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Seller Reputation, Information Signals, and Prices for Heterogeneous Coins on eBay

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Abstract

In online commerce, a buyer cannot directly examine the product and has to trust the seller for the product description and delivery. 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 typically has a positive and statistically significant impact on a buyer's willingness to pay in online auctions. The results also indicate that negative comments about a seller have large negative impact on price. However, these reputational effects tend to be of greater importance for more heterogeneous goods, and are also sensitive to the presence of other information signals about the item-specific characteristics of the good.

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1. Introduction

It has long been recognized that a market with asymmetrically distributed information may 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.

With some exceptions (McDonald and Slawson, 2000), 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 (Miller and Plott, 1985; DeJong, Forsythe, and Lundholm, 1985; Camerer and Weigelt, 1988; Holt and Sherman, 1990). 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] 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 the online environment.[2] 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.[3] 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. The most recognized of these websites is eBay.com. It has experienced rapid growth in its user base since its birth in September 1995, and by September 2003 its user base had surpassed 85 million.[4]

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

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[1] See Dellarocas (2003) for a recent survey of many of these empirical studies. There is also some empirical work on reputation impacts 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] 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.

[4] eBay user statistics are available on the eBay website at http://invester.ebay.com/news/2003Q3.pdf .

[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 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) have 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

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[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 typically has a positive and statistically significant effect on the willingness of buyers to pay for the heterogeneous good, 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. However, these reputational effects tend to be of greater importance for more heterogeneous goods, and are also sensitive to the presence of other information signals about the item-specific characteristics of the 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

It is straightforward to show that a seller's reputation can have a positive impact on a buyer's willingness to pay. 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.

Perhaps surprisingly, however, it is also 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

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[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.

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.[11] Morgan dollars were minted in the U.S. between 1878 and 1904 and in 1921, and are very popular among U.S. coin collectors.[12] We collected observations from the online auction website eBay.com between 1 August 2002 and 30 September 2002. In total, our dataset consists of 3828 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.[13] Table 1 provides detailed summary statistics for *Price*, as well as for all other 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

[11] The *Standard Catalog of World Coins* (Krause and Mishler, 2001) defines AU coins as coins where "all detail will be visible. There will be wear only on the highest point of the coin. There will often be half or more of the original mint luster present".
[12] 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.
[13] eBay uses a proxy bidding system. The highest bidder in an auction wins the auction, and pays a price equal to the price bid by the second highest bidder plus a bid increment.

by the overall rating of the seller (*Rating*), calculated as the difference between positive and negative comments left by unique users who have completed a transaction with the seller. *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 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.

Aside from these three direct indicators of reputation, there are several other channels by which information signals may be transmitted to buyers. 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 better coin quality. 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 lowest. All of these coins fall into the broadly defined AU grade category, which in numerical form includes all grades from AU-50 to AU-58. 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. Perhaps even more importantly, certification clearly reduces, if not completely eliminates, uncertainty about the quality of the coin. Consequently, although certification should not necessarily eliminate the impact of the seller's reputation on price, it does seem likely to restrict the role of reputation to that of an indicator of the reliability of the seller when it comes to compliance with the terms of the transaction, similar to its effects for homogeneous goods. In contrast, with non-certified coins, the buyer may view the seller's reputation as an indicator of the probability that the seller is providing an accurate description of item-specific details (as well as an indicator that the seller will comply with the transaction). In a first set of regressions in which all coins are included (denoted "Estimation Results I"), we include a dummy variable (*Certified*), equal to 1 if the coin is certified and 0 otherwise. Our expectation is the *Certified* should have a positive impact on *Price*.

Importantly, we also investigate the effects of reputational measures in auctions of non-certified and certified coins separately (Estimations Results II and III, respectively).[14] In particular, if certification reduces uncertainty about the quality of the coin, then the impact of *Rating* on the willingness to pay for certified coins should be significantly reduced relative to its

[14] We are grateful to an anonymous referee for this suggestion.

impact on non-certified coins, and limited mainly to that of an indicator about the reliability of the seller in complying with the terms of the transaction.

Since the value of the coin is expected to be a function of its condition, we include dummy variables for each numerical grade category in all three sets of regressions. These grades also provide information signals, and 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.

