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WP 07-18

November 2007

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Abstract

This study explores how seller reputations affect auction prices, and concludes that earlier findings may be biased due to the misspecification of seller reputation. This paper contributes to the literature by offering significant empirical evidence using Taiwanese Internet auction data. Our study reveals that the influence of seller reputations on auction prices is significant, irrespective of the assumptions of linear and non-linear relationships with price. However, failure to consider the non-linear setting of seller reputation would have led us to overestimate the impact of reputations on prices because marginal returns to an incremental increase in reputation declines rapidly for sellers who have more than 15 scores. In addition, using quantile regression, this study finds evidence of considerable differences in their impact on auction prices dependent on the distribution of price levels.

Keywords: Internet auction, reputation, Taiwan, Yahoo! Kimo, quantile regression

JEL classification: D8, D44, L86

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1. Introduction

The impressive growth of Internet auctions, such as eBay or Yahoo! Auction, is, to a large extent, built on sellers' integrity. Sellers do not deliver goods to winning bidders unless they have received the payments. Therefore, Internet frauds or scams due to asymmetric information are not unusual these days. Such potential flaws are similar to the 'lemon' problem described by Akerlof (1970), resulting in market failure. So, why are bidders willing to risk such uncertainty when sellers might not enforce the contracts honestly? Because they expect that it would be costly for sellers who have already established better reputations to cheat. Hence, the success of Internet auctions rests largely on the mechanism of self-enforcement, using the seller reputation measured by the number of positive (or negative) scores posted by bidders, which, to some extent, mitigates asymmetric information and indirectly discourages cheating.

A large body of empirical studies has examined how reputation can help alleviate the market failure problem. Most empirical results, while focusing on the influence of seller reputations on auction prices, show evidence that higher seller reputations increase prices (Standifird, 2001; McDonald and Slawson, 2002; Bajari and Hortacsu, 2003; Durham et al., 2004; Dewan and Hsu, 2004; Melnik and Alm, 2002, 2005). As for the influence of negative scores on prices, the empirical results generally agree that negative scores lead to lower prices, except for Eaton (2002). For example, Lucking-Reiley et al. (2006) find that bidders significantly punish sellers who receive negative feedbacks, and that the impact of negative feedbacks is much greater than positive feedbacks.[1]

The objectives of this paper are threefold. In earlier studies, the examination of the relationship between auction prices and reputation was often assumed to be linear, leading to a very small effect on prices.[2] Such an assumption is misleading if the seller reputations are dispersed widely (see Figure 1). Following Livingston (2005), in contrast, this study classifies overall sellers into four quartiles, except for unrated sellers (see Table 5 for details). In addition to using ordinary least squares (OLS) to investigate the impact of auction characteristics on auction prices, it is likely that the number of bids is endogenously determined by other auction characteristics. Therefore, this study undertakes the joint estimation using seemingly unrelated regression (SUR) estimation.

[1] For more examples, refer to Standifird (2001), McDonald and Slawson (2002), Cabral and Hortacsu (2004), Melnik and Alm (2002, 2005).

[2] For example, McDonald and Slawson (2002) show that an additional score in reputation would increase the price by \$0.04 (for a collector-quality Harley-Davidson Barbie with mean price \$263.21).

