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Reputation, Information Signals, and Willingness to Pay for Heterogeneous Goods in Online Auctions

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Abstract

In online commerce, a buyer cannot directly examine the product and has to rely heavily on the reliability of the seller. In this setting, the reputation of the seller, together with any other information signals on the quality of the product, can play an important role in determining the buyer's willingness to pay for the good. However, while the impact of reputation on willingness to pay for homogeneous goods has been examined, its impact on heterogeneous goods is largely unknown. This paper examines the effects of the seller's reputation and information signals in online auctions, using U.S. silver Morgan dollar coins in almost uncirculated condition that are sold on eBay. The empirical results indicate that a seller's overall reputation has a positive and statistically significant impact on a buyer's willingness to pay in online auctions, an impact that is larger than for homogeneous goods. The results also indicate that negative comments about a seller have larger, and negative, impact on price.

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1. Introduction

It has long been recognized that a market with asymmetrically distributed information my experience a market failure (Akerlof, 1970). This insight is especially relevant for the rapidly expanding area of online commerce, where information is not uniformly distributed between the buyer and the seller. In online transactions, the buyer cannot examine the product directly, and has to rely upon the seller's description of the product and upon the accuracy of any such description; the buyer also has to rely upon the seller for compliance with the terms of transaction. However, it may be the case that the past reputation of the seller may act as a mechanism by which information about the current behavior of the seller can be transmitted to the buyer. In such a setting, a seller's reputation may well reduce information asymmetries, and thereby allow the market to function. For heterogeneous goods in particular, where product characteristics may vary significantly from one good to another, it seems likely that a seller's reputation and other information measures may play an important role in persuading buyers to participate in a market. In this paper we examine the impact of seller reputation and various information variables on buyers' willingness to pay for a heterogeneous good sold via internet auctions. We find across a variety of specifications that a seller's overall reputation has a positive and statistically significant effect on the willingness of buyers to pay for the product. We also find that negative comments about a seller decrease the realized price.

Although there are some exceptions, theoretical models have typically generated a positive relationship between the reputation of the seller and the resulting price of the transaction, in large part because the seller's reputation is a proxy for quality characteristics that are unobserved prior to the completion of the transaction (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984; Houser and Wooders, 2000). Experimental findings have also tended to support the theoretical conclusions (Camerer and Weigelt, 1988). However, until recently empirical analysis of this issue has been limited, largely because of the absence of reliable measures of reputation.

The rapid growth of ecommerce, in combination with the establishment of reputation measures by many consumer-to-consumer websites, has now enabled researchers to analyze the issue empirically.[1] In particular, online consumer-to-consumer auction websites such as eBay.com, Yahoo.com, and Amazon.com provide a unique opportunity to study the effects of a seller's reputation in online consumer-to-consumer environment.[2] eBay, one of the most famous online auction websites, has experienced rapid growth in its user base since its birth in September of 1995, and by December of 2002 its user base surpassed 49.7 million.[3] These websites assume no responsibility for the items listed on their sites, and simply act as auctioneers. The seller assumes full responsibility for the description of the product and for the compliance with the terms of transaction. Importantly, in almost all instances the shipment of the product occurs after the payment is received, so that the buyer assumes a risk when sending a payment.[4] For instance, the seller may ship a damaged item, the seller may not correctly describe the product in the auction, or the seller may not send the item at all.

However, most online auction websites, including eBay, have set up a mechanism that allows buyers to rate the seller and to post short comments about their experience with the seller following the completion of their transaction.[5] The feedback system used by eBay enables the buyer to classify any comment about the seller as positive, negative, or neutral, and the

[1] Several empirical studies have been done on reputation measures outside of ecommerce. For example, Landon and Smith (1998) examine the impact of reputation on the price of Bordeaux wines.
[2] For a more detailed description of internet auction mechanisms, see Lucking-Reiley (2000).
[3] eBay user statistics are available on eBay website at http://www.ebay.com.
[4] For instance, in cases where personal checks are accepted sellers typically require a check clearing period that can range between 5 and 14 days before the good is shipped. In the case of credit card or online payment methods, the shipping occurs following the completion of the payment.
[5] The seller can also post comments about the buyer.

difference between the number of positive and negative comments left by unique buyers constitutes the seller's *Rating*. This rating is then displayed prominently on every auction presented by this seller. Each visitor to the seller's auction can also examine the rating in more detail, including the breakdown of the rating in terms of its positive, negative, and neutral comments. The comments themselves are also available, and vary greatly from praises like "Excellent seller, friendly communications, Thank You!" to warnings aimed at other perspective buyers, such as "Collected payment, never shipped the item, avoid this seller".[6] If information on the seller's reputation can reduce information asymmetries, then such mechanisms may play an important role in facilitating the growth of these websites.