Other information signals provide additional channels of information transmission. 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 the case of circulated coins, the presence of the images of the coin offered for sale can act as an important signaling mechanism when it comes to the item-specific characteristics of the coin. These visual descriptions are included in all three sets of regressions. In addition, we restrict our sample to non-certified coins only (Estimation Results IV), and perform separate estimations on these non-certified coins with and without the visual description present in the auction. In the case of certified coins, little uncertainty exists about item-specific characteristics, and a visual description is expected to play at most a limited role; in contrast, for non-certified coins the visual description is likely to be very important.

A number of other control variables are included in the estimations. Our dataset consists of observations on coins minted in different years and with different "mint marks".[15] To account

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

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.[16] No sellers in our dataset allow cash-on-delivery (COD) as a payment option. However, a large number list multiple options for the method of payment. For example, looking at all the sellers in our dataset, 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

[16] 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.

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 dummy variables for four six-hour periods and also dummy variables for the days of the week. Closing auction time is entered according to the Pacific time zone.

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. Supply variables have typically been ignored in most auction research. To incorporate some supply of coins considerations, 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.[17]

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 3828 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

[17] Ideally, we would like to estimate a complete two-equation model of the demand for and supply of coins. Unfortunately, however, we do not have sufficient information that would allow us to specify the supply of coins. Although the inclusion of *CoinFrequency* captures some supply considerations, we recognize that this variable is likely to be an imperfect reflection of all supply factors. We are grateful to an anonymous referee for this observation.

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.[18] 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) $$Y_i = Y_i^o \ \ if \ \ Y_i^o > Y_i^*$$

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

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

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

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

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

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).

To summarize, we examine the impact on *Price* of various channels of information transmission by presenting separate estimation results for all coins (I), for non-certified coins only (II), for certified coins only (III), and for non-certified coins with and without a visual description (IV). The separate estimations of non-certified coins, certified coins, and non-certified with and without a visual description allow us to analyze the impact of the seller's reputation in the presence of different information signaling mechanisms. Our underlying hypothesis is that the role of reputation will increase with the increased uncertainty about the item-specific characteristics of the item; that is, reputation becomes more important when the item exhibits greater heterogeneity. The next section presents our estimation results.

3. Estimation Results

Tables 2 to 5 report our estimation results (with robust standard errors in parentheses) for a number of different specifications.[19] Table 2 presents the results of the estimations performed on the entire dataset (I); Tables 3 and 4 contain results of estimations performed on non-certified

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[19] 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.

(II) and certified (III) coins, respectively; and Table 5 presents results for non-certified coins with and without a visual description (IV). The various specifications (1 to 9) start with the simplest specification in which only reputational measures are included, and then progressively add other types information signals as well as variables that capture features of the auctions.

Results in Table 2 for the entire dataset illustrate that *Rating* generally has a positive and statistically significant effect on the buyer's willingness to pay.[20] The average value for the ln*Rating* coefficient across all specifications is 3.11. 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 0.17 cents; similarly, a 10 percent increase in *Rating* will generate a $0.30 increase in the buyers' willingness to pay. While statistically significant, these impacts are clearly quite small. Given the average *Price* of coins in the full 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 0.32 percent. Indeed, a doubling in the rating from 1889 to 3778 will increase the willingness to pay by only $2.18, or by 2.3 percent of *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 $23.79, and an extra rating point for the newcomer starting with a *Rating* of zero will increase the willingness to pay by $2.19.[21]

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[20] In specification 6, the coefficient on ln*Rating* is statistically significant only at the 88.4 percent confidence level.

[21] It is of some interest that the impact of reputation on price for this heterogeneous good seems greater than its impact for a homogeneous good. Melnik and Alm (2002) examine a 1999 mint condition U.S. $5 gold coin with an average value of $32.73, and also find a positive impact of reputation on price. Their estimates indicate that a doubling of *Rating* will increase the price by about 0.5 percent of the coin's price; recall that a doubling of Rating here will increase the willingness to pay by 2.3 percent of the price. Of course, it is risky to generalize from the results of only these two studies.