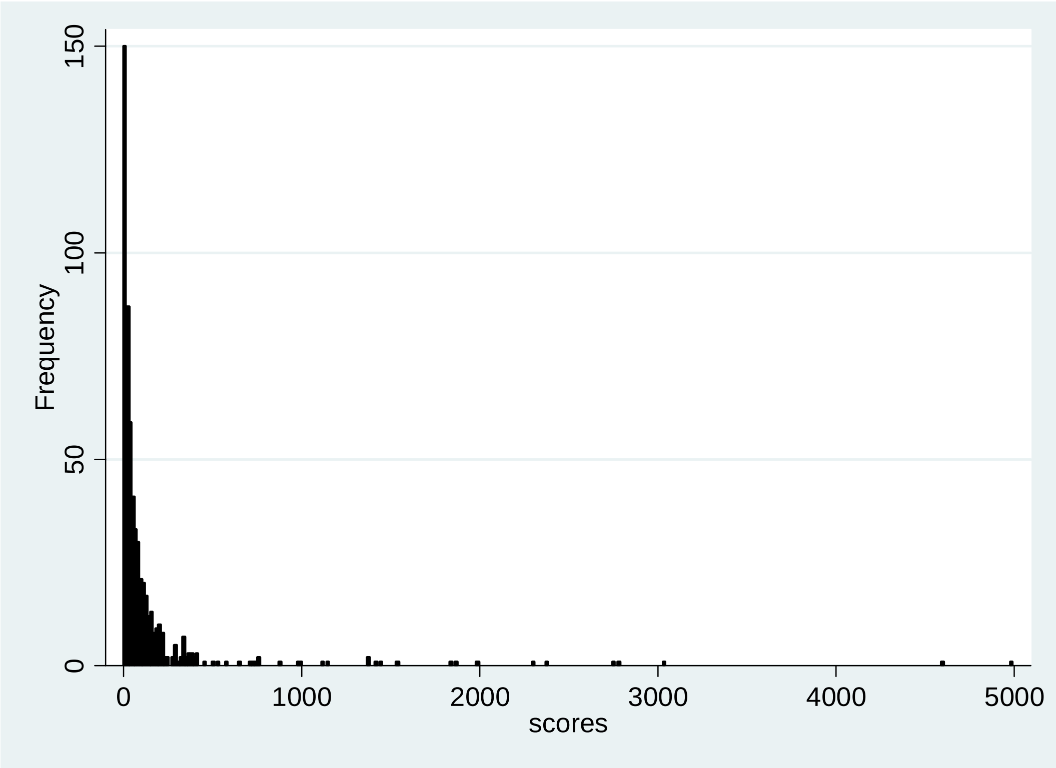


Figure 1 Distribution of seller reputation scores

This study further focuses on the differences between various auctions in different quantiles of auction prices. Although there is a consensus on the importance of seller reputation on auction prices, the existing empirical studies only provide the 'mean' impact of seller reputation on prices. For instance, Dewan and Hsu (2004) estimate that the elasticity of seller reputation with respect to auction prices of 'collectible stamp' is 0.03 using the OLS regression, implying that a 10 percent increase in reputation is associated with a 0.3 percent increase in auction price. That is, given a median price (=$9.50) and scores (=543), 54 additional scores will raise the auction price by only 2.85 cents (i.e., 0.053 cents per score)! Note that auction prices in different quantiles of our sample have significantly different sensitivities to the explanatory variables, for example, seller reputation and auction length. Quantile regression allows us to explore the whole distribution of online auctions, rather than a single measure of the central tendency of the auction price distribution. Consequently, this paper is able to evaluate the relative importance of explanatory variables at different points of auction price distribution.

The rest of the paper is organized as follows. Section 2 presents a brief discussion of methodologies used in recent empirical studies. Section 3 outlines the empirical models and Section 4 describes data sources and variables descriptions. Section 5 presents OLS, SUR and quantile regression results. Section 6 summarizes the findings and provides a conclusion.

2. A brief discussion of recent empirical studies

This section reviews previous Internet auction studies according to the choices of the dependent variable and the corresponding methodologies used. To conserve space, these empirical results are not presented in this study, but some of the results are available in Bajari and Hortacsu (2004, Table 1).

When the dependent variable is the auction price (or winning bid, or the highest bid), most studies utilize the OLS regression analysis (including Standifird, 2001; Ba and Pavlou, 2002; Eaton, 2002; Bajari and Hortacsu, 2003; Durham et al., 2004; Cabral and Hortacsu, 2004; Dewan and Hsu, 2004; Livingston, 2005; Lucking-Reiley et al., 2006).[3] In addition to studies on successful transactions, a number of studies, for example, Bajari and Hortacsu (2003), Dewan and Hsu (2004), Melnik and Alm (2002, 2005), use Tobit models to study the determinants of both successful and unsuccessful auctions.

Livingston (2005) adopts the sample selection model to avoid possible biased estimates caused by the constraints of the Tobit model; Lucking-Reiley et al. (2006) employ the censored-normal maximum-likelihood estimation procedure, which is exactly like a standard Tobit regression except that the censoring point is different across observations. Instead of using the winning bid, Houser and Wooders (2006) utilize the second-highest bid plus the shipping cost as the dependent variable. They then estimate the coefficients of the system equations through generalized least squares (GLS) procedures.

If the dependent variable is the probability of a sale, or a dummy variable which takes a value of 1 if ended with a sale or 'Buy It Now' (BIN), these studies usually apply the probit or logit model in the estimation. The probit model includes Dewan and Hsu (2004) and Livingston (2005), and the logit model Eaton (2002), Resnick and Zeckhauser (2002), and Durham et al. (2004).

When the dependent variable consists of the number of bidders, numbers of bids or last-minute bids, Bajari and Hortacsu (2003) apply poisson regression to analyze the determinants of entry (number of bidders). They regress the numbers of bids or last-minute bids on the number of bidders and other determinants using the OLS regression. McDonald and Slawson (2002) specify two dependent variables: the winning bid and the number of bids, depending on several auction characteristics, and estimate the system equations simultaneously using the SUR estimation.

[3] Bajari and Hortacsu (2003) normalize their dependent variables; that is, the winning bid or number of bids divided by the book value.

To the best of our knowledge, this study is unique in examining how bidders reward seller reputations in different quantiles. Thus, one of the contributions of this paper is to apply quantile regression to examine the influence of seller reputation on different levels of auction prices.

3. Empirical models

This study first explores how these auction characteristics affect prices using the conventional OLS regression as specified in equation (1). For example, it is expected that higher seller reputations, a greater number of bids, longer duration, and BIN will increase auction prices. The dependent variable is *PRICE*, measured by the highest winning bid in an auction.

$$PRICE_i = \alpha_0 + \alpha_k x_{ki} + \varepsilon_i, \qquad i = 1,2,...,n \tag{1}$$

where α_0 and α_k denote the intercept term and coefficients, and x_k includes *SCORE*, *NEGSCORE*, *BIDS*, *NEGDUMMY*, *OPBIDONE*, *BIN*, *SHIPPING*, *BONUS*, Q_j, BT_j ($j = 1,2,...,4$), *VOLUME* and so on. Table A.1 in Appendix describes the variables used in this study.

However, it is likely that the number of bids is endogenously determined by other auction characteristics (Lucking-Reiley et al., 2006; Bajari and Hortacsu, 2003; McDonald and Slawson, 2002). Seller reputations and other characteristics, such as auction length, could affect auction price indirectly by influencing the number of bids. This study establishes an additional equation (2) for the number of bids, and estimates the system equations (1) and (2) simultaneously using the SUR estimation, which allows error terms which exhibit contemporaneous correlation: $E(\varepsilon_i) = E(u_i) = 0$ and $E(\varepsilon u) = \sigma_{12}$. The dependent variable is *BIDS* measured by the number of bids.

$$BIDS_i = \beta_0 + \beta_m z_{mi} + u_i, \qquad i = 1,2,...,n \tag{2}$$

where β_0 and β_m denote the intercept term and coefficients; z_m includes *SCORE*, *OPBID*, Q_j ($j = 1,2,...,4$), *LENGTH*, *WEEKEND* and so on.

