Does a Seller's eCommerce Reputation Matter? Evidence from eBay Auctions

Mikhail I. Melnik and James Alm*

Abstract

With internet commerce, a buyer cannot directly examine the product and so has to rely upon such things as the accuracy of the seller's product description and the reliability of the seller's product delivery in deciding whether and how much to bid for the good. In this setting, the seller's reputation can become an important factor in the size of the bid. This paper examines the impact of the seller's reputation on the willingness of buyers to bid on items sold via internet auctions, using a 1999 mint condition U.S. $5 gold coin whose average price was $32.73 in the period analyzed. The empirical results show that the quality of a seller's reputation has a consistent, statistically significant, and positive impact on the price of the good.

* Department of Economics, Andrew Young School of Policy Studies, Georgia State University.
We are grateful to Dave Lucking-Reiley, two anonymous referees, and, especially, Ken Hendricks for helpful comments and discussions.
Please address all correspondence to Mikhail Melnik, Department of Economics, Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA 30303-3083 (email: **ecomim@langate.gsu.edu**).

Introduction

Does a seller's reputation matter in determining the price that buyers are willing to pay for the seller's product? Akerlof (1970) demonstrated that markets in which sellers cannot reliably signal product quality may experience market failure. However, it may well be that the past reputation of the seller can act as a mechanism by which information about the current behavior of the seller can be transmitted to buyers. In such a setting, a seller's reputation may well reduce information asymmetries, and thereby allow the market to function.

This issue has received much attention in the industrial organization literature. Theoretical models have typically generated a positive relationship between the reputation of the seller and the price (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984; Houser and Wooders, 2000), in large part because the seller's reputation is a proxy for quality characteristics that are unobserved prior to the transaction. Experimental analysis has tended to support the theoretical results (Camerer and Weigelt, 1988). However, empirical analysis of this issue has been quite difficult, due largely to difficulties in quantifying and measuring a seller's "reputation".[1] The growth of internet commerce in recent years has created an environment in which this issue can be tested empirically, and there are now several studies that use online-generated data to study the effects of the seller's reputation on the buyer's willingness to pay (Lucking-Reiley, Byran, Prasad, and Reeves, 2000; McDonald and Slawson, 2000; Houser and Wooders, 2000). In this paper we use data collected from internet-based auction websites, including the website's own index of the seller's reputation, to estimate the impact of reputation on the price of the seller's product, and we find that reputation has a consistent, statistically significant, and positive effect on the willingness of buyers to pay for the good.

[1] See, however, Landon and Smith (1998), who find a positive relationship between reputation and the price of Bordeaux wines.

Auction websites such as **eBay.com**, **Yahoo.com**, and **Amazon.com** are becoming more popular each day. According to **eBay.com**, its site has over 22 million registered users[2], and a recent study of online auction websites by Lucking-Reiley (2000) estimates that the largest internet auction websites have experienced revenue growth rates of approximately 10 per cent per month during 1998 and 1999. The design of these auctions gives an opportunity to study the effects of the seller's e-commerce reputation on the price of the seller's good. Typically, auction websites assume no responsibility for items listed on their site, and simply act as auctioneer. Instead, the seller assumes the responsibility of describing the product, shipping it, and explaining the details of such things as delivery and payment methods. Importantly, in almost all instances the shipment occurs only *after* the payment is received.[3] The buyer thus assumes a risk when sending a payment. For instance, the seller may ship a damaged item, the item may have been incorrectly described in the auction, or the seller may not send the item at all.[4]

However, most auction sites have set up a mechanism that allows the buyer to leave comments about the seller after the transaction is complete.[5] This feedback can be positive, neutral, or negative, and comes in the form of statements like "It's been three months and the item hasn't arrived yet" or "Excellent seller, thank you!" The auction site compiles these comments as the number of positive feedbacks minus negative feedbacks, and calls this number the seller's *Rating*. Both the rating and feedback comments are then available for future buyers. The seller's rating is actually displayed on top of each auction of that seller, and is easily visible to each visitor of the auction.[6]

---

[2] See the eBay press release on March 14, 2001, "eBay to celebrate and reward half billionth listing".
[3] For instance, in most auctions where personal checks are accepted, a 5 to 14 day waiting period is required for checks to clear.
[4] For a more detailed description of internet auction mechanisms, see Lucking-Reiley (2000).
[5] In fact, the seller can also make comments about the buyer.
[6] These comments are easily accessible in the feedback section for each member of **eBay.com**.