Negative feedback also has effects on willingness to pay across the different specifications in Table 2. The coefficient on ln*Negative* is consistently negative and statistically significant. Its magnitude is also much larger than on ln*Rating*, which suggests that complaints are more important than (net) praises.[22] The average value of the ln*Negative* coefficient across all nine specifications is –4.50, and the level of statistical significance is consistently above 95 percent. Given that the seller with average characteristics in the full dataset has slightly more than 7 complaints, the cost of one additional complaint to the average seller is a reduction in $0.55 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 176 *Negative* comments will face the same willingness to pay as a newcomer with a zero *Rating* and zero complaints. These results are consistent with most of the existing empirical investigations on the impact of a seller's reputation measures in eBay markets (Melnik and Alm, 2002; Lucking-Reiley et al., 1999).

However, a seller's reputation appears to play a much more complicated role when a distinction is made between certified and non-certified coins. Table 3 presents estimation results for the subsample of non-certified coins. In all specifications of Table 3 *Rating* has a positive and statistically significant impact on the buyer's willingness to pay, with an average coefficient of 2.90; given the lower average *Price* of non-certified coins, the relative impact of reputation is greater than for the full sample of coins in Table 2.[23] Further, the statistical significance of the overall reputation measure *Rating* now increases sharply, generally to the 99 percent confidence

[22] Recall that *Rating* is constructed as the difference between praises and complains left by unique users with whom the seller had transaction experience.
[23] The average price of certified coins is $327.50, and that of non-certified coins is $58.08. The average price of all coins in the full sample is $93.39.

level or better. Interestingly, the statistical significance of *Negative* declines dramatically compared to the full sample results in Table 2.

When certified coins are examined (Table 4), *Rating* is no longer a statistically significant determinant of buyer's willingness to pay. However, the number of complaints (*Negative*) now has a negative and statistically significant impact in all specifications, and the magnitude of the coefficient on ln*Negative* is much larger than that in Tables 2 and 3. It is important to note here that the number of sellers who sell certified coins is relatively small, and the average rating in this group of sellers is significantly larger than in the group of sellers who sell exclusively non-certified coins. The average magnitude of the coefficient on ln*Negative* in Table 4 is 39.64, while the average negative rating in auctions for certified coins is 10. Thus, an increase in negative rating from 10 to 11 will result in a decline in the buyer's willingness to pay by $3.78, which represents a 1.1 percent decline in the average price of certified coins in our dataset. Most sellers who sell certified coins tend to be professional dealers.[24] As suggested earlier, *Negative* may remain important mainly as an indicator of the probability that the seller will comply with the terms of transaction.

These results suggest that the overall reputation measure *Rating* plays an important role in auctions mainly for non-certified coins, which are very heterogeneous goods where the accuracy of the seller's description of the item is especially important. However, this same reputation measure appears to be much less important in auctions where uncertainty about item-specific characteristics of the good is low because of the presence of other informational signals (e.g., certification). Complaints (*Negative*) play a much more significant role in auctions of certified coins, which also tend to be more expensive than non-certified coins, a result that is

[24] Dealers are also more likely to accept credit cards directly. Credit cards are accepted in only 8.3 percent of all auctions for non-certified coins, while credit card acceptance is 47.2 percent in certified coin auctions.

consistent with the buyer viewing the negative rating as some measure of the probability of the delivery of the item.[25]

It should be noted that the seller's neutral rating (*Neutral*) has a differential impact on the buyer's willingness to pay in auctions for all coins, for non-certified coins, and for certified coins. However, the coefficient on ln*Neutral* is seldom statistically significant in any of the various specifications.

As for other information signals, the visual description of the coin may sometimes act as an important item-specific information signal. Nearly 80 percent of all auctions in the full dataset have complete, two-sided scan of the coin, and a partial or one-sided scan is present in only 13 percent of the auctions. Starting with specification 3 in Tables 2 to 4, we include *FullScan* and *PartialScan* dummy variables. When the estimation is performed on the entire dataset (Table 2), the impact of these information signals is positive, as expected, but is also statistically insignificant. However, this result may be somewhat misleading because the dataset includes two different groups of coins, certified and non-certified coins, and the visual description could well play a different role for each of these groups. Indeed, a visual description would seem of more importance for non-certified coins than for certified coins. Tables 3 and 4 confirm this notion. In the case of non-certified coins (Table 3), both of these dummy variables have positive and statistically significant coefficients across most all specifications; for certified coins (Table 4), the coefficients on *FullScan* and *PartialScan* are never statistically significant. These results reinforce our earlier suggestion that the inclusion of an additional information signal is more important in auctions for goods that exhibit greater heterogeneity in item-specific characteristics.