Indeed, anecdotal evidence suggests that reputation matters in online auctions. For example, an individual seller has recently brought a $2.6 million suit against both eBay.com and a buyer for negative comments posted by the buyer about the quality of the services provided by the seller (Reuters, 23 January 2003). More generally, several empirical studies have used data generated by online auction websites, including these various measures of reputation, to examine the impact of a seller's reputation and other informational variables on buyers' willingness to pay for auction goods. Lucking-Reiley et al. (1999), McDonald and Slawson (2000), Houser and Wooders (2000), Dewan and Hsu (2001), Kalyanam and McIntyre (2001), and Melnik and Alm (2002) all find a positive and statistically significant relationship between the seller's overall reputation and buyers' willingness to pay; these studies also sometimes find that negative reputation indicators (e.g., the number of complaints) has a negative and statistically significant impact on willingness to pay.[7] The magnitudes of the impacts of reputation measures vary significantly across these studies, in part due to the variety in the choices of the products across

[6] These comments are easily accessible in the feedback section for each member of eBay.com
[7] Note that not all auctions listed on eBay website complete successfully. Auctions where insertion price exceeds buyer's willingness to pay receive no bids.

these studies and in part due to the choices of control variables. However, a general conclusion from these studies is that overall reputation has a significant but small impact on the realized price, while the impact of negative reputation is often much larger.[8]

One of the key aspects in all of these studies is the choice of the product for such analysis. Almost all of the existing literature on the effects of reputation in online auctions is based on homogeneous goods. For example, Houser and Wooders (2000) examine willingness to pay for a Pentium III, 500 Mhz processor, Resnick and Zeckhouser (2001) use Rio MP3 digital audio players and Britannia Beanie Babies in mint condition, Melnik and Alm (2002) choose a mint condition U.S. $5 coin, and Lucking-Reiley et al. (1999) examine U.S. Indian-head pennies with grades in near mint state. The selection of a homogeneous good allows the researcher to better control for the characteristics of the product, and so to better capture the signaling aspects of the seller's reputation. Nevertheless, the role of the seller's reputation in such a setting seems likely to be somewhat limited because there is little if any variation in the quality of a homogeneous good. In contrast, with a heterogeneous good a seller-provided description of the product may become more important to a buyer unable to determine the precise quality of the auctioned good, so that reputation may play a stronger role with a heterogeneous good than with a homogeneous good. However, this notion is largely untested.[9]

In this paper we examine buyers' willingness to pay for a heterogeneous product, using data collected from an internet-based auction website, eBay.com, including the website's own measures of the seller's reputation. We focus on U.S. silver Morgan dollar coins in "Almost

[8] Note that Eaton (2002) and Resnick et al. (2002) fail to find a statistically significant impact of the seller's reputation on the realized price, but do find a positive effect of reputation on the probability of a successful completion of the auction. Two controlled experimental studies have been done as well. Katkar and Lucking-Reiley (2000) focus on the effects of reserve prices on willingness to pay, using reputation as a control variable, and Resnick and Zeckhouser (2001) find that an established seller receives a price premium of 7.6 percent over a newcomer.

[9] A recent exception is Eaton (2002), who finds reputation to be statistically insignificant in eBay auctions for PRS guitars.

Uncirculated" (AU) condition with a mean price of $93.39, and we estimate the impact of overall reputation, negative reputation, and a variety of other informational variables and auction characteristics on buyers' willingness to pay. We find that overall reputation has a positive and statistically significant effect on the willingness of buyers to pay for the product, a result that is robust across a wide range of alternative specifications; a negative rating for a seller is also shown to have an important – and negative – impact on willingness to pay. In both cases, the impacts on price are greater than in the case of a homogeneous good.

In the next section we discuss our data and our empirical specification. In section 3 we present our estimation results. We conclude with a summary and some implications of our results.

2. Data and Empirical Specification

Perhaps surprisingly, the impact of reputation on price is theoretically ambiguous. For example, Houser and Wooders (2000) assume an auction with honest and dishonest sellers, in which the honest seller always delivers the promised good after receipt of the payment and the dishonest seller never delivers the good. They assume that a seller's reputation can be measured by the probability that the seller is honest, which they term his or her reputation score. If this information is assumed to be publicly available, it is then straightforward to show that the expected utility of any buyer is an increasing function in the reputation score of the seller, and the buyer is willing to pay more the higher is the reputation score of the seller.[10] Klein and Leffler (1981), Shapiro (1983), and Allen (1984) derive a similar conclusion. However, it is also

[10] Houser and Wooders (2000) show that in equilibrium the buyer with the highest expected value of winning the auction wins the auction, and pays the expected value of the buyer with the second highest value. This expected value is given by $b_2 = r^S v_2$, where b_2 is the second-highest bid, r^S is the reputation score of the seller, and v_2 is the value of the good to the second-highest bidder.

possible to construct models in which reputation provides no information and is useless. McDonald and Slawson (2000) assume that reputation is needed to provide sellers with an incentive to provide high quality service. However, the reputation score itself provides little information about seller quality because in equilibrium all sellers will choose to be high quality.