The existence of information used to construct *Rating* provides a convenient mechanism for estimating the impact of a seller's reputation on the price of products sold by the seller. This is the purpose of this paper. Using data collected from auctions on **eBay.com**, we estimate a reduced-form equation that relates various features of the good, the details of the auction, and several measures of the seller's reputation to the auction price of the good. We examine in particular a 1999 mint condition U.S. $5 gold coin whose average price was $32.73 in the period we analyzed. Our estimation results indicate that buyers are willing to pay more for a good the more favorable is the seller's reputation, a result that is robust across a variety of specifications. However, the impact of reputation is generally small.

Theoretical Considerations

There are several ways in which the effects of reputation on price can be examined. Perhaps the most intuitive approach is that of Houser and Wooders (2000). They assume an auction with two types of sellers, *honest* and *dishonest*. The honest seller always delivers the promised good after receipt of the payment, while the dishonest seller never delivers the good. The seller's *reputation score* is simply the probability that the seller is honest, information that is publicly available. It is then straightforward to show that the expected utility of any buyer is an increasing function in the reputation of the seller, and the buyer is willing to pay more the higher is the reputation score of the seller.[7] Other approaches often generate a similar result (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984).

However, it is also possible to construct models in which reputation provides no information and is useless (McDonald and Slawson, 2000). Here reputation is needed only to

[7] More precisely, 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

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. In the next section we present our approach for estimating this impact.

Empirical Specification

Observations from the on-line auction website **eBay.com** are collected from May 19 to June 7 of 2000. In total, 450 observations are collected over the period, observations generated from 91 unique sellers. Table 1 provides descriptive statistics for the entire data set.

One of the problems with analyzing private auctions like the ones displayed on **eBay.com** is the heterogeneity of the product. People sell different products, and, even when the same general product type is offered for sale, the condition of the product often varies. Because there is no consistent method to measure product differences, any statistical approach may be problematic. However, identical products offered for sale by different sellers can be found. In particular, collectible coins of the same date and same grade can be considered a homogeneous product (e.g., a 1999 Georgia State quarter in mint condition).[8] The main difficulty with using identical items is finding enough observations, a problem that can be addressed if observations are collected over a long-enough time period. Such an approach creates a further difficulty, if there is a changing trend over this period in the behavior of coin collectors. However, the trend problem can be reduced by examining a bullion coin that has a small numismatic value and that derives the bulk of its value from the content of the bullion in it.

---

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.

For these reasons, we collect information on a 1999 $5 U.S. gold coin in mint condition. This coin has a small numismatic value, and derives the bulk of its value from its gold content. The average price (*Price*) of this coin was $32.73 (in U.S. dollars), while its gold value was $27.46 (based on the average gold price during the period of data collection). It is *Price* that is the dependent variable in our estimations.

As suggested by Landon and Smith (1998), Lucking-Reiley, et al. (2000), 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 include the seller's reputation, the underlying value of the gold content of the coin, and the auction features.

Of primary interest is the impact of the reputation of the seller on the buyer's willingness to pay for the good. Reputation is measured by the overall rating of the seller (*Rating*), calculated by **eBay.com** as the number of positive feedbacks minus the number of negative ones left by unique users. *Rating* exhibits great variation. Its mean value is 452, but it ranges from a minimum value of 3 to a maximum value of 3583. The information contained in *Rating* is also used to construct another reputational variable that focuses more precisely on the negative rating of the seller (*NegativeRating*), equal to the number of feedback responses that rate the seller as negative.[9]

Our expectation is that *Rating* will have a positive impact on the auction price, while *NegativeRating* will have a negative impact. However, as noted above, it is possible to construct a theoretical model in which the informational content of reputation is in equilibrium worthless. In addition, our measures of reputation are likely to be somewhat imperfect indicators, for several reasons: not every transaction results in a feedback comment, there is little economic

---

[8] Coins have previously been used to study online auctions. Lucking-Reiley, Bryan, Prasad, and Reeves (2000) provide an excellent overview of online coin auctions.