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[25] Direct comparison of the coefficients across Tables 3 and 4 should be done cautiously, due to differences in the distributions of *Rating* and *Negative* between the sellers of the two categories of coins.

It is also of interest that the inclusion of *FullScan* and *PartialScan* generally reduces the magnitude of the coefficient on ln*Rating*, although not its statistical significance. Similarly, the addition of dummy variables for acceptable methods of payment (*PersonalCheck*, *OnlinePayment*, *CreditCard*) tends to generate positive and statistically significant coefficients mainly in auctions for non-certified coins, and their addition reduces the impact of *Rating*. The inclusion of these additional information signals is important to buyers, but mainly in auctions for non-certified coins, and their inclusion reduces the role of reputation as an information signal.

To explore further the role of reputation, we report in Table 5 several specifications performed on auctions of non-certified coins. For non-certified coin auctions, scans are often, but not always, available, so in Table 5 we focus only on non-certified coins and, for comparative purposes, we do not include any of the scan variables in these specifications even when they are available. Specifications 1, 2, and 3 are for auctions of non-certified coins for which a visual description is available; specifications 4, 5, and 6 are for auctions where no visual description is available. For both types of coins, *Rating* has a positive and statistically significant impact on the buyer's willingness to pay. However, the average coefficient on ln*Rating* for auctions with no visual scan (or in specifications 4, 5, and 6) is 4.87, nearly double the average magnitude for auctions with a visual scan (specifications 1, 2, and 3). For example, a 10 percent increase in the *Rating* of the average seller will increase the willingness to pay by 0.48 percent for auctions of non-certified coins with a visual description and by 0.84 percent for non-certified coins with no visual description.[26] Similarly, a one-point increase in *Rating* (from 0 to 1) will increase the willingness to pay by 3.48 percent for non-certified coins with a visual description and by 6.12 percent for non-certified coins without visual description. Further

[26] Percent changes are computed based on the average prices of coins in each of the two categories. The average price for non-certified coins with a visual description is $58.34, and is $55.13 for non-certified coins with no visual description.

Negative does not have a significant impact on *Price* in auctions for non-certified coins with scans, but plays an important role in auctions of non-certified coins with no scans. These results suggest that the seller's reputation plays a much smaller role in auctions where a visual scan allows the buyer to verify by himself or herself the quality of the coin.[27]

These reputational effects appear to be larger than those found in other studies that focused on relatively homogeneous goods. For example, Melnik and Alm (2002) find that a seller whose rating doubles (from 452 to 904) would increase willingness to pay by only 0.55 percent. Similarly, Houser and Wooders (2002) estimate that a ten percent increase in the positive feedback will translate into an increase in the willingness to pay by only 0.17 percent, and Lucking-Reiley et al. (1999) estimate that a one percent gain in positive feedback will only lead to a 0.03 percent increase in willingness to pay.

Overall, then our findings show that the impact of the seller's reputation on the buyer's willingness to pay depends on the degree of heterogeneity of the good in combination with the availability of other informational signals. In the case of certified coins, where uncertainty about item-specific characteristics is low, the seller's reputation has no statistically significant impact on the buyer's willingness to pay. However, in auctions of non-certified coins *Rating* has a positive and statistically significant impact on *Price*, and the magnitude of this impact increases further for auctions with no visual description of the coin.

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

[27] It should be noted that there may be an issue with self-selection here since 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.

specifications. The magnitude of its coefficient suggests that a one dollar increase in the market value of the coin generates an increase in the willingness to pay but only by \$0.25 in the case of non-certified coins (Table 3) and by \$0.28 in the case of certified coins (Table 4).

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 4 and above in Table 2 to 4 are largely consistent with this notion. Acceptance of a personal check as a payment method has a positive and statistically significant impact on auctions of non-certified coins, while the effect on auctions of certified coins is statistically insignificant. The use of online payment methods has statistically insignificant impacts on willingness to pay.[28] As for credit cards, direct acceptance of credit cards by the seller has a positive and statistically significant impact on *Price* but only in auctions for non-certified coins. Credit card acceptance may be yet another mechanism that can signal to the buyer whether the seller has an established business or not.