The actual impact of reputation on selling price is therefore an empirical issue. Following the approaches of Landon and Smith (1998), Lucking-Reiley, et al. (1999), McDonald and Slawson (2000), and Houser and Wooders (2000), we assume that the *Price* of the coin depends upon a vector of characteristics (*X*) that includes the seller's reputation, the market value of the coin, and the auction features. Each of these factors is discussed.

One of the main issues that must be addressed when analyzing private auctions like the ones displayed on eBay.com is the heterogeneity of the product. Most of the items sold on eBay tend to be relatively heterogeneous in nature. This heterogeneity is typically captured in the seller's description of the item, thereby signaling to the buyer information on item-specific characteristics, and prices can vary significantly between auctions for the same good because of variations in quality. In contrast, with homogeneous goods, the homogeneity of the good largely eliminates quality differences between items offered by different sellers.

Accounting for heterogeneity is difficult. Accordingly, we select a good that satisfies two criteria. First, the item must be graded by the seller based on some standardized and generally accepted scale. Second, information about any item-specific quality characteristics of the item must be captured by any such grading scale. The first requirement is essential in order to have a measure that allows a comparison across different auctions listed by different sellers, and the second requirement assures that such a measure captures item-specific characteristics. Collectible coins satisfy both criteria. Coins are graded on a widely accepted standard scale, with coin grading varying from "mint" state (or "uncirculated" condition) to "good" (where hardly any detail on the surface of the coin remains visible). Coins in mint condition can be considered as perfectly homogeneous goods, while coins in less than mint condition exhibit heterogeneity.

Coins in less than mint condition allow for an analysis of reputation and other information signals. For these reasons, we use U.S. Morgan silver dollar coins in "Almost Uncirculated" (AU) condition for this study. Morgan dollars were minted in the U.S. between 1878 and 1904 and in 1921, and are very popular among U.S. coin collectors.[11] We collected observations from the online auction website eBay.com between 1 August 2002 and 30 September 2002. In total, our dataset consists of 3830 observations, generated by 639 unique sellers. The average price (*Price*) for completed auctions in the dataset is $93.39, and it is *Price* that is the dependent variable in all of our specifications.[12] Table 1 provides detailed summary statistics for all variables in the dataset.

There are several variables that may affect the price of the coins. Our primary interest is in the impact of the seller's reputation on the buyer's willingness to pay. Reputation is measured by the overall rating of the seller (*Rating*), calculated as the difference between positive and negative comments left by unique users. *Rating* has a mean value of 1889, and it exhibits substantial variation, ranging from a minimum value of 0 to a maximum value of 13,890. The information contained in *Rating* is also used to construct two additional reputation variables. One focuses more precisely on the negative rating of the seller (*Negative*), and is equal to the number of feedback responses from unique users that rate the seller as negative. In addition, a

[11] As a sign of their popularity among collectors, one the nation's leading professional coin grading services, PCGS, lists market values for all Morgan dollar coins on its website. The PCGS website can be found at http://www.pcgs.com.
[12] The highest bidder in an auction wins the auction, but the winner pays the price bid by the second highest bidder.

measure *Neutral* is included, equal to the number of neutral comments about the seller left by unique users.

Our expectation is that *Rating* will have a positive impact on the auction price, while *Negative* will have a negative impact and *Neutral* seems likely to have a negative impact as well. However, our measures of reputation are likely to be somewhat imperfect indicators, for several reasons. Not every transaction results in a feedback comment because there is little economic motivation for buyers to provide feedback after a transaction has been completed. Also, there are no real standards to distinguish deliberate seller fraud from honest mistakes, the measures do not provide a complete indicator of seller quality, and sellers (and buyers) may attempt to manipulate the measures, perhaps by changing their internet identities. Note that, even though bidders can see all of the seller's feedback information, they do not know the total number of transactions completed by the seller.