[9] Recall that buyers are allowed to leave positive, neutral, or negative feedbacks.

motivation for buyers to provide feedback after a transaction has been completed, sellers can change their internet identities, 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.[10]

Nevertheless, *Rating* and its breakdown into negative, neutral, and positive comments are fully observable by the bidders. Further, there is some informal evidence that the feedback mechanism is valued both by **eBay.com** and its users. In particular, **eBay.com** has recently gone to court to prevent other auction sites from using its reputation feedback, and comments from buyers in chatrooms suggest that buyers pay some attention to the feedback.

We include several variables that reflect the features of both the good and auction. The gold content of the coin is measured by the New York closing price of gold on the closing date of the auction (*Gold*). The New York closing price of gold on the closing date of the auction is chosen rather than the price on any other day during the auction because items in the closing stage of the auction are given a higher priority and are placed on the top of their category page.

Auction characteristics include the shipping and handling charges charged by the seller (*Shipping&Handling*). Shipping and handling costs are included because the buyer seems likely to consider the total cost of the transaction, rather than only the cost of the product itself.[11] Differences in shipping and handling costs should be reflected (or capitalized) in the total price.

Many sellers include shipping insurance costs in the shipping and handling charges, and many also provide shipping insurance on the item. However, not all sellers include these insurance charges. This seller difference is adjusted by including the dummy variable *Insurance*, equal to one if insurance is provided and zero otherwise. Insurance is provided in slightly more than 80 percent of the auctions.

[10] Note that bidders see all feedback indicators, while they do not see the total number of seller transactions.

Inclusion of the scanned picture of the actual item offered for sale (*Scan*) may increase the buyer's willingness to bid on the item because a picture improves the description of the item. The acceptance of credit cards as a method of payment (*CreditCard*) speeds up the shipping of the item, and some bidders may be willing to pay a higher price to receive the item faster. Both variables are dummy variables, and in both cases roughly 80 percent of the auctions in our sample include scans or accept credit cards.

The length of the auction (*Length*) is included because a longer auction increases the number of potential buyers who may visit the site. Auctions offered on **eBay.com** can last 10, 7, 5, or 3 days. Further, the time of the day when the auction closes may have an impact on the selling price. More people may view auctions that close early in the evening than auctions that close early in the morning. Also, auctions tend to receive the most attention from bidders during the last four hours of the auction, and many auctions have no bids until the last 4 hours of the auction. During those last four hours, auctions are not only displayed on top of the page in their category, but they are also placed on the *Going, Going, Gone* page of **eBay.com**, a page that only lists auctions closing within the next four hours. To investigate these issues, we include the dummy variable *ClosingTime*, equal to one if the auction's closing time is between 3 pm and 7 pm Pacific time and zero otherwise. We also include the dummy variable *FSS*, which equals one if the auction closes on Friday, Saturday, or Sunday, and zero otherwise; alternatively, in some specifications we include the dummy variable *SS*, equal to one if the auction closes on Saturday or Sunday and zero otherwise.

We estimate a wide variety of specifications. Model I includes only *Rating* and *NegativeRating* (plus a constant); other models introduce the additional variables defined above. In all of these models the dependent variable is *Price* (entered in linear form), the reputational

---

[11] The product is identical, and all sellers use the identical method of shipping (the U.S. Postal Service).

variables are entered in logarithmic form, and the other continuous variables are entered in linear form. Other specifications test the robustness of the estimation results to these functional forms. All specifications are estimated using Tobit maximum likelihood estimation with variable but known cutoffs.[12] Some auctions have a specified starting bid (or opening price) and receive no bids at all, in which case the true price is below the starting bid and its precise value is unknown; these starting bids can vary from auction to auction. There are 117 observations that are left-censored, in the total sample of 450 observations. As a result, we face a censoring problem with different cutoff points, and the Tobit method ensures unbiased and consistent estimates. Defining Y_i as the unobserved index variable for observation i with cutoff value C_i , then Y_i equals

$$Y_i = X_i\beta + \varepsilon_i \quad \text{if } Y_i > C_i$$

$$Y_i = C_i \qquad \text{otherwise}$$

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 standard likelihood function l, or

$$l = -\frac{1}{2}\sum_{Y_i > C_i}[(\frac{Y_i - X_i\beta}{\sigma})^2 + \log(2\pi\sigma^2)] + \sum_{Y_i < C_i}\log\Phi(\frac{C_i - X_i\beta}{\sigma})$$

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

Estimation Results

[12] See Tobin (1958) and, especially, Amemiya (1984) for detailed discussions of this estimation method.

