The Role of Reputation in Online Markets for Small-Ticket Goods:

An eBay Case Study

By

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Abstract

In transactions that entail large amounts of information asymmetry, sellers must use some sort of signaling strategy to differentiate their products and or services. This paper examines the effectiveness of the most prominent of these strategies used on the auction website Ebay.com: the Seller's feedback score. Many studies (Jin and Kato 2002, Livingston 2002, Ba and Pavlou 2002, Livingston 2002) have shown the significance of reputation in markets for collectible goods and or high-ticket goods, but few have examined whether a higher reputation is profitable in small-ticket and or more homogenous markets. Although in these markets information asymmetry is considerably less, its presence is still significant. Looking at the online market for used and new DVDs, this study will examine whether building a strong reputation is necessarily a worthwhile strategy sellers of small-ticket and homogenous good. The findings of this study could prove useful in forecasting the future for Ebay.com, for if reputation does not alleviate the information asymmetry in small ticket items, the market for these items could deteriorate.

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1.1 Introduction

Online financial transactions carry some inherent risk. Often, sellers have more information about the quality of the product they are selling and the service they will provide than prospective buyers. Thus, buyers must place large amounts of trust in sellers in order for a transaction to be successfully completed. This disproportion of information is referred to as information asymmetry, and according to George Akerlof (1970), the pioneer for this field, its presence can lead to market failure[1].

In order to persist, online marketplaces need some manner in which they can alleviate information asymmetry. One way is to create a system that quantifies a seller's reputation. A quantified reputation gives a buyer some insight into how a particular seller has behaved in the past. The buyer can then use this information to speculate as to how the seller will behave in the future. Many online markets have enacted these types of systems.

This paper will examine the effectiveness of the reputation system implemented by the online auction behemoth eBay.com in facilitating trust among participants in the market for DVDs. The remainder of this paper is divided into seven sections. Section two provides a brief description of the institutional details of eBay.com. Section three examines the theoretical literature. Section four examines the previous empirical literature. Section five illustrates this study's conceptual model. Section six describes the actual data used in this paper. Section seven explains the results. Finally, section eight explains the limitations of this experiment and gives suggestions for future research.

[1] Market failure can refer to either the complete collapse or inefficient operation of a market. This point will be elaborated upon more in section 3.1.

2.1 Institutional Details of eBay Auctions[2]

This section gives a brief overview of the institutional details of eBay.com. It consists of four subsections: listing items, bidding on items, the contract between the seller and buyer, and eBay's reputation system.

2.1.1 Listing items

To list an item for an eBay auction, the seller must first enter a category. In the case of this study, all items were listed under the main category "DVD's and Movies" and under the subcategory "DVD, HD DVD, and Blue-ray." After selecting a category, the seller must create a title and description for their item. In the case of selling DVD's, CD's and movies, eBay asks for the UPC code, which allows eBay to enter a basic description about the DVD and a title for the item automatically. The seller can then tailor the description to his or her specific needs. The next step is for the seller to add a picture; if they already entered the UPC code, a stock picture for the item will appear automatically.

Next, the seller must choose the parameters of his or her auction, with each parameter entailing a certain fee. The seller must choose a starting price, reserve price, if applicable, Buy it Now[3] price, if applicable, auction duration, start time, quantity to be sold, and the item's location. Also, he or she must determine the shipping cost (in the

[2] All of the information in this section can be found either in The Official EBay Bible by Jim Griffith or in the Help section of ebay.com.
[3] A Buy it Now (BIN) price is an optional feature that lets the choose a price ceiling for the auction. A buyer then has the option to enter a bid below the BIN price, or can choose to end the auction early and bid the BIN price.

case of DVD's this is usually a flat rate), available shipping services, the return policy, and payment instructions[4].

2.1.2 Bidding

Single item auctions[5] are conducted as English ascending-bid auctions with a proxy bidding system. With eBay's proxy bidding system, the buyer enters the maximum amount he or she will pay for a given item. EBay will then bid incrementally on the buyer's behalf until either he or she is the high bidder or until his or her maximum bid is reached. Buyers can also bid incrementally on their own by bidding the current maximum bid plus the minimum bid amount.

In auctions containing a reserve price, if one or more of the bid amounts is less than the seller's hidden reserve price, then the bidding proceeds as any other proxy auction. If a bidder submits a bid equal to or greater than the reserve price, then the current high bid jumps to the reserve amount. From there, the bidding proceeds as a normal proxy-bidding auction.