We also include other information signals. The visual description of the coin is represented by two dummy variables: *FullScan*, equal to 1 when scans of both sides of the coin are present and 0 otherwise, and *PartialScan*, equal to 1 when a scan of only one side of the coin is provided and 0 otherwise. In addition to visual information signals, we include several other informational variables. Our dataset consists of "certified" and "non-certified" coins. "Certified" coins receive a grade by a third party professional grading service (e.g., PCGS), of which only seven operate in the U.S. Once a coin is graded by one of these professional grading companies, the coin is sealed in a plastic holder, along with precise grading information. These grades are assigned in a numerical form, with a higher number representing a stronger quality of the coin. Four such numerical grades are present in our dataset: AU-50, AU-53, AU-55, and AU-58, with AU-58 coins being of the highest quality and AU-50 the weakest. All of these coins fall into the broadly defined AU grade category, which in numerical form includes all grades from AU-50 to AU-59. In contrast, among "non-certified" coins, a numerical grading is very uncommon, and, even when present, a grading is offered only as an opinion of the seller. Since certification of a coin may serve as a signal of the quality of the coin, as well as a verification that the coin is not fake, one would expect that certified coins would command higher valuation. We therefore include a dummy variable (*Certified*), equal to 1 if the coin is certified and 0 otherwise. In addition, we include dummy variables for each numerical grade category. Our expectation is that coins of higher grades will realize higher prices; however, the professional rating service PCGS provides no market values for each of these numerical categories, even though PCGS lists market values for all Morgan dollar coins on its website.

Our dataset consists of observations on coins minted in different years and with different "mint marks".[13] To account for the differences in coin value based on the year and the mint mark, we include a variable (*CoinValue*), which represents the market value of the coin in AU grade as of September 2002, obtained from the PCGS website.

We include several variables that reflect the features of the auction. Three of these relate to the acceptable methods of payment by the seller, and are entered as dummy variables: *CreditCard*, equal to 1 if the seller accepts credit cards directly and 0 otherwise; *PersonalCheck*, equal to 1 if the seller accepts personal checks and 0 otherwise; and *OnlinePayment*, equal to 1 if any online payment method (e.g., PayPal, BidPay, Billpoint, C2it) is an acceptable method of payment and 0 otherwise.[14] No sellers in our dataset allow COD as a payment option. However,

[13] The "mint mark" designates the mint (or place) where the coin was minted. Four unique mints are present in the dataset.

[14] These methods of payment enable the buyer to submit the payment online. They allow the seller to accept credit cards and, in the case of Paypal, bank transfers. With the exception of BidPay, which imposes a money order fee on the buyer, these services are free to buyers; however, sellers are typically required to pay a fraction of the received payment in fees if the payment is made with a credit card. In each instance, the seller is notified via email as soon as the payment is made, thereby expediting the shipment of the item.

a large number list multiple options for the method of payment. For example, all sellers accept money orders, many sellers (89 percent) accept personal checks, 77 percent accept online methods of payment, and 13 percent allow payment via credit cards. These various methods have different benefits and costs, both for buyers and sellers. Unlike money orders, personal checks have lower transaction costs because checks do not require a trip to the U.S. Post Office to purchase a money order and they do not have any additional monetary costs associated with money orders. However, use of personal checks will almost always result in a delay in the shipping of the item by the seller because, in all instances in which the seller accepts a personal check, the seller requires that the check clear prior to shipping the item. In contrast, acceptance of online payment methods may speed up the shipping and hence the delivery of the item; online methods of payment are also more convenient for the buyer because the payment can be made from a home personal computer. Credit card acceptance by a seller may also act as a signal that the seller has an established business, and the credit card issuer may provide some protection against seller fraud. Both should increase buyers' willingness to pay. There is no information about the actual method of payment chosen by the winning bidder.

The time and the day of the week when the auction closes may influence the selling price as well. eBay allows bidders to view a complete list of all current auctions in any category, based on a search query. Such lists can be very large and can involve thousands of individual listings. However, eBay allows bidders to narrow the list based on the remaining time of the auction. Bidders can select to view the list of auctions in their requested category (or to search results) that are closing in the next 24 hours or in the next four hours. Importantly, auctions that are near their closing time appear on the top of the search results page in their category. This feature suggests that auctions closing at the time when more bidders visit the eBay website may receive higher attention from bidders and so realize higher prices. To investigate this issue, we include *ClosingTime*, equal 1 if the auction closes between midnight and 6am (Pacific time zone) and 0 otherwise. We also include dummy variables for eight three-hour periods and dummy variables for the days of the week.

The length of the auction in days (*Length*) may have an impact on price, since the longer the auction remains active the greater is the likelihood that the auction will be visited by a larger number of bidders and hence realize a higher price. Currently, eBay has four different settings for the choice of the duration of the auction: 3, 5, 7, and 10 days. It is worth noting that in 2001 eBay introduced an additional fee for inserting 10-day auctions, which may signal that eBay expects longer auctions to bring higher prices.

Another factor that may influence the realized price is the supply of coins. To account for the supply of coins, we introduce *CoinFrequency*, defined as the number of auctions of the coin (determined by year and mint) that close at the same day as the auction in the observation. The closing date is chosen, rather than any other day of the auction, because auctions that are near their closing time appear on the top of the search results page in their category.