To analyze the impact of seller reputations on the different points of auction price distribution, this study carries out a more detailed investigation using quantile regression, introduced by Koenker and Bassett (1978). Quantile regression is a natural extension of classical least squares regression to an ensemble of models for conditional quantile functions. For least squares functions, squared residual error is minimized with respect to the conditional mean. Quantile regression functions are estimated by minimizing an asymmetrically weighted sum of absolute errors (Koenker and Bassett, 1978, 1982; Koenker and Hallock, 2001). In addition, quantile regression is not sensitive to dependent variable outliers and heteroscedastic errors, both of which significantly affect classical least squares estimation (Koenker and Bassett, 1978).

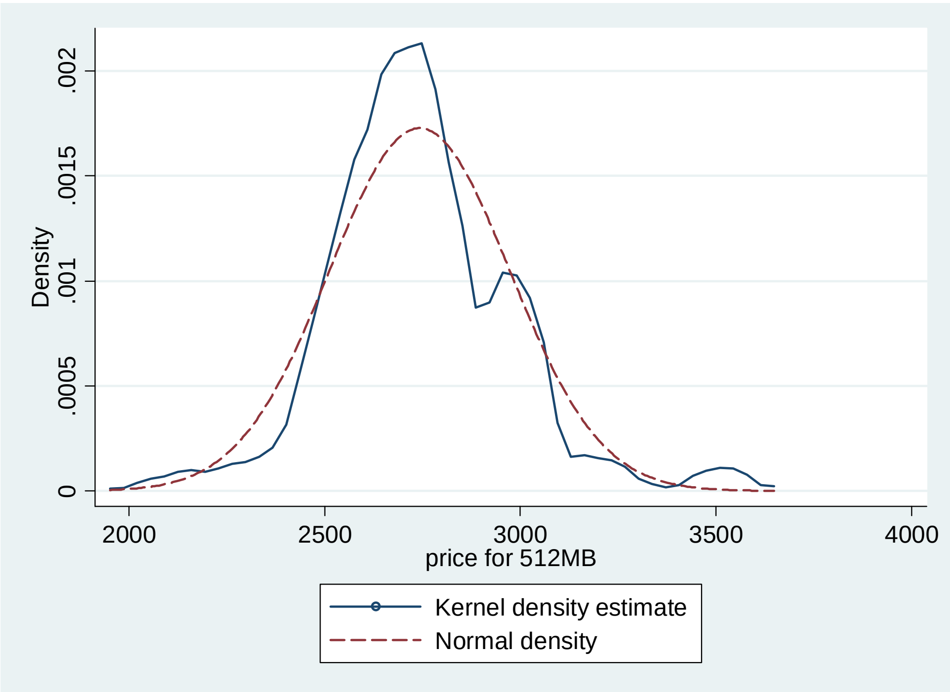
Figure 2 shows the kernel density estimates of auction prices for 512 Mb and 1 Gb. It indicates that the distributions deviate from the normal and are skewed to the right. The deviation from the normal distribution is confirmed as shown in Table 1, which presents skewness and Kurtosis tests for normality. Thus, the present study re-estimates the OLS model specified as equation (1) using quantile regression techniques. The following conditional quantiles: 0.10 (percentile 10 percent), 0.25 (lower quartile), 0.50 (median), 0.75 (upper quartile) and 0.90 (percentile 90 percent) will be taken into account. Let y_i be the $PRICE_i$ and x_i a vector of covariates representing auction characteristics. The statistical model specifies the θth quantile of the conditional distribution of y_i given x_i as a linear function of the covariates,

$$y_i = x_i'\beta_\theta + \varepsilon_i, \quad i = 1,2,\ldots,n, \quad 0 < \theta < 1 \tag{3}$$

As shown by Koenker and Bassett (1978, 1982), the quantile regression estimator (β_θ) solves the following minimization problem

$$\hat{\beta}_\theta = \arg\min_\beta \left[\sum_{i \in \{i | y_i \ge x_i\beta\}} \theta | y_i - x_i\beta | + \sum_{i \in \{i | y_i < x_i\beta\}} (1-\theta) | y_i - x_i\beta | \right], \tag{4}$$

The objective function above is a weighted sum of absolute deviations, and it can be shown that the estimator for $\hat{\beta}_\theta$ is consistent and asymptotic normal.