Table 2 reports the estimation results from several different specifications, with t-statistics in parentheses.[13] Consider first the impact of the seller's reputation. As expected, the coefficient on *ln(Rating)* is positive and statistically significant across all models, with a coefficient size that varies little by model. Also, *ln(NegativeRating+1)* has a consistently negative impact on the willingness to bid on the auction item, and is significant at the 90 percent level or better in most of the models. These results give empirical support to the notion that a seller's reputation affects a buyer's willingness to pay for auction items.

The potential impact of reputation on the willingness to pay is noticeable but small. To illustrate, the average estimated coefficient on *ln(Rating)* in the Table 2 models is 0.26. This value suggests that a seller who doubles the *Rating* from 452 to 904 will on average experience an increase in the auction price, but only by $.18. Similarly, a seller who allows the *Rating* to decline by half will suffer a fall in the auction price of only $.18; even if the *Rating* fell all the way to one, the price would decline by $1.59. An improvement in a seller's *NegativeRating* also raises the willingness to pay, but again the impact is relatively small. Using the average estimated coefficient on *ln(NegativeRating+1)* in Table 2, a seller who halves the mean *NegativeRating* from 0.96 to 0.48 will see an increase of 28 cents. Note that these results are

---

[13] Note that the estimated coefficient for independent variable X_i, or β_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 auction item; that is,

$$\frac{\partial E[Y_i \mid X_i]}{\partial X_i} = \beta$$

The impact of X_i on the actual observed variable, or *Price*, is given by

$$\frac{\partial E[\mathrm{Price}_i \mid X_i]}{\partial X_i} = \beta\Phi\left(\frac{\beta' X_i}{\sigma} + C\right),$$

Recall that $\Phi()$ is the cumulative standard normal distribution function, σ is the standard deviation, and C is the (average) cutoff value. For example, *ln(Rating)* has a coefficient of 0.262 in Model VI, which indicates that a 1 unit increase in the variable increases the unobserved index variable, or the willingness to pay for the gold coin, by 26.2 cents. However, the impact of a 1unit increase in X_i on the observed *Price* of the coin is only 20.3 cents. The discussion in the text focuses upon the impact on the willingness to pay.

unaffected by adding a reputation variable that measures the relative frequency of negative responses.[14]

Other variables have expected signs and are generally statistically significant. The price of gold (*Gold*) has a positive and statistically significant coefficient, whose value indicates that a 1 percent increase in the price of gold generates a roughly 0.7 percent change in the willingness to pay for the coin.

The coefficient on shipping and handling charges is negative and significant. Its magnitude suggests that each dollar increase in shipping and handling costs reduces the willingness to pay by approximately 55 cents. Note that this coefficient is less than one, so that these costs are not completely capitalized in the price. As expected, the presence of insurance increases the willingness to bid on the item. However, *Insurance i*s only marginally significant (at the 8 percent level) in Model VI.

The presence of a photo image of the coin increases the willingness to bid on the coin, although the coefficient on *Scan* is not significant. This result is plausible because the presence of a visual description of a perfectly homogeneous product does not offer much additional or useful information about the product. Similarly, the acceptance of credit cards has a positive but insignificant coefficient, a result that is of some interest because the acceptance of credit card use increases the seller's costs of transaction.