We estimate a wide variety of different specifications. In all models the dependent variable is *Price,* entered in linear form. The reputation variables – *Rating*, *Negative*, and *Neutral* – are all entered in natural log form because the marginal effects of additional feedback points are expected to decrease with reputation. Since the range for the reputation measures begins at zero, the natural logarithm is taken of the value of the variable plus one. Other variables are entered in linear form.

A significant number of observations are either right- or left-censored. When an auction is inserted on eBay by a seller, the seller is required to specify an opening bid; in some cases, this opening bid exceeds any buyer's willingness to pay, and the auction receives no bids. When this happens, an observation is left-censored. Out of 3830 observations, 1283 observations are left-censored.

Further, eBay introduced in 2001 a fixed price mechanism, referred to as *buy-it-now*. This option enables the sellers to list a specific price at which the auction would end if the first bidder chooses to accept that price; if the first bidder does not choose the buy-it-now price and places a bid instead, then the auction begins and the buy-it-now option disappears. The incentive to the bidder for using the buy-it-now mechanism is obvious, as the auction may take the price above the specified price. However, if the buy-it-now option is used by the first bidder, thereby ending the auction at that price, then the auction has a right-censored observation because the bidder indicates that his or her willingness to pay is at or above the seller's specified price. Only 159 auctions (or about 4 percent of the 3830 auctions in our dataset) ended with a buy-it-now option being exercised. In 2002, another fixed price mechanism was introduced, under which the seller is simply allowed to list the item with a fixed price. Fixed-price listings also generate a right-censored observation, and can be treated in the same way as the buy-it-now auctions.

Because of these right- and left-censored observations, we estimate all specifications using Tobit maximum likelihood estimation with variable cut-off points.[15] Defining Y_i* as the unobserved index variable for observation *i* with either a cutoff value from below Y_i^o (the opening insertion value) or above Y_i^b (either the buy-it-now or fixed price), and Y_i as the observed random variable, then

(1) $$Y_i^* = X_i\beta + \varepsilon_i$$

(2) $$Y_i = Y_i^o \;\; if \;\; Y_i^o > Y_i^*$$

[15] See Amemiya (1984) for a detailed discussion of this estimation method.

$Y_i = Y_i^b \;\; if \;\; Y_i^b < Y_i^*$

$Y_i = Y_i^* \;\; otherwise,$

where β is the vector of coefficients on X_i and ε_i is the error term, assumed to be normally distributed with zero mean and constant variance σ^2. The log-likelihood function l, or

$$(3) \qquad l = \sum_{Y_i^b > Y_i^* > Y_i^o} \log\left(\frac{1}{\sigma}\phi\left(\frac{Y_i - X_i\beta}{\sigma}\right)\right) + \sum_{Y_i^o > Y_i^*} \log\left(\Phi\left(\frac{Y_i^o - X_i\beta}{\sigma}\right)\right) + \sum_{Y_i^* > Y_i^b} \log\left(\Phi\left(-\frac{Y_i^b - X_i\beta}{\sigma}\right)\right)$$

is maximized over all i observations, where Φ is the cumulative standard normal distribution function and ϕ represents the normal distribution probability density function.

In addition, heteroscedasticity may be a problem due to the presence of observations collected on coins of different years and mint marks. Coins of different years and mint marks may come from distributions that differ in means and standard deviations. As noted above, we control for differences in means by including the current market coin value for each year and mint mark. To correct for heteroscedasticity, we estimate the model with the Huber-White estimation technique (Greene, 2002).

3. Estimation Results

Table 2 reports our estimation results with robust standard errors in prentices for a number of different specifications.[16] Specifications 1 to 9 are performed on the entire dataset; specification 10 excludes those observations where the buy-it-now option is used by the buyer.

[16] As discussed by Amemiya (1984), the estimated coefficient β_i for independent variable X_i gives the impact of the independent variable on the unobserved index variable Y_i* , or what might be termed the willingness to pay for the good. The impact of X_i on the actual observed variable Y_i (or, equivalently, $Price_i$) is given by

$$\frac{\partial E[Y_i \mid X_i]}{\partial X_i} = \beta'\left[\Phi\left(\frac{Y_i^b - \beta X_i}{\sigma}\right) - \Phi\left(\frac{Y_i^o - \beta X_i}{\sigma}\right)\right]$$, where E is the expectation operator.