Specification 6 introduces more precise measures of the grades.[29] The signs of the coefficients on the numerical grade measure dummy variables are generally consistent with expectations because the dummy variables on the lower quality coins graded AU-50, AU-53, and AU-55 have negative coefficients in Table 2 and the dummy variable on the higher quality coin (e.g., AU-58 grade coins) has a positive coefficient. However, these coefficients are seldom statistically significant (with the exception of AU-50 in Table 3). Note that the inclusion of

[28] 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.

[29] Note that specifications restricted to certified coins omit AU-50 grade category. In the case of non-certified coins, many coins simply have AU as the grade, which acts as the omitted category in Tables 2 and 3, but all certified coins will have a numerical grade, thus AU-50 is selected as the reference group. This also implies that the coefficient on Certified in specification 6 in Table 2 is not identified.

numerical grade variables does not have a significant impact on the magnitude or statistical significance of the coefficients on the reputation measures.

We also include the effects of the time and day of the week of the closing of the auction on the willingness to pay. Specification 7 in Tables 2 to 4 includes dummy variables for the day of the week. The results indicate that auctions that close on Saturdays and Sundays generate a higher price in the case of non-certified coins (Table 3). However, day of the week plays a less important role in the case of certified coins (Table 4), where only the coefficient on Thursday is statistically significant. As can be seen from the number of observations, certified coins are far more limited, and the closing date may be less important in the determination of winning bids. This can also be seen in the coefficients on the closing time variables, two of which are statistically significant in the case of non-certified coins but none of which are significant in the case of certified coins. The statistical significance of these dummy variables in the case of non-certified coins offers support to the notion that at least some auctions 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.

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 some specification. 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 in most all specifications in Tables 2 to 4. However, even controlling for the supply of coins on a given day of the week, we find that coins sold on Saturday and Sunday command higher winning bids, something that suggests an increased bidder activity on non-working days.

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 by dummy variables for 5, 7, and 10 day auctions, with the control group consisting of 3 day auctions.[30] 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

It is clear that buyers value information in online auctions. However, the value that buyers place on any one information mechanism seems to fall as the number of information signals increases. For example, a seller's overall reputation often has a positive and statistically significant impact on willingness to pay, a result that is consistent with reputation playing an important role in signaling the quality of item-specific characteristics in the auctions of heterogeneous goods. Similarly, a measure of complaints about the seller (*Negative*) also has an important – and negative – impact on willingness to pay, and may be interpreted by the buyer as the measure of the probability that the seller is fraudulent. However, these reputational effects tend to be of greater importance for more heterogeneous goods (e.g., non-certified coins), where it is more difficult for buyers to verify independently the quality of the auction good. These

[30] 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.

reputational effects are also sensitive to the presence of other information signals about the item-specific characteristics of the good, such as the existence of visual scans and the availability of online payment mechanisms that may also give some indication of seller reliability.

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	All Coins	Non-Certified Coins	Certified Coins
	Mean (Standard Deviation)	Mean (Standard Deviation)	Mean (Standard Deviation)
Price	93.393 (355.50)	58.080 (111.874)	327.500 (905.301)
CoinValue	182.885 (932.087)	112.159 (271.652)	651.761 (2428.235)
Rating	1889.198 (2384.371)	1877.787 (2476.495)	1964.845 (1648.103)
Negative	7.451 (15.513)	7.026 (14.843)	10.267 (19.157)
Neutral	11.454 (22.916)	11.586 (23.940)	10.582 (14.375)
Length	6.578 (1.895)	6.511 (1.909)	7.020 (1.737)
Certified	0.131	---	---
10-Day	0.117	0.111	0.157
7-Day	0.622	0.613	0.681
5-Day	0.143	0.147	0.116
AU-50	0.143	0.102	0.412
AU-53	0.040	0.020	0.167
AU-55	0.079	0.064	0.175
AU-58	0.092	0.072	0.225
PersonalCheck	0.892	0.889	0.912
OnlinePayment	0.770	0.768	0.779
CreditCard	0.114	0.083	0.472
FullScan	0.786	0.777	0.847
PartialScan	0.134	0.141	0.088
Sunday	0.223	0.220	0.245
Saturday	0.196	0.209	0.112
Friday	0.110	0.110	0.108
Thursday	0.134	0.138	0.108
Wednesday	0.103	0.100	0.124
Tuesday	0.126	0.125	0.133
Monday	0.108	0.099	0.171
CoinFrequency	12.348 (9.706)	12.104 (9.471)	13.968 (11.011)
Time 0-6	0.027	0.029	0.014
Time 6-12	0.177	0.370	0.305
Time 12-18	0.396	0.726	0.771
Time 18-24	0.400	0.376	0.566

* CoinFrequency represents the total number of coins, certified and non-certified.