A buyer may increase his or her proxy bid at any time during the auction, as long as his or her new proxy bid is higher than the current high bid. Buyers are also allowed to retract their previous bids, but eBay discourages this act by posting in the user's feedback profile the number of bids the member has retracted in the last six months.

Another bidding strategy used at eBay is referred to as sniping. Here, a bidder waits until the last minutes of an auction and submits a maximum bid, sometimes mere seconds before the auction ends. There are some inherent risks involved with this

[4] Here the seller indicates what type of payment is accepted and when it is due. Most sellers use the online payment service Paypal for their auctions. More information can be found at www.paypal.com.
[5] All data in this study was collected from single-item auctions. EBay does allow for multiple item auctions, but the bidding system is different from single-item auctions. For more information, please see www.ebay.com.

method. One is that the sniper may get caught up in the bidding frenzy and pay more than he or she may have initially wanted. A second is that if many users are sniping, the probability of winning for each sniper is diminished.

2.1.3 The Buyer-Seller Contract

According to eBay, "[B]uyers automatically enter into a legally binding contract to purchase the item from the seller if they win the online auction or use the Buy It Now feature. EBay's Unpaid Item Policy requires buyers to pay the seller for the items that they commit to purchase."

However, eBay does not enforce individual contracts. Instead, "Sellers can file an unpaid item dispute with eBay for each of their items that are purchased but not paid for. EBay will issue a strike on the account of the buyer who does not honor their obligation to pay (unless the buyer and seller mutually agree not to complete the transaction). If a buyer gets too many strikes in too short a time period, their account will be suspended indefinitely. In some cases, limits may be placed on the buyer's account in advance of suspension." Sellers can also penalize defaulting buyers by posting negative feedback to their user profile through eBay's Feedback Forum. The same is true for buyers.

2.1.4 EBay's Feedback Forum

Every registered eBay member has a Feedback Profile, which provides valuable information about how a user has acted in the past. Upon completion of a transaction, both parties have the opportunity to rate each other with a 1, 0, or -1, with 1 indicating a good transaction, 0 indifference, and -1 a troublesome transaction. All of the ratings from unique users[6] are then added together to create the users feedback score.

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[6] Users can rate other users multiple times; however, additional ratings from the same user are not calculated into the seller's feedback score.

In addition to the users feedback score, his or her profile also includes the total number of positive feedback received, the number of members that left both positive and negative feedback, a basic history of the member, and a list of all comments ever left for the member by other users. A user whose feedback score falls to -4 is automatically suspended.

Anytime a user is identified on the website, his feedback score is displayed in parenthesis. EBay also places different icons next to the feedback score depending on its quantitative level. (I.e. a user with a rating higher than 10 would have a star graphic next to his or her rating, and the color of this star will change as he or she accumulates more positive ratings).

3.1 Theory

Buyer-seller relationships are often characterized by information asymmetry where the seller often has more information about the product or service being offered than the buyer. There are two potential problems that exist in the face of information asymmetry: the moral hazard problem and the adverse selection problem (Mishra et all 1998).

Moral hazard refers to the increased risk of problematic behavior, and in turn, a negative outcome in a transaction where the party who caused the problem does not suffer the full consequences of his or her actions. In such transactions, sufficient incentives for positive actions are not provided, and Pareto-optimal risk sharing is impossible (Holmstrom 1979). Pareto-optimal risk sharing refers to an economic situation where one person cannot be made better off without hurting anybody else.

The adverse selection problem refers to a buyer's inability to determine the quality[7] of the seller and or the product for sale. In a market where adverse selection is present, the buyer is only willing to pay a price dependent on the probability that the good is of high quality. At this point sellers of high quality goods are not able to receive the true value of their product and will choose to exit the market. The outflow of high quality goods from the market leads to a market for only poor quality goods (lemons) (Akerlof 1970). This process could eventually lead a market to failure. Also, in this environment, sellers may take part in opportunistic behavior by misrepresenting their quality.

Geneseve (1993) addresses four conditions that are necessary for a market to exhibit adverse selection. First, at the time of sale, one participant is more accurately able to discern product quality of the good or service. Second, both the buyer and seller value quality. Third, the better-informed party does not determine price. Finally, extratrading institutions do not fully alleviate the information asymmetry. If any one of these conditions is not met, Geneseve argues that adverse selection is not an issue. A simple example would be if both participants had the same information, there would be no information asymmetry to lead to adverse selection.