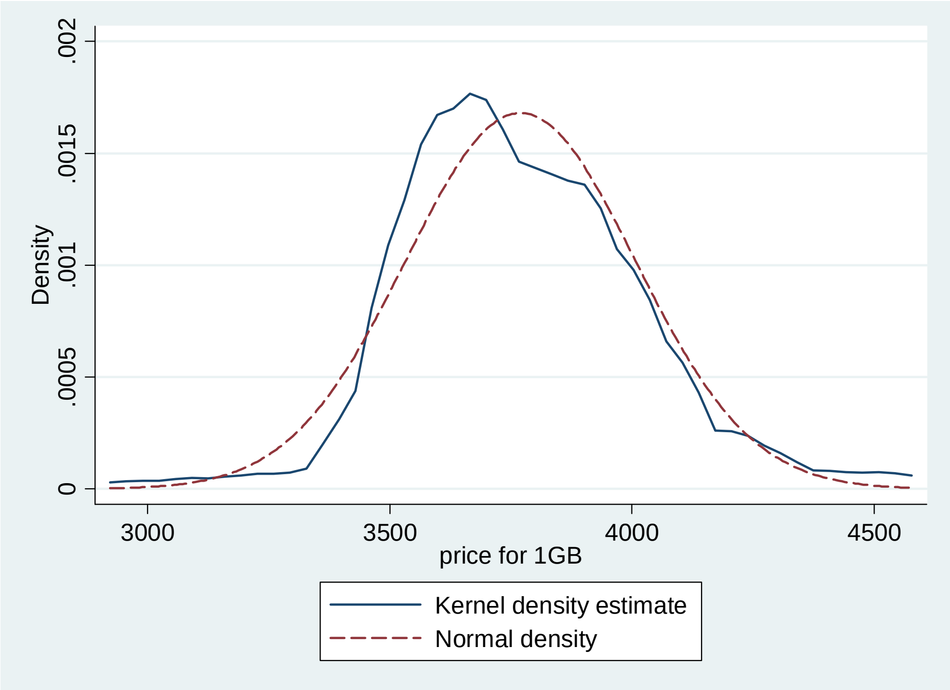


Figure 2 Kernel density estimates of prices from the least square estimator for 512 Mb and 1 Gb

Table 1 Skewness/Kurtosis test for normality

Variable	Pr(skewness)	Pr(kurtosis)	Joint Adj $\chi^2(2)$	Joint Pr > $\chi^2(2)$
Price (512 Mb)	0.000	0.000	33.63	0.0000
Price (1 Gb)	0.140	0.033	6.35	0.0417

4. Data source and description

The data used in this study is restricted to a 'brand new' Apple iPod shuffle 512 Mb or 1 Gb MP3 player, which includes earphones, neck hanging strap and so on. The data are collected by hand from Yahoo! Kimo auctions between 5 October, 2005 and 31 December 2005 (tw.bid.yahoo.com), and there were 466 iPod shuffle sales for 512 Mb and 116 sales for 1 Gb.[4] Yahoo! Kimo is a leading online auction site in Taiwan, with more than 90 percent of the market share in transaction values of Internet auctions, followed by eBay and PChome.[5] Figures 3 (a) and (b) show the histograms for prices of the iPod shuffle, 512 Mb and 1 Gb, respectively. Most of the auctions for 512 Mb and 1 Gb are, respectively, finished between $NT2,500 and $3,000 and between $NT3,500 and $4,000. Within each category (512 Mb and 1 Gb) why are prices so dispersed?

[4] Our sample is restricted to successful auctions because auctions that attract no bids and automatically re-advertise are difficult to distinguish.

[5] In June 2006, eBay and PChome agreed to form a joint online auction site and the new auction site, www.Ruten.com.tw, will begin its operations in October 2006, an effort aimed at competing with market leader Yahoo! Kimo.

We argue that the dispersion is mostly due to differences in seller reputation.

Table 2 shows the summary statistics for auction characteristic variables. The mean price and shipping cost for 512 Mb (1 Gb) are \$NT2,742 (\$3,770) and \$NT54 (\$52), respectively, and the average numbers of bids and bidders for 512 Mb (1 Gb) turn out to be 7.2 (7.9) and 3.7 (3.6), respectively. Table 3 indicates the details of the opening bid and bidding types, where BT_1, BT_2 and BT_4 are ended with BIN. Bidding type BT_2 has the highest average opening bid of \$NT2,822 for 512 Mb and \$NT3,872 for 1 Gb. In addition, a relatively higher ratio of the opening bid at \$NT1 in bidding type BT_4 resulted in the lowest average opening bid of \$NT1,370 for 512 Mb and \$1,507 for 1 Gb, respectively.