Table 2: Estimation Results I – All Coins

Independent Variable	Specification 1	2	3	4	5	6	7	8	9
lnRating	2.573***	3.749**	3.864**	3.201*	3.011*	2.643	2.871*	3.055*	3.054*
	(0.825)	(1.642)	(1.764)	(1.725)	(1.716)	(1.680)	(1.664)	(1.790)	(1.740)
LnNegative		-3.826**	-5.336***	-4.967***	-4.368**	-3.96**	-4.144**	-4.801**	-4.625**
		(1.740)	(1.873)	(1.878)	(1.850)	(1.767)	(1.922)	(1.994)	(1.824)
LnNeutral		1.139	1.764	1.406	1.086	1.172	1.18	1.541	2.907
		(2.433)	(2.594)	(2.641)	(2.628)	(2.696)	(2.746)	(2.691)	(2.396)
CoinValue	0.287***	0.287***	0.285***	0.285***	0.284***	0.284***	0.284***	0.284***	0.284***
	(0.034)	(0.034)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Certified			35.158***	35.698***	37.806***	39.639***	39.061***	39.353***	36.333***
			(6.671)	(7.510)	(7.567)	(7.346)	(7.319)	(7.497)	(6.579)
FullScan			3.067	3.391	4.351	5.053	2.442	3.141	1.842
			(3.926)	(4.330)	(4.350)	(4.402)	(4.548)	(4.648)	(3.851)
PartialScan			11.697	11.539	10.813	10.78	9.899	10.617	4.435
			(7.735)	(7.825)	(7.820)	(7.609)	(7.780)	(7.819)	(6.945)
PersonalCheck				9.562***	9.707***	10.064***	9.884***	8.821**	
				(3.563)	(3.566)	(3.597)	(3.551)	(3.565)	
OnlinePayment				1.198	1.449	1.194	1.095	0.891	
				(3.979)	(3.952)	(3.972)	(3.919)	(3.686)	
CreditCard				-0.959	-1.231	-1.943	-1.48	-1.716	
				(4.671)	(4.664)	(4.941)	(4.814)	(4.907)	
CoinFrequency					-0.829***	-0.816***	-0.958***	-0.961***	
					(0.111)	(0.109)	(0.124)	(0.124)	
AU-50						-7.378			
						(5.387)			
AU-53						-7.361			
						(17.848)			
AU-55						-0.355			
						(4.583)			
AU-58						9.193			
						(6.452)			
Tuesday							0.431	0.484	
							(5.167)	(5.167)	
Wednesday							7.757	7.676	
							(6.931)	(6.967)	
Thursday							-0.045	-0.534	
							(4.641)	(4.571)	
Friday							3.991	3.201	
							(4.809)	(4.752)	
Saturday							9.723**	8.440*	
							(4.403)	(4.449)	
Sunday							10.041*	10.661*	
							(5.567)	(5.539)	
Time 0-6								24.954***	
								(7.663)	
Time 6-12								9.001**	
								(3.739)	
Time 18-24								4.173	
								(4.667)	
10-Day									5.598
									(6.050)
7-Day									4.483
									(3.102)
5-Day									0.506
									(4.153)
Constant	4.332	-0.318	-7.888	-12.891	-2.743	-1.502	-4.435	-10.157	-11.446
	(6.635)	(9.846)	(10.036)	(11.174)	(11.296)	(11.179)	(12.348)	(13.506)	(9.998)
Chi-Square	82.05	94.26	280.8	311.97	332.14	353.37	421.44	489.11	375.11
Degrees of freedom	2	4	7	10	11	15	17	20	10
Observations	3828	3828	3828	3828	3828	3828	3828	3828	3828