Auctions that close during peak periods generate a higher price of the auction item. However, the length of the auction and the date upon which it finishes do not have a significant impact on the auction price. These combined results are consistent with the hypothesis that

[14] For example, the estimation results when a variable is included that measures the relative frequency of negative responses are

$$\underset{}{Price} = \underset{(57.749)}{39.126} + \underset{(3.648)}{0.383}\, ln(Rating) - \underset{(2.189)}{0.572}\, ln(NegativeRating+1) - \underset{(0.676)}{12.262}\, ln[(NegativeRating+1)/Rating]$$

where numbers in parentheses are t-statistics.

buyers pay most attention to an auction during its closing stages (*ClosingTime*), regardless of how long the auction has been going (*Length*) or what day the auction closes (*FSS*). These results are different from those of Lucking-Reiley *et al.* (2000), who find a significant positive relationship between the length of the auction and the price. However, they use a rarer, and more heterogeneous good (collectible Indian-head penny coins minted in different years), and the length of the auction seems likely to have a greater impact on such commodities because only a few coins with specific characteristics (e.g., mint mark, year, grade) are available at any time. In contrast, the 1999 $5 U.S. gold coin is more common and more homogeneous, and an itemized search results in many auctions available to buyers at specific instances. Consequently, buyers may limit their searches to auctions that are due to close shortly, and not browse through several pages of itemized search results.

It should be noted that these estimation results are largely unaffected by alternative functional forms for the continuous variables. For example, using the variables in Model VI of Table 2, the signs and significance levels of all explanatory variables are unaffected by entering *Price* in logarithmic form; similarly, entering all continuous (dependent and independent) variables in logarithmic form does not affect the results. In particular, the two measures of the seller's reputation have a consistent impact on the auction price in all specifications.[15]

Conclusions

[15] For example, the estimation results when all continuous variables are entered in logarithmic form are:

$$\begin{array}{l} \underset{}{\mathit{ln(Price)}} = \underset{(17.349)}{2.798} + \underset{(3.226)}{0.010}\ \mathit{ln(Rating)} - \underset{(-2.282)}{0.016}\ \mathit{ln(NegativeRating+1)} - \underset{(-3.048)}{0.033}\ \mathit{ln(Shipping\&Handling)} \\ \qquad + \underset{(1.703)}{0.014}\ \mathit{Insurance} + \underset{(3.669)}{0.596}\ \mathit{ln(Gold)} + \underset{(1.697)}{0.012}\ \mathit{ln(Length)} + \underset{(0.334)}{0.003}\ \mathit{CreditCard} + \underset{(1.394)}{0.011}\ \mathit{Scan} \\ \qquad + \underset{(2.206)}{0.014}\ \mathit{ClosingTime} + \underset{(1.602)}{0.010}\ \mathit{FSS} \end{array}$$

where numbers in parentheses are t-statistics.

This study demonstrates that a seller's ecommerce reputation is a determinant, though not a major determinant, of the price the seller receives in internet auctions. In the absence of other, more direct sources of information about a product, an internet buyer must rely upon the accuracy of the seller's product description and the reliability of the seller's product delivery in deciding whether and how much to bid for the good. Put differently, the seller's reputation becomes one consideration in the buyer's willingness to bid on the auction item. Our empirical results show that a seller with a better reputation can expect to receive a higher price for the auction good. However, although reputation is a statistically significant determinant of the auction price, its impact tends to be small.

In this regard, new website auction sellers may find it difficult to compete with existing sellers who have established a positive reputation. Further, in the absence of a mechanism that allows ratings to be transferred across sites, a seller who has a high rating with a particular on-line auction website may face a cost in switching to other on-line auction websites. "Reputation" obviously provides some benefits to consumers searching the internet for items upon which to bid. However, such "reputation" may also impose some costs on consumers, if the development of reputation by on-line auction sites acts as a barrier to entry for new on-line auction sites and gives monopoly power to already established on-line auction websites.

References

Akerlof, G. (1970). "The market for 'lemons': Quality uncertainty and the market mechanism". *Quarterly Journal of Economics* 84 (3): 488-500.

Allen, F. (1984). "Reputation and product quality". *Rand Journal of Economics* 15 (3): 311-327.

Amemiya, T. (1984). "Tobit models: A survey". *Journal of Econometrics* 24 (1): 3-16

Camerer, C., and K. Weigelt (1988). "Experimental tests of a sequential equilibrium Reputation model". *Econometrica* 56 (1): 1-36.