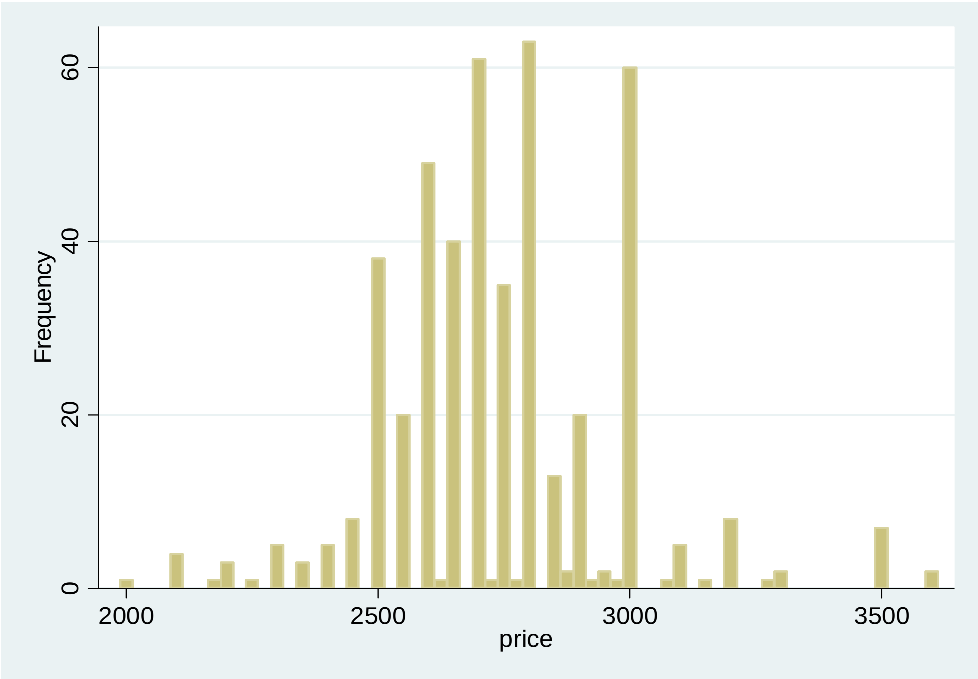


Figure 3(a) Histogram for price of the iPod shuffle 512 Mb

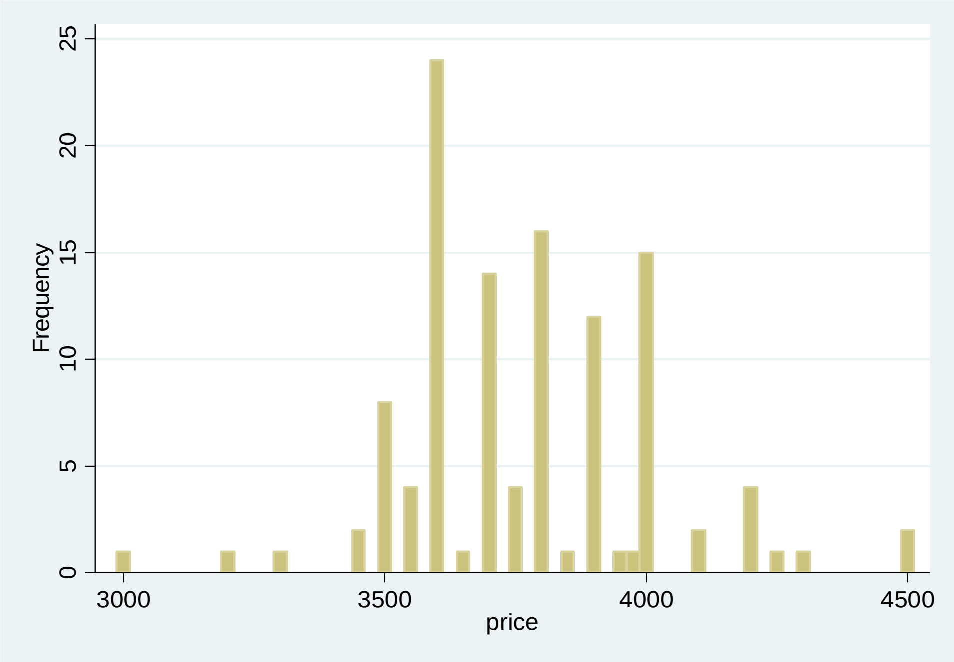


Figure 3(b) Histogram for price of the iPod shuffle 1 Gb

Table 2 Summary statistic auction characteristics variables

512 Mb	N	Mean	Std. Dev.	Median	Minimum	Maximum
PRICE ($NT)	466	2742.4	230.9	2700	2000	3600
BIDS	466	7.2	12.0	2	1	69
BIDDERS	466	3.7	4.7	2	1	31
OPBID ($NT)	466	2100.4	989.3	2500	1	3600
OPBID = $NT1	66	1	0	1	1	1
OPBID (> $NT1)	400	2446.8	539.6	2500	60	3600
SHIPPING ($NT)	466	54.0	44.2	50	0	200
VOLUME	466	6.5	2.3	7	1	11
LENGTH	466	6.3	3.4	7	1	10
1 Gb						
PRICE ($NT)	116	3770.1	237.5	3750	3000	4500
BIDS	116	7.9	15.0	1	1	78
BIDDERS	116	3.6	5.1	1	1	30
OPBID	116	3008.9	1375.5	3600	1	4500
OPBID = $NT1	16	1	0	1	1	1
OPBID (> $NT1)	100	3490.2	708.2	3600	4	4500
SHIPPING ($NT)	116	51.9	47.2	50	0	150
VOLUME	116	2.4	1.2	2	1	5
LENGTH	116	5.5	3.0	5	1	10

Table 3 Summary statistic: opening bid and bidding types

Bidding types	BT_0	BT_1	BT_2	BT_3	BT_4
512 Mb					
mean *OPBIN* ($NT)	2610	2505	2822	1601	1370
OPBID > $NT1, N =	73	60	95	136	36
OPBID = $NT1, N =	0	1	0	49	16
N =	73	61	95	185	52
1 Gb					
mean *OPBIN* ($NT)	3664	3547	3872	1690	1507
OPBID > $NT1, N =	25	19	32	17	7
OPBID = $NT1, N =	0	0	0	15	1
N =	25	19	32	32	8

Table 4 shows the summary statistics for dummy variables. In general, sellers who have no reputation receive the lowest mean price of $NT2,420 for 512 Mb, but unexpectedly attract the highest number of bids, at 12.2 on average. Auctions starting with an opening bid of $NT1 on average attract 29.3 bids for 512 Mb and 40.7 bids for 1 Gb, respectively. Auctions ending with BIN for 512 Mb have a higher mean price than non-BIN auctions at $NT192, and for 1 Gb at $156. Surprisingly, bidding type three (BT_3), which has the highest average number of bids at 14.2, receives the lowest mean price of $NT2,654 for 512 Mb and $NT3,689 for 1 Gb. The effects of weekend auctions and the length of auctions on prices differ for 512 Mb and 1 Gb. For instance, there is a higher average number of bids (7.8) during the weekend for 512 Mb, but a lower average number of bids for 1 Gb during the weekend.