In order for markets in which information asymmetry is prevalent not to fail (Akerlof 1970), sellers of high-quality goods must in some way differentiate their products and services from those of low-quality. Dewally and Ederington (2006) summarize four strategies that high-quality sellers use to differentiate their products. First, a seller may choose to offer a warranty or money-back guarantee. Second, some

[7] In the case of DVDs a high quality product is one that is an original version, that includes the case and accompanying media and that is not scratched or damaged in any way.

high-quality sellers will seek certification by a respected third party (i.e. auditors, testing organizations, bond rating agencies, etc). Third, the seller may provide additional information to prospective buyers through advertising, financial statements, test results, etc. Fourth, the seller may opt to invest resources in developing a reputation for selling high-quality products[8].

It has long been recognized that a sellers "goodwill" or good reputation is a valuable asset. A seller has a good reputation if buyers believe his or her products and or services to be of high quality. Since product qualities are often difficult to observe in the present, buyers can plausibly use the quality of products or services offered in the past as a proxy for the quality of future goods and services. Because of this, a firm's decision to produce quality goods is a dynamic one, and the benefits of doing so accrue in the form of a good reputation (Shapiro 1983).

Many Internet sites have designed reputation systems in order to alleviate the high levels of information asymmetry prevalent in online transactions. These systems quantify a participant's reputation by numerically rating past transactions. The system that this paper examines is eBay.com's Feedback Forum, which was already discussed in section 2.1.4.

For a reputation system to succeed, it must meet three conditions. It must: (1) provide information that allows buyers to distinguish between trustworthy and untrustworthy sellers, (2) encourage sellers to be trustworthy, and (3) discourage participation from untrustworthy sellers (Resnick and Zeckhauser et al. 2000).

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[8] This paper will focus on the latter.

The theoretical models on the importance of reputation are mixed. Shapiro (1983), Klein and Leffler (1981), Allen (1984), and Houser and Wooders (2000) all construct models where buyers are willing to pay a price premium for a good reputation. However, it is also possible to construct a model where reputation is not useful in determining an individual sellers' quality (McDonald and Slawson 2000). This variance in theoretical models has led to the growth of empirical examinations of the importance of reputation.

4.1 Previous Empirical Research

This section will focus on previous empirical research pertaining to online auctions. Online transactions are inherently risky in that the buyer and seller are usually anonymous, they may be geographically separated, and the transaction is frequently a one-time – non-repeated – event. All of these factors lead to greater potential for fraud and deceit. Empirical research on the role of reputation in e-commerce has grown almost as fast as the Internet itself. Two important factors for this phenomenon are that Internet auctions offer a large amount of information and that most auction sites have a system in place that aims at quantifying a participant's reputation.

Over the past 7 years or so, researchers have examined the role that reputation plays in online transactions with two methods: hedonic regression analysis and field experiments. Since this paper will use hedonic regression analysis, it will focus its attention on previous work using this technique. However, it will give a brief description of the field experiments used.

Research using hedonic regression models can be placed into four categories determined by the dependent variable used: final price, the number of bids received, price premiums, and the probability of a sale. This section will be organized accordingly, with a brief description of field experiments at the end. Many studies ran simultaneous and/or reduced form regressions, thus using two dependent variables. In these cases, this paper will examine the stages of these models separately according to the dependent variable used.

4.1.1 Reputation Effect and Final Price

This section examines seven papers that look at the effect of reputation on price; three using OLS, two using simultaneous or reduced form regressions, and two using censored normal/tobit regressions.

Kalyanam and McIntyre (2001 as cited in Bajari 2004) looked at a data set of Palm Pilot PDAs with a mean price of $238. They modeled the price of sold items only against total positive and negative feedback, with product type, presence of a picture (dummy variable), and the number of bids as covariates. They found that a seller with a total feedback of 3000 and zero negatives receives a 12% higher price than a seller with a total feedback of 10 with 4 negatives.

Dewan and Hsu (2001) used an OLS regression to examine reputation's effect on price for a set of collectible stamps with a mean price of $37. For covariates they used the natural log of the difference between positive and negative feedback scores, book value, number of bids, and buyer's net rating, among others. They found that a five-cent increase in auction price correlates with a 20 point increase in the seller's rating.

Jin and Kato (2002), looking at a set of sports trading cards with a mean price of $166, ran OLS regressions in double-log form for sold items only on the final price against the sellers net feedback score and a dummy variable for whether or not he or she has any negative ratings. They controlled for when the auction closed, the presence of pictures, and shipping charges, among others. They found no significant effect on price.

