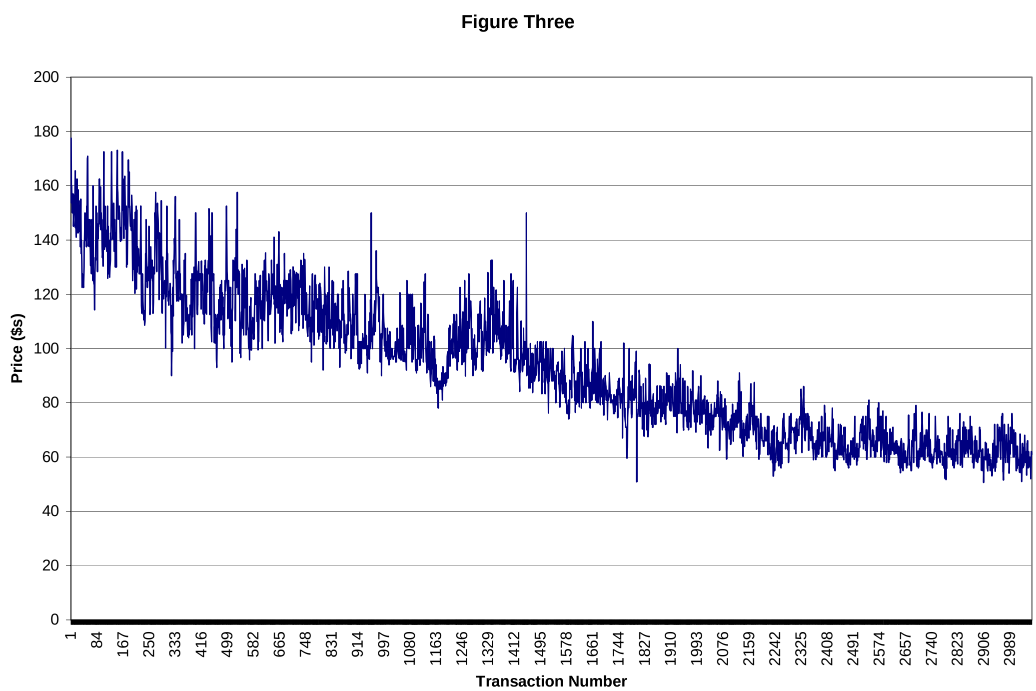
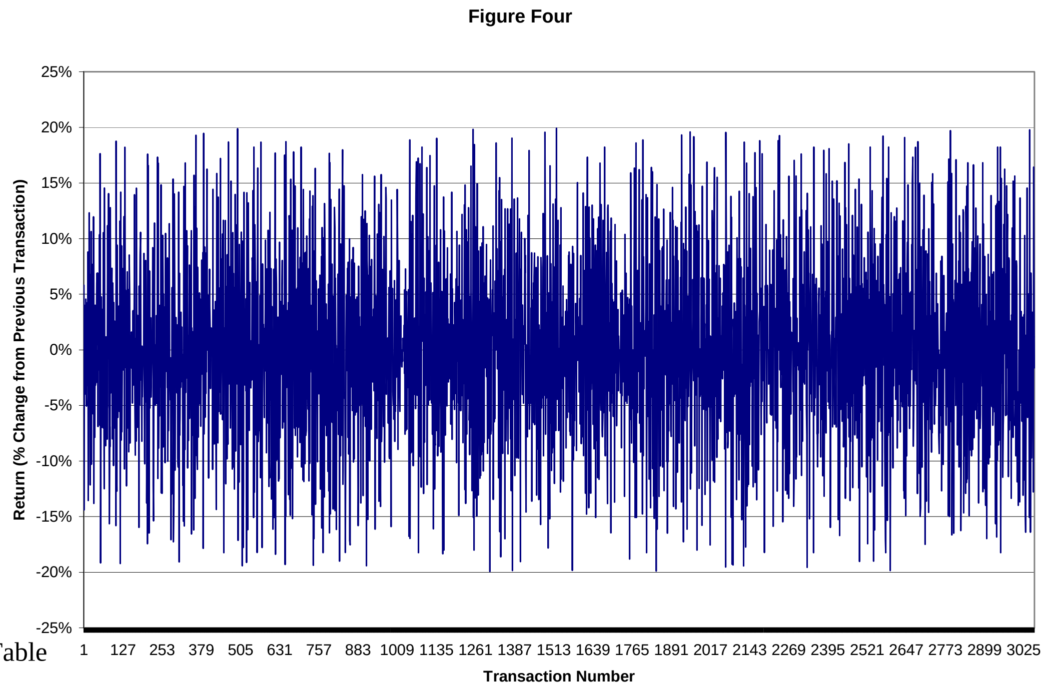