Table 4 Summary statistics for dummy variables: price and bids

	512 Mb			1 Gb		
Reputation	N	Mean bids	Mean price	N	Mean bids	Mean price
Q_0 (unrated)	10	12.2	2420	3	4.0	3900
Q_1 (1st quartile)	112	6.6	2701	25	3.2	3610
Q_2 (2nd quartile)	117	7.0	2747	25	5.6	3759
Q_3 (3rd quartile)	112	7.9	2763	34	10.5	3788
Q_4 (4th quartile)	115	6.9	2786	29	11.2	3883
OPBID ($NT)						
OPBID = $NT1	66	29.3	2740	16	40.7	3725
OPBID (> $NT1)	400	3.6	2743	100	2.7	3777
BONUS						
1	40	7.3	2868	18	3.9	3930
0	426	7.2	2731	98	8.6	3741

BIN						
1	208	3.1	2849	59	19.7	3847
0	258	10.5	2657	57	13.8	3691
Bidding types						
BT_0	73	1.0	2664	25	1.0	3692
BT_1	61	1.0	2888	19	1.0	3814
BT_2	95	1.0	2825	32	1.0	3872
BT_3	185	14.2	2654	32	23.9	3689
BT_4	52	9.3	2847	8	9.6	3825
MONTH						
October	144	7.4	2723	32	11.2	3717
November	156	6.4	2750	46	9.0	3784
December	166	7.4	2752	38	3.8	3799
WEEKEND						
1	174	7.8	2727	46	7.4	3777
0	292	6.8	2751	70	8.3	3766
LENGTH						
1 day	60	2.0	2760	13	1.6	3775
2 days	38	3.6	2758	16	1.1	3813
3 days	30	9.5	2741	5	4.0	3750
4 days	31	12.2	2815	12	1.3	3754
5 days	33	5.8	2733	14	10.1	3689
6 days	30	7.3	2786	9	5.4	3831
7 days	48	9.9	2705	15	14.1	3779
8 days	22	4.1	2732	9	17.8	3782
9 days	23	7.7	2803	6	19.2	3792
10 days	151	8.5	2715	17	10.0	3756
EXPERIENCED						
1	153	6.8	2765	47	9.0	3779
0	313	7.4	2732	69	7.1	3758
NEGDUMMY						
1	103	8.4	2745	26	10.2	3774
0	363	6.9	2742	90	7.2	3769
Ending day[#]						
Monday	66	7.6	2750	15	12.9	3729
Tuesday	59	5.9	2766	11	2.1	3870
Wednesday	78	6.0	2757	21	5.6	3773
Thursday	89	7.6	2738	23	10.7	3732

Friday	65	5.9	2717	19	7.2	3828
Saturday	62	8.4	2725	10	8.4	3736
Sunday	47	10.0	2745	17	7.0	3744
Total	466	7.2	2742	116	7.9	3770

Note: [#]Ending day is excluded in the regression analyses due to its insignificance.

Figure 1 presents the distribution of seller reputation scores. More than half of the sellers have less than 45 scores, and sellers who have more than 1,000 scores only account for about 3 percent of total sellers. Summary statistics for seller reputations are presented in Table 5. Notably, the seller with the highest reputation has 4,983 positive scores, and only one negative score, and has had as many as 5,256 transactions. Except for those unrated sellers, this study classifies sellers into four quartiles. The first quartile consists of sellers who have scores between 1 and 14; the second quartile between 15 and 42; but a seller needs to obtain at least 116 scores to be grouped in the fourth quartile. As long as there are sellers without negative scores, the ratio of positive scores to the sum of positive and negative scores will be 100 percent, irrespective of the number of positive and neutral scores. As a result, the *RATIO* exceeds 99 percent across four quartiles, due to few negative scores.

Table 5 Summary statistic: seller reputations

	Mean	Std. error	Median	Max	Min
All observations (N = 582)					
RATIO (%)	97.2	14.8	100	100	0
SCORE	149.6	427.2	42	4982	0
POSCORE	150.1	428.0	42	4983	0
NEGSCORE	0.5	1.6	0	28	0
NEUSCORE	1.7	7.7	0	111	0
TRANSACTION	177.4	493.0	52	5256	0
Beginner[#] (N = 13)					
1st Quartile (N = 137)					
RATIO (%)	99.54	2.10	100	100	85.71
SCORE	6.91	4.05	6	14	1
POSCORE	6.96	4.09	6	15	1
NEGSCORE	0.05	0.22	0	1	0
NEUSCORE	0.07	0.28	0	2	0
TRANSACTION	8.10	5.12	8	22	1
2nd Quartile (N = 142)					
RATIO (%)	99.04	2.24	100	100	88.64
SCORE	26.71	8.24	25	42	15

POSCORE	26.98	8.34	25	42	15
NEGSCORE	0.30	0.75	0	5	0
NEUSCORE	0.32	0.70	0	4	0
TRANSACTION	32.47	13.27	30.5	97	15
3rd Quartile (N = 146)					
RATIO (%)	99.45	1.38	100	100	91.07
SCORE	74.19	21.63	72	115	43
POSCORE	74.60	21.69	72	122	43
NEGSCORE	0.41	1.08	0	9	0
NEUSCORE	0.86	1.39	0	9	0
TRANSACTION	88.75	28.86	86	182	45
4th Quartile (N = 144)					
RATIO (%)	99.62	0.88	100	100	93.62
SCORE	496.48	759.97	208.5	4982	116
POSCORE	497.62	761.21	210	4983	116
NEGSCORE	1.14	2.88	0	28	0
NEUSCORE	5.60	14.82	2	111	0
TRANSACTION	587.24	870.69	241.5	5256	125

Note: # indicates sellers with no scores.

5. Empirical results

5.1 Preliminary analysis – OLS regression

This study starts with the OLS regression and adds explanatory variables gradually in equation (1), as shown in Table 6. The estimated coefficients for *SIZE* are between 870 and 902, and are statistically significant at the 1 percent level in Models 1–6. This not only indicates the price difference between 512 Mb and 1 Gb (close to the mean price difference of $NT1,030), but also leads to a relatively high adjusted R^2 in the cross-sectional regression.[6] The coefficients of *SCORE* are approximately 0.07 or 0.08 and statistically significant, which is comparable to Dewan and Hsu (2004) and Lucking-Reiley et al. (2006). Thus, an additional increase in scores translates into an increase in auction price of $NT0.08. Four reputation dummies (Q_j, $j = 1,2,...,4$) also exhibit positive and significant effects on auction prices; that is, a seller who has a reputation score between 1 and 14 (or between 15 and 42) will obtain an additional $NT111 (or $170) more than a seller who has no score (Model 6, Table 6).