Livingston (2002), McDonald and Slawson (2000), and Eaton (2002) examined the effect of reputation on price using reduced form or simultaneous regressions. Livingston (2002) ran a simultaneous ML estimation of the price of sold items and the probability of a sale with reputation specified as the fraction of negative feedback and quartile dummy variables for different levels of positive reputation. He collected data on a set of Golf Clubs with a mean price of $409. He modeled product type, minimum bid, book value, and auction length as independent variables, as well as dummy variables for whether or not there is a secret reserve, availability of credit card payment, if the bidder is inexperienced, and for the day and time of the auction. He concluded that sellers with 1 to 25 positive comments receive $21 more than those with no reports. Sellers with more than 675 positive comments receive $46 more.

McDonald and Slawson (2000) estimated a simultaneous regression for sold items only. They modeled the final price against the number of bids and net reputation, and bids against minimum bid, the presence of a secret reserve price, and reputation. They did this with various specifications for reputation and a covariate for the month in which the auction closed. They concluded that high reputation sellers get a 5% higher price than those with low reputations. Higher reputation sellers also get more bids.

Eaton (2002) used a reduced form model on a data set of electric guitars with a mean selling price of $1,621. He used a logit regression on the probability of a sale and an OLS regression for sold items only on the final price. He modeled reputation with three variables: the number of positive feedback ratings, the number of negative ratings, and a dummy variable for the presence of any negative ratings. His covariates included the type of guitar, whether credit card purchases and escrow services are available, among others. He found no robust statistically significant relation between negative feedback and the final selling price or probability of a sale.

Lucking-Reiley et al. (2000) ran a reduced form, censored normal regression on the high bid against the number of positive, negative, and neutral ratings on a set of coins with a mean price of $173. For covariates they used the book value for the coins, the minimum bid, auction length, and whether or not it has a hidden reserve, among others. They found no statistically significant effect from positive feedback, but do find a statistically significant effect from negative feedback.

Melnik and Alm (2002) ran a reduced form, censored normal regression similar to that of Lucking-Reiley et al. (2000). Their data set was a set of gold coins with a mean price of $33. For covariates they used the price of gold, shipping charges, and whether or not credit cards are accepted, among others. They found that a decline in positive ratings decreases price and also that small amounts of negative feedback actually increase the final price.

4.1.2 The Reputation Effect and the Probability of a Sale

This study looked at three papers that examined reputation's affect on the probability of a sale; one using logit and two using probit. Eaton (2002), as part of his reduced form model, used a logit model to examine the effects of reputation on the probability of a sale. He used the same independent variables as above and found no robust relationship between reputation and the probability of a sale.

Jin and Kato (2002) used a probit model to predict the probability of a sale, with the natural log of the net score for an independent variable and a dummy variable for whether or not it contains any negative ratings. They also controlled for the effects of the product type, the closing time and day, the auction's length, credit card acceptance, pictures, and shipping charges. Their results show that there is a positive correlation between reputation and the probability of a sale, and a negative correlation between negative feedback and the probability of a sale.

Livingston (2002) used probit to predict the probability of a sale alone and also as part of a ML regression. He measured reputation with the fraction of total feedback that is negative and quartile dummy variables for levels of positive feedback, using the same covariates listed above for his simultaneous regression. He found a positive relationship between reputation and the probability of a sale. The first 11 reports of positive feedback increase the probability of a sale by four percent and all subsequent reports have no significant affect.

4.1.3 The reputation effect and the number of bids

This study looked at one paper that examined reputation's effect on the number of bids. As part of their simultaneous regression, McDonald and Slawson (2000) regressed the number of bids against the minimum bid, the secret reserve price (if available), and reputation, with various specifications for reputation on a set of collectible dolls. They found that higher reputation is positively related to more bids.

4.1.4 The reputation effect and price premiums

This paper examined one study that looked at reputation's affect on price premiums. Ba and Pavlou (2002) modeled, for sold items only, price premium against the natural log of all positive feedback and the natural log of all negative feedback on a broad set of electronic items. Price premiums were measured as the final price minus the average price divided by the average price, where the average price is the average of the final prices of all other auctions observed for the same item. They show that buyers are willing to pay more for products from sellers with positive feedback and less for products from sellers with negative feedback. Also, they discovered that these effects are larger for higher priced items.