Figure 4: Ty Glory Bear Beanie Babies, eBay Completed Auction, August 4th



Table

Table One
Summary Statistics for Price and Return

Table one displays summary statistics for the transaction price and return (percentage change in the price from the previous transaction) of Ty Glory Bear Beanie Babies™ with completed auctions on eBay between 12:00 AM PST July 5th and 12:00 PM PST August 4th, 1998. These summary statistics are reported for both all transactions and for a subset where the returns fall between -20% and 20%. The rational for the removal of returns falling outside the range of -20% and 20% is to eliminate "questionable" transactions. This also improves the "normalcy" of the returns by greatly reducing the kurtosis ("fat-tails"). The Augmented Dicky-Fuller test statistics demonstrate that there is not a unit-root present in the time-series of prices or returns.

Table 1: Summary Statistics for Price and Return

	All Observations		Observations with Returns between -20% and 20%	
	Price	Return	Price	Return
N	3359	3358	3058	3058
Minimum	30.13	-73.8%	50.63	-19.9%
Maximum	207.75	99.5%	177.52	19.9%
Mean	93.75	-0.03%	93.24	-0.11%
St. Deviation	27.235	11.90%	26.559	8.04%
Skewness	0.545	0.232	0.495	0.058
Kurtosis	-0.378	4.807	-0.623	-0.186
ADF Test Statistic	-13.064	-36.896	-11.565	-25.099

Each auction has a wealth of information available, starting with pricing information. The high bid on recently completed auctions as well as the current bid for this auction is readily available on the website. This information aids potential buyers and sellers in the price discovery process by making the bids transparent. By combining a high frequency of auctions and availability of past price data to give auction participants a relatively clear picture of the current "market price," bidders are less likely to suffer from the "winner's curse" frequently found in auction situations. The winner's curse occurs when, due to incomplete information about what competitors are willing to pay, the winning bid is a price greater than the minimum amount necessary to win the auction. In addition, eBay uses a bidding system incorporating proxy bidding and relatively small minimum increments that helps to minimize the winner's curse.[3]

A second important piece of information is the time at which the auction ended. This allows for an investigation into potential seasonality patterns related to time-of-day or day-of-the-week effects. Also, the ending time can be used to measure the time elapsed between auctions. Given that there is only one month's data, it is difficult to draw reliable inferences from the day-of-the-week results. The time-of-day results should be more reliable, although that is a relatively small sample as well (31 calendar days). Nonetheless, we include seasonal variables in an attempt to capture potential anomalies. We find pricing anomalies which buyers can use to lower the prices they pay. These are discussed below.

Asymmetric information problems are inherent in any auction. Once a bid is accepted, the buyer sends payment to the seller. It is then up to the seller to send the item purchased. There is always the possibility that sellers will either not deliver the item to the winning bidder or deliver it in less than a safe and timely manner. To address this potential moral hazard problem, each seller is given a feedback rating. This rating is designed to transmit information to potential bidders regarding the reputation of the seller. Upon completion of an auction the bidder and seller are each allowed the opportunity to give feedback in the form of a short description of their transaction experience. In addition, the person giving the feedback identifies it as a positive (+1), neutral (0), or negative (-1) experience. An individual seller's rating is the running total of their feedback from previous transactions.

Each seller is also allowed the option of setting a reservation price. The reservation price is not initially revealed to bidders. Instead, until the reservation is met the listed high bid will include a statement that the reserve has not yet been met. The reservation price allows the seller to avoid selling their product if they fail to obtain their private valuation.

Adverse selection may also potentially be a problem in that the item being auctioned may not be in very good condition. To address this asymmetric information problem, the seller can include a digital photo of the item to be displayed to potential bidders. The less homogeneous the item being auctioned, the more important a photo will be to help reduce the information asymmetry between buyer and seller.