Our results consistently indicate that reputation has a positive and statistically significant effect on the buyer's willingness to pay. The average value for the *Rating* coefficient across all specifications is 4.46. This magnitude suggests that, for a seller with the average characteristics in the dataset (including an average *Rating* of 1889), one extra *Rating* point will increase willingness to pay by 0.24 cents; similarly, a 10 percent increase in *Rating* will generate a $0.43 increase in the buyers' willingness to pay. While statistically significant, these impacts are clearly quite small. Given the average *Price* of coins in the dataset (or $93.39), the one point increase in *Rating* represents a miniscule impact on the willingness to pay, and even the 10 percent increase in *Rating* increases the price by only 0.5 percent. Indeed, a doubling in the rating from 1889 to 3778 will increase the willingness to pay but only by $3.09 (or by 3.3 percent of the *Price*).

Nevertheless, the difference in the buyers' willingness to pay between items auctioned by an established seller with a rating of 1889 and a newcomer with a rating of 0 is substantial, or $33.62, and an extra rating point for the newcomer starting with a *Rating* of zero will increase the willingness to pay by $3.08.

It is also the case that the impact of reputation on price for this <u>heterogeneous</u> good is much greater than its impact for a <u>homogeneous</u> good. For example, Melnik and Alm (2002) uses a similar framework to examine a 1999 mint condition U.S. $5 gold coin with an average value of $32.73. They find a positive impact of reputation on price, but an impact that is significantly smaller than its impact here. Their estimates indicate that that a doubling of *Rating* will increase the price by only $.18, or about 0.5 percent of the price of the coin; recall that a doubling of *Rating* here will increase the willingness to pay by 3.3 percent of the price. As expected, the impact of reputation on willingness to pay for a heterogeneous good is much larger than its impact on a homogeneous good.

Negative feedback also has effects on willingness to pay across the different specifications. The coefficient on *Negative* is consistently negative and statistically significant. Its magnitude is also much larger than *Rating*, which suggests that complaints are more important than praises. The average value of the *Negative* coefficient across specifications is –11.24, and the level of statistical significance continuously remains above 99 percent. Given that the seller with average characteristics in the dataset has slightly more than 7 complaints, then the cost of one additional complaint to the average seller is a reduction in \$1.42 in buyers' willingness to pay, an impact that is much greater than the benefit from one extra positive comment. Interestingly, a seller with the average *Rating* of 1889 and only 20 *Negative* comments will face the same willingness to pay as a newcomer with a zero *Rating* and zero complaints. As with *Rating*, the impact of negative comments for the heterogeneous good here is greater than their impact for a homogeneous good (Melnik and Alm, 2002). The seller's neutral rating (*Neutral*) has no statistically significant impact on the buyers' willingness to pay.

The results for most other variables are generally consistent with expectations, although the coefficients on these variables are not always statistically significant. The coefficient on *CoinValue* is positive and statistically significant at above the 99 percent level in all specifications. The magnitude of its coefficient suggests that a one dollar increase in the market value of the coin translates into an increase in the willingness to pay but, surprisingly, an increase of only \$0.26.

Specification 3 introduces *Certified*. The coefficient on this variable is positive and statistically significant at above the 99 percent level in all specifications, suggesting that coins certified by a professional third party are valued more highly by eBay bidders.

Specification 4 includes two other information variables, *FullScan* and *PartialScan*. The presence of scanned images of the coin is expected to reduce uncertainty about the quality of the coin, and hence lead to a higher willingness to buy. Nearly 80 percent of all auctions in our dataset have a full, two-sided scan of the coin, and a partial, one-sided scan is only present in 13 percent of the auctions. Perhaps surprisingly, however, the coefficients on both variables are statistically insignificant. It may well be that the presence of a scan does not indicate the quality of the coin, but merely enables the buyers to examine the coin for themselves; for coins with low quality, the presence of a scanned image may actually reduce the price. In fact, sellers with low quality coins have little incentive to provide a scanned image.

Another important feature of an auction is the list of acceptable methods of payment. Methods of payment influence transactions costs, and so may affect buyers' willingness to pay for the item. In fact, the empirical results in specifications 5 and above are largely consistent with this notion. The coefficient on *PersonalCheck* is positive and statistically significant at the 95 percent level or above in all specifications. The use of online payment methods and the direct acceptance of credit cards have positive but statistically insignificant impacts on willingness to pay.[17] The use of credit cards does not slow down the delivery of the payment; furthermore, buyers may be more comfortable with trusting their private credit card information to an established third party rather than to an individual seller.

Specification 7 introduces more precise measures of the grades. The signs of the coefficients on the numerical grade measure dummy variables are consistent with expectations because the dummy variables on the lower quality coins graded AU-50, AU-53, and AU-55 have

[17] Direct acceptance requires that the seller be equipped to take payments directly from Visa, MasterCard, or other credit cards; online methods of payment such as Paypal and Billpoint enable the buyer to pay with a credit card but through a third party.

negative coefficients and the dummy variable on the higher quality coin (e.g., AU-58 grade coins) has a positive coefficient. However, none of these coefficients is statistically significant. Note that the inclusion of numerical grade variables does not affect the magnitude or statistical significance of the coefficients on the reputation measures.