[6] This study also estimates the determinants of auction prices separately for 512Mb, the adjusted R^2 for 512Mb, for example, is down to about 0.35, see Table 9 for details.

Next, analogous to Bajari and Hortacsu (2003) and Durham et al. (2004), the estimates for the coefficients of *NEGSCORE* are insignificant in all specifications and exhibit alternate signs; namely, it does not lower auction prices statistically. Two alternative explanations are offered for the outcome. First, our sample data are restricted to the brand new iPod shuffle so that it significantly reduces possible complaints from buyers. If our sample products were second-hand, the impact of negative scores would be critical. Second, many buyers in Taiwan are afraid to leave a negative feedback because of the real threat of retaliation from sellers. This makes it difficult to evaluate the importance of negative scores on auction prices.

The coefficients of *BIDS*, *OPBID*, *OPBIDONE*, *BIN*, *BONUS*, and *LENGTH* are estimated to be significantly positive, suggesting that, for instance, an auction lasting for a longer period of time will have a higher auction price on average. This is in line with the finding of Lucking-Reiley et al. (2006). The impact of *SHIPPING*, *MONTH*, and *EXPERIENCED* on auction prices are statistically insignificant. The only factor which significantly lowers the auction prices in this study is the daily supply of iPod shuffles; this corresponds to a fundamental economic principle, that is, a large quantity supply lowers prices, other things remaining the same.

Table 6 Estimates of coefficients by OLS regression

Model	(1)	(2)	(3)	(4)	(5)	(6)
SIZE	896.80***	869.83***	876.64***	901.87***	872.87***	880.19***
	(34.69)	(33.27)	(33.95)	(34.56)	(33.15)	(33.86)
SCORE	0.07***	0.08***	0.08***			
	(3.42)	(3.62)	(3.79)			
NEGSCORE	6.91	7.00	3.57	–9.78	–13.04	–19.91
	(1.22)	(1.26)	(0.65)	(–0.46)	(–0.63)	(–0.97)
Q_1				142.71**	111.98*	111.34*
				(2.45)	(1.94)	(1.79)
Q_2				191.49***	171.99***	169.65***
				(3.27)	(2.98)	(3.00)
Q_3				208.93***	195.49***	195.18***
				(3.57)	(3.39)	(3.46)
Q_4				218.96***	205.69***	199.41***
				(3.69)	(3.52)	(3.46)
BIDS	5.04***	5.91***	5.49***	5.14***	5.98***	5.58***
	(4.27)	(4.90)	(4.61)	(4.33)	(4.95)	(4.68)
OPBID	0.12***	0.16***	0.15***	0.12***	0.16***	0.15***
	(7.30)	(8.47)	(7.79)	(7.02)	(8.44)	(7.75)
OPBIDONE	223.44***	273.43***	255.19***	209.83***	262.33***	245.29***

	(4.62)	(5.54)	(5.24)	(4.29)	(5.28)	(5.01)
BIN	186.24***			186.20***		
	(10.58)			(10.50)		
BT_1		217.64***	239.84***		211.82***	233.76***
		(7.37)	(8.02)		(7.15)	(7.80)
BT_2		124.15***	131.92***		123.70***	131.49***
		(4.67)	(4.97)		(4.60)	(4.89)
BT_3		13.92	3.76		19.79	8.61
		(0.51)	(0.14)		(0.73)	(0.32)
BT_4		280.89***	282.94***		295.92***	296.66***
		(7.87)	(8.03)		(8.25)	(8.39)
SHIPPING			–0.23			–0.28
			(−1.25)			(–1.51)
BONUS			108.61***			113.47***
			(3.91)			(4.11)
VOLUME			–7.81**			–6.97**
			(−2.52)			(–2.25)
MONTH			7.82			9.73
			(0.78)			(0.96)
LENGTH			8.34***			8.42***
			(3.05)			(3.08)
EXPERIENCED			10.04			1.10
			(0.58)			(0.06)
Constant	2316.24***	2212.67***	2248.24***	2153.67***	2059.64***	2095.06***
	(51.36)	(39.84)	(36.56)	(31.81)	(27.97)	(27.06)
Adjusted R^2	0.8227	0.8283	0.8360	0.8220	0.8282	0.8362
N	582	582	582	582	582	582

Notes: 1. *t*-values are in parentheses.

2. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively.

3. The adjusted R^2 for 512 Mb is down to about 0.35, see Table 9 for details.

5.2 Eliminating a possible endogenous factor – SUR estimation

Table 7 shows the coefficients estimates of auction characteristics using the SUR estimation. The estimated coefficients, such as *SIZE*, *SCORE*, *BIDS*, *OPBINONE*, *OPBID*, *BONUS* and *LENGTH*, remain positive and statistically significant, and the estimates for *NEGSCORE* (or *NEGDUMMY*), *SHIPPING*, *MONTH*, and *EXPERIENCED* continue to be insignificant in the system equations. The coefficient estimate of *SCORE* is significantly positive (0.08) in equation (1), but becomes smaller and negative (–0.0008) in equation (2), despite being statistically significant at the 10 percent level in Model 7. Contrary to McDonald and Slawson (2002) and Bajari and Hortacsu (2003), this study shows that a seller who has a higher reputation does not necessarily attract more bids, resulting in a higher auction price. Regardless of the assumptions of linear and non-linear relationships with price, seller reputations do not have any positive and significant impact on the number of bids.