4.1.5 Field Experiments

Ba and Pavlou (2002) and Resnick et al. (2003) both examined the reputation effect using controlled field experiments. Ba and Pavlou posted an on-line experiment where participants were given a page that described five seller's feedback profiles. The participants were then asked to indicate how much they trusted each seller. They found that buyers placed more trust in sellers with higher feedback scores.

Resnick et al. (2003) worked with an already established eBay dealer. They used his existing eBay account, as well as a new one with zero feedback and sold identical items with each seller. They found that the market rewarded the higher reputation seller with higher prices.

5.1 Conceptual Model

This paper uses a simultaneous modeling technique to examine how reputation affects two aspects of an online auction: the probability that an item will sell, and if sold, the item's final price[9]. For the first stage, a binary dependent variable for whether or not an auction resulted in a sale is used. It is modeled as a function of the seller's stated

[9] This model is similar to the reduced form model used by Eaton (2002).

shipping costs (-), the minimum or starting bid (-), the length of the auction (+), the number of concurrent auctions for the same good ending on the same day (-), the seller's reputation score (+), and the percentage of positive feedback for the seller (+)[10].

Shipping costs are hypothesized to have a negative effect on the probability of a sale. Higher shipping costs will directly impact the price of the item, and in a market with a large supply of substitutable goods, a rational buyer will likely choose the cheaper good. The starting bid is hypothesized to have a negative impact on the probability of a sale because, assuming that there is no secret reserve price, buyers are more likely to bid on an item with a lower initial value. The length of the auction should positively impact the probability of a sale due to the fact that the auction has a longer period of time to attract potential bidders. The number of concurrent auctions for the same item ending on the same day will negatively impact the probability of a sale. The larger the supply of substitutable goods, ceteris peribus, the less likely any single item will sell. Finally, both of the reputation variables should have a positive impact on the probability of a sale. A higher reputation indicates to a buyer that the probability of having a successful transaction is higher, and the buyer will participate in transactions with the lowest level of risk.

The second stage of the model looks at reputation's effect on the auction's final price. It models final price as a function of the number of bids (+), shipping costs (-), number of concurrent auctions for the same item (-), the length of the auction (+), the seller's reputation score (+), and the percentage of positive feedback for the seller (+).

[10] The expected signs for each variable are given in parenthesis.

The number of bids should have a positive effect on price since each additional bid raises the price of the item. Shipping costs are hypothesized to be negatively correlated for price for the same basic reason stated in for the previous model. The same goes for the signs for the number of concurrent auctions and the length of the auction. The seller's reputation should be positively related to price since buyers theoretically will reward sellers for their investment in a reputation.

This paper uses two variables to represent a seller's reputation. The reason for this is that alone neither one is adequate. One must control for the magnitude of the seller's reputation, as well as the percentage of positive feedback. For example, a seller may have a reputation score of 30,000, and alone this would indicate a reputable seller; however, this same seller may have a percentage of positive feedback of 75%, indicating that this seller is not very reputable. Also, a seller may have a percentage of 100%, indicating a highly reputable seller, but have a score of 1. In this case, a buyer cannot be sure of the seller's reputation because his history of positive transactions is rather short.

6.1 Data

This paper uses data collected from www.ebay.com from September 3rd, 2006 through October 28th, 2006. It includes auction statistics for a set of four DVD's. The data was collected manually by searching for completed auctions for each product and recording the relevant data[11]. The titles of the DVDs chosen and their descriptive statistics can be found in figure 6.1. Descriptive statistics for the independent variables for reputation can be found in figure 6.2

[11] The same search criterion was used for each product in order to control for variance in the listing techniques used by individual sellers.

Table 6.1

Descriptive statistics: price for each product (in $US)						
Product	Number of observations	Percentage Sold	Mean*	Standard deviation*	Max*	Min*
All products	1442	50.4	9.88	7.75	38.00	0.01
Once Upon a Time in Mexico (2004)	527	31.1	1.84	1.47	7.42	0.01
Arrested Development Season 1 (2004)	242	68.4	14.23	3.19	25.00	7.00
Constantine (2005)	367	43.5	2.21	1.49	7.01	0.01
Family Guy Volume 3 (2005)	306	77.1	17.60	4.09	38.00	3.25

*Calculated for sold items only

Table 6.2

Descriptive statistics: seller's reputation						
Feedback	Number of observations	Mean	Median	Standard deviation	Max	Min
Feedback Score	1442	14502.98	859	48716.53	315815	0
Percent Feedback	1442	98.5	99.7	8.65	100	0

This study took a different approach than many past studies with respect to the items observed. Most previous research has concentrated on auctions for higher cost and more heterogeneous products. This study aims to extend the body of research in this field to include lower cost and more homogeneous goods. The DVD market was chosen for two reasons. First, it has an extremely high volume of transactions. This made it possible to collect a large sample in a short period of time. Second, the DVD market falls prey to a number of issues regarding transaction security that make reputation valuable to buyers. One example is that many sellers attempt to sell pirated merchandise as if it were original. Not only is this against eBay's policies, but also it is also illegal in most countries.