Table 2 also reports the effects of the time and day of the week of the closing of the auction on the willingness to pay. Specification 8 includes dummy variables for the day of the week. All of the coefficients on these variables are statistically insignificant, although they exhibit variation in sign. It may well be that fluctuations in supply are in part responsible for daily fluctuations in prices. To investigate this, *CoinFrequency* is also included in Specification 8. Recall that *CoinFrequency* is equal to the number of identical coin auctions closing on the same day. Its coefficient has a negative and statistically significant coefficient. These results suggest that the day of the week on which the auction closes has no significant impact on the realized price, but that the total supply of coins on the closing day has a negative and statistically significant impact.

To investigate the effects of closing time on *Price*, we divide the day into 8 three-hour segments and represent these with dummy variables; the omitted category is the time between noon and 3pm (Pacific time zone). These results are given in specification 9. Three of the closing time dummy variables are statistically significant. In particular, auctions closing between midnight and 6am experience significantly higher bids, while auctions closing between 9am and noon receive lower bids. These findings offer support to the notion that at least some auctions may receive more attention from bidders in their closing states. Auctions closing between midnight and 6 am will appear in the top of search results of perspective bidders during the evening hours of the previous day; in contrast, auctions closing in late morning hours may not receive as much attention from perspective bidders.

Many previous econometric studies of auctions have attempted to control for the length of the auction. The length of the auction is measured in specification 10 by dummy variables for 5, 7, and 10 day auctions, with the control group consisting of 3 day auctions.[18] The coefficient on 10 day auctions is positive and only marginally significant, while the coefficients on 7 and 5 day auctions are statistically insignificant. Recall that auctions near their closing time tend to be more visible to the perspective bidders because search results can be sorted via the default option by the remaining auction time; given the large number of Morgan dollar coins listed on eBay at any given point in time, it is likely that bidders may limit their search to those auctions that are near their completion, and this will reduce the impact of the duration of the auction on the realized price.

4. Conclusions

Our findings indicate that the seller's overall reputation (*Rating*) has a positive and statistically significant effect on buyers' willingness to pay in online auctions for heterogeneous goods, and that a seller's negative reputation (*Negative*) has an even more powerful, and negative, impact on price. These results are quite robust across a wide variety of specifications, and are consistent with the notion that buyers in online auctions interpret the various measures of a seller's reputation, earned over previous auctions, as a signal about the current behavior of the seller. Although changes in reputation have a relatively small effect on the price for heterogeneous goods, their impact is generally larger than that observed in previous studies on

[18] Note that auctions that close with an exercise of the buy-it-now option must be excluded from this specification because they do not last a pre-determined period.

homogeneous goods. Further, the difference in buyers' willingness to pay for goods auctioned by established sellers with the average characteristics in our sample and goods auctioned by newcomers is quite large.

The buyer's interpretation of a seller's previous reputation as a signal about the current behavior of the seller in online auctions reinforces the notion that measures of sellers' reputation can reduce the problem of asymmetric information in online auctions. However, it is also important to note that no uniform measures of reputation exist in online commerce today, and proprietary measures of reputation such as the eBay rating mechanism are not transferable to other websites; indeed, eBay has gone to court to maintain its reputation measures as its own. Although our results suggest that any such measures help to reduce the problem of asymmetric information in online auctions, these measures may also help to erect barriers to entry for new auction websites because their existence can establish a barrier to entry for new auction websites by making it costly for established sellers to switch from one auction website to another. Consequently, there may be a need for a uniform and universal measure of online reputation, a measure that is maintained by other than the auction website and that is transferable across websites.

Table 1: Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Price	93.39	355.50	1	10000
CoinValue	182.89	932.09	12	18000
Rating	1889.198	2384.371	0	13890
Negative	7.451	15.513	0	126
Neutral	11.454	22.916	0	167
ClosingTime	0.654	0.183	0.003	0.993
Length	6.578	1.895	0	10
Certified	0.131		0	1
10-Day	0.117		0	1
7-Day	0.622		0	1
5-Day	0.143		0	1
AU-50	0.143		0	1
AU-53	0.039		0	1
AU-55	0.079		0	1
AU-58	0.092		0	1
PersonalCheck	0.892		0	1
OnlinePayment	0.770		0	1
CreditCard	0.134		0	1
FullScan	0.786		0	1
PartialScan	0.134		0	1
Sunday	0.223		0	1
Saturday	0.196		0	1
Friday	0.110		0	1
Thursday	0.134		0	1
Wednesday	0.103		0	1
Tuesday	0.126		0	1
Monday	0.108		0	1
CoinFrequency	12.348	9.706	1	45
Time 0-3	0.004		0	1
Time 3-6	0.023		0	1
Time 6-9	0.064		0	1
Time 9-12	0.113		0	1
Time 12-15	0.185		0	1
Time15-18	0.211		0	1
Time 18-21	0.336		0	1
Time 21-24	0.064		0	1