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

Table 3: Estimation Results II – Non-Certified Coins Only

Independent	Specification								
Variable	1	2	3	4	5	6	7	8	9
LnRating	2.497***	3.946***	3.432***	2.904***	2.854***	2.567**	2.512**	2.782***	2.592**
	(0.695)	(1.115)	(1.162)	(1.115)	(1.101)	(1.116)	(1.086)	(1.081)	(1.175)
LnNegative		-0.522	-0.573	-0.342	0.319	0.682	0.351	-0.456	-0.277
		(1.528)	(1.523)	(1.551)	(1.507)	(1.485)	(1.530)	(1.589)	(1.519)
LnNeutral		-1.833	-1.090	-1.813	-2.394	-2.372	-2.019	-1.657	-0.010
		(1.434)	(1.514)	(1.562)	(1.547)	(1.544)	(1.555)	(1.593)	(1.457)
CoinValue	0.251***	0.252***	0.251***	0.251***	0.252***	0.252***	0.251***	0.251***	0.246***
	(0.031)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
FullScan			9.812***	9.055***	9.455***	9.902***	8.351***	9.116***	8.999***
			(2.004)	(2.132)	(2.169)	(2.197)	(2.190)	(2.283)	(1.891)
PartialScan			5.885**	6.159**	5.427*	5.278*	5.184*	5.784*	-0.121
			(2.825)	(2.829)	(2.833)	(2.847)	(2.919)	(3.003)	(2.319)
PersonalCheck				6.927**	6.716*	6.851*	6.711*	5.997*	
				(3.499)	(3.520)	(3.525)	(3.537)	(3.555)	
OnlinePayment				3.334	3.845	3.621	3.299	3.228	
				(2.886)	(2.896)	(2.854)	(2.923)	(2.923)	
CreditCard				9.021**	10.073***	9.130**	9.142**	8.301**	
				(3.543)	(3.534)	(3.684)	(3.791)	(3.885)	
CoinFrequency					-0.729***	-0.725***	-0.890***	-0.881***	
					(0.128)	(0.127)	(0.141)	(0.142)	
AU-50						-7.173**			
						(3.299)			
AU-53						5.436			
						(6.466)			
AU-55						0.072			
						(4.886)			
AU-58						4.567			
						(4.984)			
Tuesday							3.972	4.279	
							(4.558)	(4.585)	
Wednesday							7.732	8.063*	
							(4.894)	(4.894)	
Thursday							5.456	5.198	
							(3.812)	(3.777)	
Friday							5.188	4.708	
							(4.169)	(4.138)	
Saturday							14.309***	12.900***	
							(3.511)	(3.580)	
Sunday							12.868***	13.863***	
							(3.964)	(3.981)	
Time 0-6								18.756***	
								(4.733)	
Time 6-12								8.495***	
								(2.721)	
Time 18-24								1.456	
								(2.749)	
10-Day									7.802
									(5.044)
7-Day									3.080
									(1.08)
5-Day									-0.809
									(3.394)
Constant	2.848	-3.386	-9.432	-13.969**	-5.443	-3.998	-8.869	-14.290*	-9.626
	(4.495)	(6.194)	(6.358)	(7.135)	(6.863)	(6.885)	(7.309)	(7.695)	(6.865)
Chi-Square	96.09	103.42	168.49	221.73	235.09	267.96	242.50	314.75	214.29
Degrees of freedom	2	4	6	9	10	14	16	19	9
Observations	3328	3328	3328	3328	3328	3328	3328	3328	3178