Also, there have been reports of another source of risk in these transactions. Sellers scan other retail sites such as Amazon.com for cheap products and list the same item for sale on eBay.com. Then, if someone purchases the item on eBay, the seller quickly purchases the same item from Amazon.com and ships it directly to his purchaser. This often leads to longer than expected shipping times, as well as inventory shortages because the eBay seller cannot guarantee that when his item is purchased, that the equivalent will still be for sale on Amazon.com. Even though this method is not illegal or against eBay policies, it has compounded the uncertainty surrounding online transactions in this market

7.1 Results

The conceptual model above is estimated using a two-stage Heckman procedure. The Heckman procedure is used because of the inherent selection bias in the data; there is only final price data on those transactions that ended in a sale. Because of this, the model must in some way control for all unmeasured characteristics that are related to the sale variable. The first stage, or selection equation, is a binary logistic regression with the probability of a sale as the dependent variable and shipping costs, the starting bid, the length of the auction, the number of concurrent auctions for the same good ending on the same day, the seller's reputation score, and the percentage of positive feedback for the seller. It is modeled using the following equation. The results are summarized in table 7.1.

$$P(\text{sale})=1/(1+e^{-(\alpha - ß1(\text{Shipping}) - ß2(\text{Starting Bid}) + ß3(\text{Length}) - ß4(\text{Concurrent Auctions}) + ß5(\text{Rep. Score}) + ß6(\text{\% Score})})$$

Table 7.1

Selection Equation – Binary Logistic Regression		
Variable	B	SE
Constant	1.861*	.705
Shipping Costs	-.087*	.033
Starting Bid	-.068**	.009
Concurrent Auctions	-.200**	.018
Auction Length	.083*	.030
Seller Reputation Score	.000*	.000
Seller Percent Positive	.001	.007
-2LogLikelihood	1814.076	
Sample size	1442	

* $p<.01$, ** $p<.001$

The predicted probabilities from this equation were used to calculate the control variable Lambda which is used in the second stage, or substantial analysis. An OLS regression was estimated using Lambda as a control variable. The coefficients estimates of this procedure are unbiased. However, the standard errors obtained from the substantial estimate are biased due to the heteroskedasticity inherent in the two-stage Heckman procedure. These were corrected using a WLS estimation technique. Below is the OLS equation.

$$\text{Final Price} = \alpha - \beta_1(\text{Shipping}) + \beta_2(\text{Bids}) - \beta_3(\text{Concurrent auctions}) + \beta_4(\text{Auction Length}) + \beta_5(\text{Reputation Score}) + \beta_6(\text{\% Score}) + \beta_7(\text{Lambda})$$

The results for this estimation are summarized in table 7.2. This table also contains t-scores calculated with the corrected standard errors from the WLS correction technique.

Table 7.2

2-Stage Heckman – Substantial Analysis		
Variable	OLS	With Corrected SE's
Constant	1.712 (1.186)	1.712 (1.572)
Shipping Costs	-.323 (-4.116) ***	-.323 (-4.852) ***
Number of Bids	1.479 (46.258) ***	1.479 (40.607) ***
Concurrent Auctions	-.951 (-17.341) ***	-.951 (-16.234) ***
Auction Length	.259 (4.053) ***	.259 (2.525) **
Reputation Score	.000 (-2.191) *	.000 (-2.035) *
% Positive Feedback	-.007 (-.523)	-.007 (-.187)
Lambda	10.071 (14.346) ***	10.071 (12.748) ***
Adj. R-squared	.656	.656
F-value	392.788	392.788
Sample size	1442	1442

The t-values are given in parentheses.
*   Significant at the 95% level
**   Significant at the 97.5% level.
*** Significant at the 99% level.