Additionally, the seller has the option to place their item for sale in a featured category. This costs the seller an additional $9.95, but places the auction in a more prominent place within the page layout, giving the item a greater exposure to more potential bidders. The seller must consider this additional cost relative to the price received. Obviously, this approach is not beneficial to the seller if the revenue generated by an item in a featured category is $9.95 or less than that generated in a non-featured category.

eBay, Inc. runs many auctions for a single item, but there are also auctions run with multiple items for sale at the same time. These auctions can take one of two forms. The first is to sell the entire quantity to the highest bidder. For example, instead of running N auctions selling a single Glory Bear Beanie Baby™ per auction, the seller can list N and sell them all to the highest single bidder. Another technique is to run a Dutch auction. In this form, a single auction is run for all N Glory Bear Beanie Babies™, but instead of going to a single bidder, up to N individuals can place winning bids. The bids are ranked from highest to lowest with the N highest bids getting their item for the lowest successful bid price. Dutch auctions and auctions selling multiple items as a single lot may result in lower prices if the market does not have enough depth to handle larger transactions. We would expect multiple items being sold as a single lot to suffer from this depth issue to a greater extent as the personal collector will be less likely to participate and instead the market will be reduced to speculators and dealers.

HYPOTHESES

The above information will be used to examine several issues. First, is there seasonality in the prices yielded from Internet auction markets? For example, prices may be lower during the weekends when people are busy with other activities. Alternatively, prices may be lower during the day while people are at work and higher during the evenings when they are at home and have time to participate in such auctions. Any systematic factor related to the day of the week or the time of day that influences supply or demand could cause seasonality to be present in prices. These seasonality issues are analyzed through two different approaches. First, the observations are segmented into day-of-the-week categories and into time-of-the-day categories.[4] Mean prices across the different time periods are then compared. Second, day-of-the-week dummy variables and time-of-the-day dummy variables are included in a regression analysis that controls for other effects (discussed below).

In addition to seasonality issues, there is also potential for an information signaling effect to be conveyed from the seller to potential buyers. When making purchases from Internet auction markets, the buyer typically pays for the item first and upon payment, the seller ships the item to the buyer. This places the buyer at risk. If payment is made and the seller is dishonest (fails to ship item or misrepresents the quality of the item) the buyer loses. Alternatively, a careless seller that delays shipment for an unreasonable time or packages the item poorly will also result in the bidder getting less "value" than was expected at the time of placing their bid. eBay, Inc. attempts to solve these asymmetric information issues with several approaches. Sellers with higher feedback ratings should be able to capture reputational capital in the form of higher average transaction prices. In our analysis we use the log of the feedback rating (instead of the actual number itself) as it is reasonable to assume that each additional positive rating would carry a decreasing marginal value. For example, someone with a feedback rating of 15 would seem far less risky than someone with a feedback rating of 2. Conversely, the difference between a feedback rating of 213 and 200 would seem relatively minor.[5] By using the log of the feedback rating, the skewness of the variable is also reduced. Additionally, digital pictures can help to provide information about the quality of the item to the bidder. Therefore, items that are sold with a digital image attached should sell for a higher price than items with no digital image.

Another area to examine is the depth of the market. What happens when there are multiple auctions for the same item very close together and/or single auctions with multiple quantities available (either as a Dutch auction or as a single lot) at the same time? If the market is not significantly deep, such auctions will likely yield lower prices. This issue is examined by including three different variables. First, a measurement of time between transactions (LTBT) is used. This variable is represented by the log of the time between transactions measured in seconds. By using the log, this variable will exhibit less skewness. While the LTBT variable is primarily a liquidity variable (is the market able to support multiple auctions ending in close proximity to one another without impacting price), it may also be a proxy for the impact of the winner's curse. If there are many auctions ending in a short period of time there is less of a need to win a specific auction. Therefore, the bidder is less apt to overbid. However if the auctions are spaced far apart, bidders may feel a greater need to win a specific auction and thus bid a little higher. Given the liquidity and winner's curse implications, a positive relationship for the time between transactions and the price realized for the item is expected. Two other closely related measurements are DUTCH, a dummy variable that equals one if the auction was a Dutch auction, and QUANTITY, a variable that captures the number of Glory Bears™ available as a lot to the highest bidder. Inclusion of these variables allows us to test which form of auction yields greater revenue to the seller. The coefficients (reported below) quantify the average price in a regular auction, the average price in a Dutch auction, and the average price in an auction where multiple items are sold to the highest bidder. Again, if there are issues regarding the depth of these markets, it is reasonable to expect to observe negative relationships with the price for both DUTCH and QUANTITY.