Greene, W. H. (1993). *Econometric Analysis* (Englewood Cliffs, NJ: Prentice-Hall Inc., 2nd edition).

Houser, D., and J. Wooders (2000). "Reputation in Auctions: Theory and evidence from eBay". University of Arizona Working Paper.

Klein, B., and K. B. Leffler (1981). "The role of market forces in assuring contractual performance". *The Journal of Political Economy* 89 (4): 615-641.

Landon, S., and C. Smith (1998). "Quality expectations, reputation, and Price". *Southern Economic Journal* 64 (3): 628-647.

Lucking-Reiley, D., D. Bryan, N. Prasad, and D. Reeves (1999). "Pennies from eBay: The determinants of price in online auctions". Vanderbilt University Working Paper.

Lucking-Reiley, D. (2000). "Auctions on the internet: What's being auctioned and how?" *Journal of Industrial Economics* 48 (2): 227-252.

McDonald, C. G., and V. C. Slawson (2000). "Reputation in an Internet Auction Market". Louisiana State University Working Paper.

Shapiro, C. (1983). "Premiums for high quality products as returns to reputation". *Quarterly Journal of Economics* 98 (4): 659-680.

Tobin, J. (1958). "Estimation of relationships for limited dependent variables". *Econometrica* 26 (1): 24-36.

Table 1:Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Price	32.727	3.094	26.000	50.000
Rating	452.742	765.896	3.000	3583.000
NegativeRating	0.956	1.569	0.000	13.000
Gold	274.598	4.907	269.900	289.100
Shipping&Handling	2.845	0.698	0.000	5.500
Insurance	0.802	0.399	0.000	1.000
Scan	0.809	0.394	0.000	1.000
CreditCard	0.804	0.397	0.000	1.000
ClosingTime	0.338	0.473	0.000	1.000
Length	6.629	2.494	3.000	10.000
SS	0.407	0.492	0.000	1.000
FSS	0.504	0.501	0.000	1.000

Table 2: Estimation Results
(t-statistics in parentheses)

Independent Variable	I	II	III	IV	V	VI	VII
ln(Rating)	0.420	0.217	0.202	0.223	0.244	0.262	0.261
	(4.728)	(2.171)	(1.977)	(2.134)	(2.330)	(2.503)	(2.501)
ln(NegativeRating+1)	-0.687	-0.371	-0.321	-0.370	-0.478	-0.503	-0.511
	(3.421)	(1.766)	(1.463)	(1.639)	(2.055)	(2.159)	(2.205)
Gold		0.068	0.067	0.066	0.069	0.074	0.074
		(3.552)	(3.510)	(3.469)	(3.594)	(3.820)	(3.871)
Shipping&Handling		-0.524	-0.534	-0.548	-0.556	-0.543	-0.545
		(3.134)	(3.193)	(3.262)	(3.320)	(3.247)	(3.272)
Insurance		0.364	0.391	0.363	0.402	0.463	0.465
		(1.412)	(1.506)	(1.386)	(1.540)	(1.757)	(1.777)
Length		0.064	0.056	0.050	0.058	0.052	0.054
		(1.707)	(1.429)	(1.257)	(1.461)	(1.317)	(1.353)
CreditCard			0.206	0.154	0.162	0.105	0.126
			(0.768)	(0.564)	(0.595)	(0.384)	(0.464)
Scan				0.236	0.300	0.395	0.381
				(0.921)	(1.167)	(1.498)	(1.472)
ClosingTime					0.411	0.458	0.487
					(1.911)	(2.113)	(2.283)
FSS						0.317	
						(1.581)	
SS							0.395
							(2.019)
Constant	29.933	12.934	13.129	13.216	12.305	10.488	10.390
	(8.371)	(2.480)	(2.521)	(2.540)	(2.368)	(1.973)	(1.979)
Log-likelihood	-730.243	-718.526	-718.232	-717.808	-715.989	-714.741	-713.596
Observations[a]	450	450	450	450	450	450	450

[a] The dependent variable is *Price*, or the U. S. dollar price of a mint condition 1999 U.S. $5 gold coin.
[b] 117 observations are left-censored.