Table 2: Estimation Results

Independent Variable	Specification									
	1	2	3	4	5	6	7	8	9	10
lnRating	2.774*	5.347**	5.021**	5.277**	4.414**	4.579**	4.524**	4.565**	4.901**	3.714*
	(1.425)	(2.298)	(2.253)	(2.338)	(2.186)	(2.175)	(2.163)	(2.183)	(2.225)	(2.227)
LnNegative		-11.653***	-12.119***	-11.802***	-11.138***	-11.183***	-11.248***	-10.789***	-10.654***	-9.561**
		(4.284)	(4.113)	(4.175)	(4.26)	(4.216)	(4.214)	(4.171)	(4.184)	(4.314)
LnNeutral		3.225	3.524	2.866	1.920	1.284	1.265	1.415	0.812	1.518
		(4.633)	(4.481)	(4.658)	(4.516)	(4.487)	(4.459)	(4.551)	(4.519)	(4.444)
CoinValue	0.266***	0.265***	0.263***	0.263***	0.263***	0.263***	0.263***	0.263***	0.262***	0.263***
	(0.034)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Certified			51.790***	51.752***	52.425***	56.238***	57.733***	55.884***	54.606***	50.438***
			(12.181)	(12.209)	(12.618)	(12.934)	(12.118)	(12.888)	(12.800)	(12.900)
FullScan				-6.196	-7.129	-5.55	-5.619	-5.121	-5.131	-8.002
				7.108	(7.315)	(7.412)	(7.508)	(7.355)	(7.575)	(7.371)
PartialScan				1.658	1.366	1.665	1.261	2.718	2.447	1.688
				10.401	(10.417)	(10.254)	(10.234)	(10.442)	(10.435)	(10.648)
PersonalCheck					11.799**	11.556**	11.986**	11.854**	11.218**	8.592
					(5.438)	(5.437)	(5.461)	(5.446)	(5.450)	(5.480)
OnlinePayment					1.791	1.477	1.606	2.562	2.412	-0.614
					(7.897)	(7.822)	(8.237)	(7.780)	(7.458)	(7.925)
CreditCard					9.348	10.629	12.145	10.298	10.605	12.144
					(13.148)	(13.003)	(13.173)	(13.167)	(13.461)	(13.103)
CoinFrequency						-0.819***	-0.808***	-0.855***	-0.869***	
						(0.136)	(0.136)	(0.137)	(0.136)	
ClosingTime						26.690***	26.798***			
						(7.434)	(7.568)			
AU-50							-1.138			
							(6.784)			
AU-53							-18.189			
							(23.312)			
AU-55							-0.348			
							(5.520)			
AU-58							7.410			
							(7.116)			
Tuesday								0.378	0.085	
								(5.406)	(5.386)	
Wednesday								9.200	9.244	
								(7.430)	(7.499)	
Thursday								-1.565	-1.748	
								(4.766)	(4.726)	
Friday								0.939	0.934	
								(5.312)	(5.234)	
Saturday								3.893	3.643	
								(5.325)	(5.318)	
Sunday								6.855	7.285	
								(7.221)	(7.098)	
Time 0-3									51.881**	
									(25.214)	
Time 3-6									21.020***	
									(8.061)	
Time 6-9									12.253	
									(8.824)	
Time 9-12									-16.380**	
									(8.538)	
Time 15-18									11.330	
									(11.390)	
Time 18-21									-15.730	
									(11.969)	
Time 21-24									7.435	
									(8.103)	
10-Day										9.818
										(6.997)
7-Day										-1.187

										(4.842)
5-Day										-1.488 (5.489)
Constant	5.04 (9.536)	-4.134 (12.517)	-8.734 (12.564)	-5.161 (13.073)	-10.161 (13.749)	-1.993 (13.972)	-2.013 (14.240)	-6.038 (15.300)	-5.501 (15.251)	-5.082 (14.143)
Chi-Square Degrees of freedom	3420.95 77	3454.3 79	3442.41 80	3419.48 82	3421.86 85	3008.99 87	3058.17 91	3033.92 92	3209.92 99	3989.65 88
Observations	3830	3830	3830	3830	3830	3830	3830	3830	3830	3671

* - statistically significant at 90% and above, ** - statistically significant at 95% and above, *** - statistically significant at 99% and above.

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