Three final issues to be addressed are visibility, reserve pricing, and a trend. In order to increase visibility of the auction, the seller can select (for an additional fee) to place the item as a featured item. Thus, a dummy variable, FEATURE, is introduced that takes a value of one if the auction was listed in the featured category and a zero otherwise. If this visibility is important, we should expect to see a positive relationship with the price realized. Reserve prices can be set by the seller to ensure that the item is not sold unless it meets a specific price. To recognize this, a dummy variable, RESERVE, is included to examine whether auctions with reserve prices increase the average realized price. It is expected that reserve pricing will lead to higher average prices due to the elimination of accepting lower bids. The third issue, apparent from looking at Figures One and Three, is that there is a significant downward trend in prices. As more of the Glory Bears™ became available, their market value declined. To control for this downward trend in prices a variable, COUNT, is introduced that represents the transaction number. See Table Two for a summary of the independent variables (excluding seasonality dummy variables).

Tables Two and Three
Variable Definition and Correlation Matrix

The following tables provide a description of the independent variables used in the regression analysis component of this paper along with the correlation matrix for these variables. The only variables which appear to have moderately high degrees of correlation are the Feature, Quantity, and Dutch.

Table 2: Description of Independent Variables

Variable	Description
Dutch	A dummy variable that is 1 if the auction is a Dutch auction and 0 otherwise. A Dutch auction signifies that multiples of the same item are being sold in one auction to multiple bidders at the lowest accepted price.
Reserve	A dummy variable that is 1 if the auction has a reserve price and a 0 otherwise. A reserve price is the minimum price at which the item can be sold for, but is not revealed until the reserve has been met.
Picture	A dummy variable that is 1 if the auction description includes a picture of the item and a 0 otherwise.
Quantity	The number of items being sold to the high bidder. This is different than a Dutch auction in that the high bidder buys ALL items being sold in that auction.
Feature	A dummy variable that is 1 if the auction is placed in a featured category and 0 otherwise. An item can be placed in a featured category for $9.95 that enhances the visibility of the item to potential bidders.
LRating	The log of the seller's rating. Each seller has a rating based on feedback from previous transactions. Each "positive" feedback increases the sellers rating by 1 point while each "negative" feedback decreases the sellers rating by 1 point.
LTBT	The log of the time (in seconds) from the previous completed auction for the same item.
Count	A trend variable that is equal to the auction number with the first auction taking a value of 1.

Table 3: Correlation Matrix of Independent Variables

	Dutch	Reserve	Picture	Quantity	Feature	LRating	LTBT	Count
Dutch	1.000	-0.152	-0.002	-0.071	0.414	0.029	0.053	0.057
Reserve		1.000	-0.137	0.115	-0.062	-0.103	0.049	-0.139
Picture			1.000	-0.030	0.050	0.167	0.056	0.038
Quantity				1.000	0.326	-0.019	0.054	0.052
Feature					1.000	0.159	0.019	0.058
LRating						1.000	-0.007	0.084
LTBT							1.000	-0.101
Count								1.000

The primary data analysis method used is a regression model with a correction for autocorrelation. Even with the inclusion of a trend variable, the regression model still exhibits auto correlated errors. This issue is addressed through two different approaches. The first technique is to an autocorrelation correction based on maximum likelihood methodology. The results from this methodology are presented in Table Five. The second technique is to fit the price observations to an ARIMA model and then use the residuals from this model in the regression analysis. The results from this methodology are presented in Table Six. The results are robust to the methodology involved and the discussion of the results will focus on the maximum likelihood results. The reason for choosing the maximum likelihood model is that by using the price (as opposed to a residual) for the dependent variable, the coefficients produced provide useful information to analyze selling strategies.

There is also some concern over potential outliers in the data set. While the recorded price represents the highest acceptable bid, there is no way to determine if the transaction was legitimately conducted and completed.

Occasionally, there are some transactions that appear to be abnormal. For example the price change between some transactions is as much as a 99.5% increase or -73.8% decline. It seems unreasonable to assume that the value of the product changed by such a large amount within a single transaction. To account for this the primary results are presented using (1) all data points and (2) only those data points where the price change between transactions is between ±20%.[6]

RESULTS

Seasonality appears to be present in the prices of our collectibles market. In examining Table Four, one can see that the average price ranges from a low of $91.52 for Mondays to a high of $101.94 on Thursdays. For time periods, the lowest average price is $91.99 from 9:00 PM to 12:00 AM PST while the highest average price is $104.57 from 12:00 AM to 6:00 AM PST. Results from ANOVA analysis show that for the classifications, there is statistically significant seasonality at the 1% level. However, looking at these seasonality patterns in isolation can be misleading. Two other important components must be considered. First, remember from Figures One and Three that there is a noticeable downward trend in prices from the start of the sample period to the end of the sample period. Thus, the first day of the sample will likely have an upward bias while the last day of the sample will likely have a downward bias. Second, we hypothesize that market depth may have an influence on prices. Specifically, prices may be higher when fewer Glory Bears™ are available for auction and lower when a large amount of Glory Bears™ are available for auction. In looking at Table Four, it is apparent that both average transactions per day and average transactions per period vary dramatically. Thus, it is not clear whether the differences are due to seasonality or market depth without controlling for both in a regression framework.