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

Table 4: Estimation Results III – Certified Coins Only

Independent	Specification								
Variable	1	2	3	4	5	6	7	8	9
LnRating	-3.005	-4.588	1.323	-1.208	-2.135	-2.344	-2.080	-2.888	3.474
	(4.087)	(12.269)	(10.594)	(11.305)	(11.313)	(12.402)	(11.816)	(12.796)	(10.381)
LnNegative		-43.119***	-38.537**	-38.312**	-39.709**	-38.863**	-38.519**	-44.163***	-35.906*
		(12.952)	(15.823)	(17.147)	(17.142)	(17.335)	(18.150)	(17.143)	(14.981)
LnNeutral		45.119*	41.149*	40.897	43.866*	42.869	42.376	45.126	38.906*
		(24.607)	(23.916)	(25.699)	(25.594)	(27.025)	(26.805)	(28.520)	(21.864)
CoinValue	0.287***	0.285***	0.283***	0.282***	0.280***	0.281***	0.281***	0.280***	0.283***
	(0.037)	(0.038)	(0.037)	(0.037)	(0.038)	(0.038)	(0.037)	(0.038)	(0.037)
FullScan			-10.258	-2.791	8.650	6.183	-1.419	2.483	-18.120
			(31.759)	(38.732)	(41.839)	(43.563)	(42.570)	(40.994)	(33.721)
PartialScan			95.502	93.661	100.307	98.482	92.665	97.296	99.543
			(76.416)	(77.057)	(76.196)	(72.590)	(75.960)	(77.910)	(76.972)
PersonalCheck				17.879	23.441	24.763	21.808	25.419	
				(23.472)	(25.264)	(24.381)	(26.913)	(31.655)	
OnlinePayment				-26.373	-29.019	-27.413	-32.679	-44.974	
				(28.150)	(28.770)	(29.499)	(29.550)	(27.479)	
CreditCard				1.691	-4.807	-5.134	-11.758	-15.214	
				(18.563)	(19.788)	(20.045)	(22.567)	(22.224)	
CoinFrequency					-1.554**	-1.496**	-0.987	-1.061*	
					(0.727)	(0.738)	(0.618)	(0.622)	
AU-53						-20.631			
						(37.818)			
AU-55						0.890			
						(15.581)			
AU-58						23.342			
						(25.230)			
Tuesday							-27.422	-27.073	
							(24.665)	(28.586)	
Wednesday							16.824	14.947	
							(30.686)	(29.931)	
Thursday							-40.136**	-48.240**	
							(17.977)	(19.577)	
Friday							-10.319	-7.620	
							(17.403)	(18.220)	
Saturday							-23.088	-26.406	
							(26.199)	(26.833)	
Sunday							-36.902	-37.653	
							(29.249)	(26.946)	
Time 0-6								-58.699	
								(45.890)	
Time 6-12								-17.375	
								(38.902)	
Time 18-24								23.370	
								(41.343)	
10-Day									9.673
									(28.432)
7-Day									26.329
									(28.432)
5-Day									-2.576
									(40.487)
Constant	71.723**	74.8311	35.058	51.629	68.180	66.633	95.100	105.507	-0.129
	(28.685)	(49.709)	(45.551)	(51.151)	(52.119)	(67.517)	(50.827)	(75.389)	(58.130)
Chi-Square	60.86	137.91	138.61	186.58	239.67	286.84	395.01	648.78	392.75
Degrees of freedom	2	4	6	9	10	13	16	19	9
Observations	500	500	500	500	500	500	500	500	493

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

Table 5: Estimation Results IV – Non-certified Coins Only with and without Scans

Independent Variable	Non-certified Coins with Scans			Non-certified Coins without Scans		
	1	2	3	4	5	6
LnRating	3.511***	2.869***	2.391**	4.960***	4.626***	5.016***
	(1.170)	(1.142)	(1.123)	(1.391)	(1.311)	(1.354)
LnNegative	-0.045	0.207	1.104	-5.364*	-7.419**	-9.959***
	(1.587)	(1.614)	(1.586)	(2.844)	(3.177)	(3.401)
LnNeutral	-1.303	-2.004	-2.247	-0.984	0.372	1.978
	(1.500)	(1.545)	(1.550)	(2.929)	(2.983)	(2.978)
CoinValue	0.253***	0.254***	0.254***	0.194***	0.195***	0.195***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)
PersonalCheck		7.272**	6.958*		-0.294	0.764
		(3.639)	(3.687)		(2.729)	(2.822)
OnlinePayment		3.555	3.606		5.763*	5.794*
		(3.009)	(3.107)		(3.132)	(3.040)
CreditCard		8.406**	8.409**		26.082***	27.377***
		(3.583)	(3.845)		(8.592)	(8.926)
CoinFrequency			-0.950***			0.086
			(0.149)			(0.198)
Tuesday			4.068			5.436
			(4.918)			(6.659)
Wednesday			8.287			8.812
			(5.116)			(7.831)
Thursday			4.057			5.345
			(4.168)			(6.424)
Friday			5.292			12.292*
			(4.370)			(7.264)
Saturday			14.761***			10.820
			(3.633)			(6.751)
Sunday			13.819***			13.720
			(4.177)			(8.557)
Constant	-1.232	-6.078	-0.797	-9.938	-11.938	-23.234**
	(6.575)	(7.175)	(7.363)	(6.500)	(7.422)	(9.952)
Chi-Square	102.52	143.19	164.24	62.03	73.08	92.21
Degrees of freedom	4	7	14	4	7	14
Observations	3059	3059	3059	269	269	269

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

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