An important note is that in the above regression, Lambda is statistically significant at the 99% level. This indicates that there was a significant amount of unmeasured characteristics in the data, that Lambda was successful in capturing it, and that the 2-stage Heckman model has improved the accuracy of the model. Also, the WLS standard errors do not change dramatically, signifying that the extent to which the original model suffered from heteroskedsticity was limited. The significance of all but one coefficient remained the same: that for the length of the auction.

The adjusted-R^2 of .656 indicates that this model explains 65.6% of the variation in final price. The F-value of 392.788 (p=.000) indicates that this model is more effective is explaining the variation in the dependent variable than a model with only a constant. What is interesting about the results is not their overall ability to predict changes in price, but rather the individual coefficient estimates. The signs for the coefficients for shipping costs, the number of bids, concurrent auctions, and auction length all follow their theoretical signs. All of these coefficients are also statistically significant at the 99% except that for the auction length which is statistically significant at the 97.5% level.

However, the coefficients for reputation tell a different story. The coefficient for the seller's reputation score (.000) indicates a correlation with a magnitude of zero between reputation score and the final price of an auction. This relationship is statistically significant at the 99% level[12]. The coefficient for the seller's percentage of positive feedback (-.007) indicates that a higher percentage of positive feedback actually has a negative correlation with the final price of an auction. However, it is not statistically significant, and given its magnitude, it can be concluded that it has no significant statistical correlation with the final price of an auction.

The binary logistic regression tells a similar story. The results for this regression are listed above in table 7.1. This is the same regression that was used to calculate Lambda. A chi-square of 184.861 (significance .000) indicates that this model more accurately estimates the probability of a sale than a model with only a constant. However,

[12] Two other models were also estimated with different measurements for reputation. In the first, reputation is measured as the total reputation divided by 10,000. In this case, reputation had a coefficient estimate of -.053 and was significant at the 95% level. In the second reputation was measured as the natural log of the reputation score. Here reputation had a coefficient estimate of -.054 and was significant at the 99% level. Full results of for each model can be found in Appendices B and C, respectively.

with a -2LL of 1814.076, there is still a large amount of uncontrolled variance. The model correctly predicted a sale 64.7% of the time compared to 50.4% with only the constant, again indicating that the model is effective, to some degree, in predicting the probability of a sale.

Again with this model, like the OLS/WLS model, the cause for concern is not the model as a whole, but rather the individual coefficients. The coefficients for the shipping price, starting bid, number of concurrent auctions, and the auction length are all statistically significant and their signs follow the theory. However, the coefficients for the reputation variables again go against the theory. The coefficient for seller's reputation score (.000), statistically significant at the 97.5% level, again indicates a correlation with a magnitude of zero with the dependent variable, in this case the probability of a sale. The coefficient for the seller's percentage of positive feedback has a small economically significant impact on the probability of a sale (.001). However, it is not statistically significant at any level. With such a small magnitude, it can confidently be concluded that the percentage of positive reputation has no statistically significant effect on the probability of a sale.

8.1 Conclusion, limitations, and suggestions for future research

Following the theoretical platform set down by George Akerlof in 1970, markets that suffer from information asymmetry require some mechanism to help evenly distribute information. Online auctions through eBay.com are a perfect example of this phenomenon. In response to this concern, eBay constructed its Feedback Forum with hopes of alleviating the information asymmetry inherent in online transactions. The results of this study show that this system may not be effective in reducing this problem.

This study finds no significant positive correlation between reputation and the outcome of a transaction. These results follow those of many previous researchers. Other papers that found a negative or insignificant relationship between reputation and the outcome of an auction include Jin and Kato (2002), Eaton (2002), Lucking-Reiley et al. (2000)[13] and Melnik and Alm (2002).

Does this mean that reputation is not a significant contributor to the outcome of an online transaction? Not necessarily. There are many factors that could be influencing these results. First, the model presented in this paper could suffer from some unknown specification errors, thus undermining the effect of reputation on the outcome of an auction. Second, the information asymmetry found in auctions for low-cost homogenous goods may not be severe enough to necessitate an effective reputation system. The potential cost of the risks involved in these transactions may not be enough to merit paying a premium to sellers with higher reputations. Third, eBay.com may be so efficient in its ability to filter out poor sellers in this market that the large majority of sellers are of high quality. Buyers then would not see the need to invest financial resources in securing the outcome of a transaction if they trust that the market only includes, for the most part, high quality sellers.