Table Four
Seasonality Analysis

This table illustrates the degree of seasonality present in the data. Two issues are examined. First, do prices tend to be higher on certain days (day-of-the-week analysis) and second, do prices tend to be higher at certain times of the day (time-of-day analysis). The time periods are based on Pacific Standard Time and are described below.

Table 4: Average Price by Date and Time of Day

All Observations	**Mon.**	**Tues.**	**Wed.**	**Thur.**	**Fri.**	**Sat.**	**Sun.**
Average Price	$91.52	$91.83	$93.13	$101.94	$95.73	$90.48	$93.37
Total Transactions	483	426	384	379	553	563	571
Trans. per Day (Avg.)	96.60	85.20	76.80	94.75	138.25	140.75	114.20
Restricted Observations*	**Mon.**	**Tues.**	**Wed.**	**Thur.**	**Fri.**	**Sat.**	**Sun.**
Average Price	$91.27	$91.95	$92.26	$101.05	$94.83	$89.77	$93.47
Total Transactions	444	391	328	334	499	525	537
Trans. per Day (Avg.)	88.80	78.20	65.60	83.50	124.75	131.25	107.40
All Observations	**Per. 1**	**Per. 2**	**Per. 3**	**Per. 4**	**Per. 5**	**Per. 6**	**Per. 7**
Average Price	$104.57	$98.04	$92.28	$93.45	$92.20	$94.12	$91.99
Total Transactions	73	359	454	549	679	826	419
Trans. per Period (Avg.)	2.28	11.22	14.19	17.16	21.22	25.81	13.09
Restricted Observations*	**Per. 1**	**Per. 2**	**Per. 3**	**Per. 4**	**Per. 5**	**Per. 6**	**Per. 7**
Average Price	$104.38	$98.52	$91.97	$92.15	$91.53	$93.80	$91.21
Total Transactions	66	333	412	490	626	751	380
Trans. per Period (Avg.)	2.06	10.41	12.88	15.31	19.56	23.47	11.88

*The restricted observations only include those transactions where the price change from the previous transaction was within ±20%. This removes approximately 9% of the observations.

Equality of Means Test for Day of the Week (ANOVA)

$F_{6,\,3352}$ = 8.61 (Significant at the 1% level)

*$F_{6,\,3051}$ = 7.34 (Significant at the 1% level)

Equality of Means Test for Time of Day (ANOVA)

$F_{6,\,3352}$ = 4.35 (Significant at the 1% level)

*$F_{6, 3051}$ = 5.33 (Significant at the 1% level)

The 1% level for an F-Statistic with 6, 3352 degrees of freedom is 2.807
The 1% level for an F-Statistic with 6, 3051 degrees of freedom is 2.808

	Start	Finish
Period 1:	12:00 AM	6:00 AM
Period 2:	6:00 AM	10:00 AM
Period 3:	10:00 AM	2:00 PM
Period 4:	2:00 PM	5:00 PM
Period 5:	5:00 PM	7:00 PM
Period 6:	7:00 PM	9:00 PM
Period 7:	9:00 PM	12:00 AM

In Table Five, the results of three separate regressions are reported. All three usethe transaction price as the dependent variable. The first includes the full complement of independent variables discussed earlier along with day-of-the-week dummy variables. The second includes the full complement of independent variables with no seasonality dummy variables. Finally, the third includes the full complement of independent variables with time-of-day dummy variables. This allows us to capture any seasonality on transaction prices while controlling for other effects. F-Tests are performed to determine if the unrestricted models (seasonality) contain significantly more information than the restricted model (no seasonality). The results indicate that the day-of-the-week seasonality is significant while the time-of-the-day seasonality appears to be insignificant.[7] When controlling for other factors, it appears that prices are depressed somewhat on weekends with Thursday, Friday, and Saturday exhibiting the lowest coefficients.

Table Five
Seasonality with Regression Analysis

This table examines the issue of seasonality in a regression format. The transaction price is regressed on potential explanatory variables in addition to the seasonality variables. All independent variables are strongly significant with the anticipated signs. An F-Test is then performed to see if the seasonality variables make a significant contribution to the analysis. The regression analysis detects a significant degree of autocorrelation which is accounted for through Maximum Likelihood methodology out to five lags. Observations where the percentage change from the previous transaction exceeds ±20% have been removed. Results using all observations are consistent with those reported below and are available upon request.

Table 5: Seasonality of Transaction Price with Regression Analysis

Variable	Coef.	T-Value	Variable	Coef.	T-Value	Variable	Coef.	T-Value
INT			INT	131.179	98.957	INT		
DUTCH	-2.696	-4.963	DUTCH	-2.697	-4.977	DUTCH	-2.713	-5.002
RESERVE	1.031	3.444	RESERVE	1.070	3.544	RESERVE	1.044	3.457
PICTURE	2.853	8.654	PICTURE	2.842	8.646	PICTURE	2.867	8.705
QUANT	-0.774	-14.446	QUANT	-0.775	-14.510	QUANT	-0.777	-14.528
FEATURE	4.359	8.243	FEATURE	4.383	8.314	FEATURE	4.382	8.300
LRATING	0.305	4.163	LRATING	0.299	4.094	LRATING	0.291	3.982
LTBT	0.737	8.944	LTBT	0.742	9.021	LTBT	0.733	8.843
COUNT	-0.026	-48.491	COUNT	-0.025	-40.516	COUNT	-0.025	-41.964
MON	134.735	84.461				PER1	133.083	77.849
TUES	133.380	80.122				PER2	133.468	88.154
WED	135.594	78.868				PER3	132.190	88.593
THUR	130.913	82.074				PER4	129.957	89.586
FRI	128.052	87.494				PER5	130.183	92.432
SAT	128.743	86.160				PER6	130.771	94.003
SUN	133.116	89.160				PER7	132.402	89.212
AR(1)	-0.382	-21.023	AR(1)	-0.393	-21.673	AR(1)	-0.392	-21.575
AR(2)	-0.163	-8.438	AR(2)	-0.172	-8.873	AR(2)	-0.169	-8.718
AR(3)	-0.061	-3.096	AR(3)	-0.653	-3.330	AR(3)	-0.066	-3.342
AR(4)	-0.094	-4.842	AR(4)	-0.100	-5.136	AR(4)	-0.098	-5.043
AR(5)	-0.056	-3.064	AR(5)	-0.066	-3.633	AR(5)	-0.064	-3.522
SSE	144,278		SSE	145,621		SSE	145,022	

F-Test for Day-of-the-Week Effect

$$F_{7,3039} = \frac{(145{,}621 - 144{,}278)/7}{144{,}278/(3059 - 20)} = 4.04 \qquad \text{(Significant at the 1\% Level)}$$

F-Test for Time-of-the-Day Effect

$$F_{7,3039} = \frac{(145{,}621 - 145{,}022)/7}{145{,}022/(3059 - 20)} = 1.80 \qquad \text{Not Significant}$$

The 1% level for an F-Statistic with 7, 3039 degrees of freedom is 2.645
The 5% level for an F-Statistic with 7, 3039 degrees of freedom is 2.012

Table Six
Regression Results Using ARIMA Residuals

Table 6 presents the regression results for the model using ARIMA residuals as the dependent variable. First, an ARIMA model (1,1,1) is fit to the PRICE variable. Then the residuals from the ARIMA model are used as the dependent variable. This procedure removes the time-series elements from the PRICE variable and allows the remaining variation to be modeled by the independent variables. In the process, the high degree of autocorrelation is eliminated. The results are consistent with those presented in Table Five with price used as the dependent variable and are also consistent with expectations. The results are presented without either of the seasonality dummies (results using day-of-the-week and time-of-the-day dummy variables are available upon request.) Results are presented using all observations and with outliers removed.

Table 6: Regression Result

All Observations			**Observations with Price Fluctuations Between ±20%**		
Variable	Coef.	T-Value	Variable	Coef.	T-Value
INTERCEPT	-6.2102	-8.97**	INTERCEPT	-5.1954	-9.14**
DUTCH	-4.7409	-6.99**	DUTCH	-3.0065	-5.17**
RESERVE	1.2870	3.53**	RESERVE	0.9386	3.12**
PICTURE	3.5826	8.83**	PICTURE	2.9174	8.70**
QUANT	-1.1021	-16.81**	QUANT	-0.7483	-13.17**
FEATURE	7.3126	11.48**	FEATURE	4.2351	7.64**
LRATING	0.3374	3.76**	LRATING	0.3109	4.18**
LTBT	0.9083	9.69**	LTBT	0.6926	8.95**
COUNT	0.0004	2.71**	COUNT	0.0003	2.31*