This paper does not necessarily conclude that reputation does not have an effect in online transactions for DVD's. More research is needed to be able to make a strong conclusion that reputation is not important in this market. Future research should use a broader data set collected over a much larger period of time. Also, like many econometric models, it is possible that this model falls prey to some level of specification error. Future

[13] They do however find a significant negative correlation between negative feedback and outcome of an auction.

research should work to detect any other variables that are essential in predicting the outcome of an auction. Future work should also look at the effect of substitute and complementary goods on the market price for DVD's.

In conclusion, the study of online markets is a rather new topic and is still in its early stages of development. Because of the extraordinary impact that online markets have had on the world economy and daily life, continued research is necessary so that we may better understand this recent phenomenon. This paper examined an area more or less ignored by previous research, and more research is necessary to understand the level of information asymmetry inherent in transactions for low-cost homogeneous goods, and whether an effective reputation system is necessary for the efficient operation of this type of market.

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Appendix A: Correlation Matrix

Coefficient Correlations(a)

		LAMBDA	percent	score	auction	shipping	bids	concauct
Correlations	LAMBDA	1.000	0.033	0.200	0.323	-0.584	0.292	-0.796
	percent	0.033	1.000	0.000	-0.004	0.007	-0.012	-0.055
	score	0.200	0.000	1.000	0.095	-0.187	0.022	-0.157
	auction	0.323	-0.004	0.095	1.000	-0.120	0.053	-0.270
	shipping	-0.584	0.007	-0.187	-0.120	1.000	-0.167	0.566
	bids	0.292	-0.012	0.022	0.053	-0.167	1.000	-0.077
	Concauct	-0.796	-0.055	-0.157	-0.270	0.566	-0.077	1.000

a. Dependent Variable: finalprice

Appendix B: Results with reputation measured as the reputation score divided by 10,000.

Selection Equation – Binary Logistic Regression		
Variable	B	SE
Constant	1.861*	.705
Shipping Costs	-.087*	.033
Starting Bid	-.068**	.009
Concurrent Auctions	-.200**	.018
Auction Length	.083*	.030
Seller Reputation Score	.033*	.013
Seller Percent Positive	.001	.007
-2LogLikelihood	1814.076	
Sample size	1442	

* p<.01, ** p<.001

Substantial Analysis – OLS/WLS		
Variable	OLS	With Corrected SE's
Constant	1.712 (1.186)	1.712 (1.572)
Shipping Costs	-.323 (-4.116) ***	-.323 (-4.852) ***
Number of Bids	1.479 (46.258) ***	1.479 (40.607) ***
Concurrent Auctions	-.951 (-17.341) ***	-.951 (-16.234) ***
Auction Length	.259 (4.053) ***	.259 (2.525) **
Reputation Score	.000 (-2.191)*	.000 (-2.035)*
% Positive Feedback	-.007 (-.523)	-.007 (-.187)
Lambda	10.071 (14.346) ***	10.071 (12.748) ***
Adj. R-squared	.656	.656
F-value	392.788	392.788
Sample size	1442	1442

The t-values are given in parentheses.
* Significant at the 95% level
** Significant at the 97.5% level.
*** Significant at the 99% level.

Appendix C: Results with Reputation measured as the Natural Log of the Reputation Score. Each observation was increased by one in order to avoid taking the natural log of zero.

Selection Equation – Binary Logistic Regression		
Variable	B	SE
Constant	2.318*	.335
Shipping Costs	-.073	.033
Starting Bid	-.061**	.009
Concurrent Auctions	-.195**	.018
Auction Length	.067	.030
Natural Log of Reputation Score	-.061*	.022
Seller Percent Positive	.001	.007
-2LogLikelihood	1799.393	
Sample size	1442	

*   p<.01, **   p<.001

Substantial Analysis – OLS/WLS		
Variable	OLS	With Corrected SE's
Constant	.546 (.123)	.546 (.123)
Shipping Costs	-.238 (-3.059***	-.238 (-3.059)***
Number of Bids	1.447 (45.191)***	1.447 (45.191)***
Concurrent Auctions	-.969 (-16.917)***	-.969 (-16.2917)***
Auction Length	.149 (2.337)**	.149 (2.337)**
Natural Log of Seller's Reputation Score	-.539 (-10.382)***	-.539 (-10.382)***
% Positive Feedback	.041 (.943)	.041 (.943)
Lambda	10.573 (13.981)***	10.573 (13.981)***
Adj. R-squared	.653	.653
F-value	392.788	392.788
Sample size	1442	1442

The t-values are given in parentheses.
*   Significant at the 95% level
**   Significant at the 97.5% level.
*** Significant at the 99% level.