* significant at the 5% level
** significant at the 1% level

ARIMA Model All Observations

Model Parameter	Estimate	T-Value
Intercept	-0.0283	-1.72
Moving Average, Lag 1	0.9173	117.80**
Autoregressive, Lag 1	0.1724	8.97**

ARIMA Model with Price Fluctuations Between ±20%

Model Parameter	Estimate	T-Value

Intercept	-0.0314	-1.72
Moving Average, Lag 1	0.9109	100.26**
Autoregressive, Lag 1	0.3502	17.00**

There are other points of note from the regressions using price as the dependent variable aside from the discussion of seasonality. First, the coefficients of the other independent variables are all highly significant and consistent regardless of whether or not seasonality is included in the analysis. The signs on the each of the coefficients are also consistent with expectations.

The coefficients on DUTCH and QUANTITY allow us to draw some inferences regarding the optimal strategy for sellers. When there are larger quantities of Glory Bears™ available, prices seem to decline. On the other hand, listing multiple auctions can result in higher fees.[8] The answer to whether it is better to list multiple auctions of a single item or one auction for multiple items to a single high bidder depends on the quantity of items being sold, the initial listing fee, and the average selling price per item. However either of these selling methods appears to be a better alternative than a Dutch auction. To illustrate this, consider a person auctioning 12 (a common quantity seen in our sample) Ty Glory Bears™. Assume that the final selling price per bear is $93.75 (the mean of our entire sample) if the seller sells these items through 12 separate auctions. The fee to list an auction can range from $0.25 to $2.00 assuming that it is not listed as a featured item. In addition, the seller will pay fees of $2.97 based on the selling price for a total cost of $3.22 to $4.97 per auction. This would net the seller between $88.78 and $90.53 per item. Selling the 12 together as a package should lower the sales price by approximately $0.78 per bear for a final auction value of $1115.64. Taking out fees ranging from $39.82 to $41.57 would result in a realized price per bear of $89.51 to $89.65. Listing items in a Dutch Auction lowers the amount received per item by approximately $2.70 for a final auction value of $1092.60. For Dutch auctions the listing fee is multiplied per item up to a maximum of $2.00. This leaves the seller with $88.65 per item. Therefore, the optimal strategy would be to list each item separately with an opening price of $9.99. If the opening price were raised beyond $49.99, then it would be slightly more profitable to move to a quantity auction of all items. The least profitable strategy is a Dutch auction. One possible explanation for this is that shipping cost per bear (an additional fee paid by the seller) would likely be smaller for a quantity auction than it would for a Dutch auction.

There appears to be some impact of information signaling. The two variables used to designate information content, PICTURE and LRATING, both have positive coefficients ($2.85 and $0.30, respectively). For most sellers, posting a digital picture will have no monetary cost since the majority of Internet Service Providers provide the ability to store a limited number of pictures in a personalized area for no additional cost. In the event that commercial services are used, the fees are generally less than $2.00 per picture. Thus, in a net sense, the seller can receive an excess rent of at least $0.85 and more reasonably $2.85 by displaying a picture. This indicates that buyers are willing to pay a premium for a product that they can see (at least in a photo) and for a quality reputation by the seller. Visibility apparently does not benefit the seller unless the seller has at least 3 items for sell as a group or in a Dutch auction. Featured auctions tend to bring in a higher average selling price (approximately $4.40), but costs the seller $9.95. This is clearly a losing proposition for the seller who is selling one or two items.[9]

Finally, the longer the time between transactions (LTBT), the higher the price that is realized. The positive coefficient for the RESERVE variable indicates that having a reserve price, as expected, keeps the item from selling at an "unacceptably" low price. However, the positive coefficient on the RESERVE variable needs to be viewed with caution. As only completed auctions are used in our sample, auctions that failed to meet the reserve price were not included. If the seller still desires to sell the item, it would need to be relisted. Given the trend of declining prices over our sample period, the item would likely receive a lower bid during the second listing than it would have without a reserve initially. The final independent variable, COUNT, is merely a control for the downward trend in prices and exhibits a strong, negative relationship with price and is consistent with the graphs of transaction prices presented in Tables One and Three.

CONCLUSION

The purpose of this paper has been to examine a market with different characteristics than a typical "financial" market using high frequency continuous transactions data to see if some of the same patterns (signaling of information and seasonality) appear as well as to examine the depth of this alternative market. The market selected is an Internet auction market for collectibles, specifically the auction results for Ty Glory Bears™ on the eBay, Inc. web site. This market was selected for its relatively high activity and homogeneity among collectibles markets. Also, it provided a wealth of information related to signaling content, seasonality, and market depth. The results indicate that Internet auction markets may indeed resemble typical financial markets, at least to some degree. There is evidence of signaling related to seller's reputation and product information. Seasonality appears to exist to some degree based on the day of the week. There is also evidence that market depth may have an impact on transaction prices. Finally, visibility to buyer's and reserve pricing also appear to generate slightly higher transaction prices.

There are several avenues for future research on Internet auction markets. First, while our data set has a large number of observations, the time period is relatively short. It would be interesting to examine similar issues over a time period of one or more years. Second, do these patterns hold in other internet auction markets either outside of eBay or outside of the collectibles arena? A third avenue, closely related to the previous two, might explore how market patterns differ as the volume of transactions and evolution of Internet auction markets change. Finally, if similar seasonality patterns are shown in different Internet auction markets, can these be explained by a structural characteristic of these markets?

ENDNOTES

[1]Typically, inefficiencies are uncovered, however these inefficiencies are usually recognized and disappear in a relatively short time period or are small enough that they can not generate profits in excess of trading costs.

[2]For instance, Houser and Wooders (2000) examine Pentium III transactions and obtain a sample size of 94 observations over the course of a three-month period. McDonald and Slawson (2000) examine Harley-Davidson Barbie dolls and obtain a sample of 451 auctions during a seven-month period.

[3]Consider a situation where the current high bid is $20.00 and the minimum bid increment is $0.50. If I bid $25.00, this will raise the current bid only to $20.50. If another bidder would then try to bid $22.00, the eBay system of proxy bidding would raise the current price to $22.00, but maintain me as the high bidder.

[4]The segmentation of the day into seven time-of-day dummies is arbitrary. The intent was to segment according to "reasonable" time blocks (early morning, middle-of-day, early afternoon, etc.) while trying to keep average transactions from varying by too large of a degree from period to period. The specific breakdowns are presented in Table Four.

[5]In the rare event that a seller had feedback rating with a negative value that transaction was dropped from the sample. In each case where this occurred the comments associated with the rating indicated that the transaction was not completed (i.e. the seller never delivered the item). If the feedback rating was 0, the actual feedback rating was used instead of the log.

[6]The elimination of data points where price changes are greater than ±20% is arbitrary. We also examined a cutoff level of ±30% and found similar results. The elimination of these data points reduces the number of transactions by just less than 10% from the full sample. In addition, it allows the autocorrelation to be truncated much more rapidly.

[7]All times are recorded in Pacific Standard Time which is consistent with the timing system used by eBay, Inc. However, time zone issues may make it more difficult to document time-of-the-day seasonalities due to time zone differences between east and west coast (as well as international) bidders.

[8]The listing fees are based on the opening price set by the seller. At the time this data was collected, these fees were $0.25 for opening prices less than $9.99, $0.50 for opening prices between $10 and $24.99, $1.00 for opening prices between $25.00 and $49.99, and $2.00 for opening prices $50 and up. Currently, these fees are $0.30 for opening prices less than $9.99, $0.55 for opening prices between $10 and $24.99, $1.10 for opening prices between $25.00 and $49.99, $2.20 for opening prices between $50 and $199.99 and $3.30 for opening prices $200 and up. Reserve

fees were not charged at this time, but they are currently $0.50 up to $24.99 and $1.00 beyond $25.00). Also, optional fees for gift icons, gallery, featured gallery, bold, and highlight were not available. In addition, sales fee were 5% of the final sales price up to $25 plus 2.5% of the additional price between $25.01 and $1,000 plus 1.25% of the additional price beyond $1000.01. Currently, sales fees are 5.75% of the final sales price up to $25 plus 2.75% of the additional price between $25.01 and $1000 plus 1.5% of the additional price beyond $1000.01. Finally, the "Buy-it-Now" option was not available at the time this data was collected.

[9]While it may appear that sellers are not earning back their $9.95 additional fee to place an item in the featured category, in actuality they are likely to be earning back their fee plus a profit. Many featured items are on Dutch and quantity listings. As long as three or more units are for sale per listing, the featured item would earn back the $9.95 fee plus a profit. The $9.95 represented the cost of listing an item as featured within a category at the time the data was collected. This price has currently been raised to $19.95.

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