The estimated coefficients of *OPBID* and *LENGTH* are negatively related to the number of bids, despite being counterintuitive for *LENGTH*. The outcome is apparently caused by auctions ending on day four for 512 Mb items, which have the highest average number of bids of 12.2 (see Table 4). Additionally, weekend auctions do not increase the number of bids compared to weekday ones. Turning to the differentiation of the bidding process, the estimates of BT_1, BT_2, and BT_4 are positive and statistically significant in both the OLS regression and SUR estimation. This implies that the presence of a BIN price significantly raises the prices regardless of any types of BIN.[7] For instance, an auction ending with a BIN increases the auction prices ranging from $NT124 ($BT_2$ in Model 5) and up to $297 ($BT_4$ in Model 6). Overall, the empirical findings of this study appear to be consistent and robust across all specifications (Models 1–9).

Table 7 Estimates of coefficients by the SUR model estimation

Model	(7)		(8)		(9)	
PRICE	Coefficient	Z	Coefficient	Z	Coefficient	Z
SIZE	875.80***	(34.44)	879.03***	(34.44)	878.87***	(34.45)
SCORE	0.08***	(3.81)				
Q_1			111.75**	(2.02)	111.31**	(2.01)
Q_2			169.60***	(3.05)	168.55***	(3.03)
Q_3			195.65***	(3.53)	193.46***	(3.49)
Q_4			200.23***	(3.54)	196.85***	(3.48)
NEGSCORE	3.55	(0.65)				
NEGDUMMY			–20.98	(–1.04)	–19.48	(–0.96)
BIDS	5.84***	(4.98)	6.14***	(5.25)	6.26***	(5.35)

[7] The theoretical explanations of a BIN's impact on auction prices from the viewpoint of sellers have been analyzed in Budish and Takeyama (2001), Mathews (2004), and Reynolds and Wooders (2006).

OPBID	0.15***	(8.05)	0.15***	(8.10)	0.15***	(8.14)
OPBIDONE	255.63***	(5.32)	245.43***	(5.11)	245.22***	(5.10)
BT_1	239.67***	(8.14)	233.50***	(7.94)	233.60***	(7.94)
BT_2	131.61***	(5.03)	130.87***	(4.96)	130.77***	(4.96)
BT_3	0.82	(0.03)	3.96	(0.15)	3.07	(0.12)
BT_4	280.40***	(8.08)	292.59***	(8.43)	291.81***	(8.41)
SHIPPING	–0.23	(–1.25)	–0.28	(–1.52)	–0.28	(–1.52)
BONUS	108.21***	(3.96)	112.73***	(4.16)	112.68***	(4.16)
VOLUME	–7.73**	(–2.53)	–6.85**	(–2.25)	–6.84**	(–2.25)
MONTH	7.91	(0.80)	9.79	(0.99)	9.80	(0.99)
LENGTH	8.31***	(3.08)	8.38***	(3.12)	8.36***	(3.11)
EXPERIENCED	10.27	(0.61)	1.34	(0.08)	1.40	(0.08)
Constant	2240.67***	(36.99)	2083.61***	(27.40)	2082.80***	(27.38)
Adjusted R^2	0.8405		0.8415		0.8414	
BIDS						
SCORE	–0.0008*	(–1.75)	–0.0008	(–1.63)		
NEGSCORE	0.13	(1.00)	0.13	(1.03)		
Q_1					0.24	(0.19)
Q_2					0.50	(0.38)
Q_3					1.07	(0.82)
Q_4					1.39	(1.06)
NEGDUMMY					–0.59	(–1.25)
OPBID	–0.001***	(–3.91)	–0.001***	(–3.93)	–0.001***	–4.42)
BIDDERS	2.31***	(36.53)	2.31***	(36.52)	2.28***	(36.60)
LENGTH	–0.10*	(–1.65)	–0.09*	(–1.65)	–0.09	(–1.49)
WEEKEND	0.59	(1.54)	0.58	(1.53)	0.54	(1.39)
Constant	1.55*	(1.83)	1.56*	(1.83)	1.15	(0.79)
Adjusted R^2	0.8758		0.8758		0.8764	
N	582		582		582	

Notes: 1. t-values are in parentheses.

2. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively.

5.3 Testing the equality of the coefficients

Table 8 shows the equality tests of bidding types and reputations coefficient estimates using F-test and χ^2-test. Although the null hypothesis that the coefficients of BT_1 and BT_4 are equal is not rejected, the null hypothesis that the coefficients of BT_1, BT_2, and BT_4 are equal is statistically rejected at the 1 percent level, implying that the impact of three different types of BIN on auction prices differ significantly. In other words, our study suggests that it is indispensable to differentiate the bidding process while analyzing the impact of BIN on the prices. Next, the estimates for the coefficients of seller reputations (Q_j, $j = 1,2,...,4$) are positive and statistically significant in the SUR estimation, and their impact on auction prices are comparable to those in the OLS regression. Nevertheless, marginal returns to an incremental increase in reputation declines rapidly when sellers have more than 15 scores because the null hypothesis of $Q_2 = Q_3 = Q_4$ coefficients is not rejected, suggesting that the incremental effects on price level of moving from quartile 1 to quartile 2, from quartile 2 to quartile 3, and quartile 3 to quartile 4 are statistically insignificant.

Table 8 Test of bidding types and four quartiles scores coefficients

	OLS (3)		OLS (6)		SUR (7)		SUR (8)		SUR (9)	
Null hypothesis	F	p-value	F	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value
$BT_1 = BT_2$	14.58	0.0001	13.04	0.0003	15.07	0.0001	13.69	0.0002	13.63	0.0002
$BT_1 = BT_4$	1.44	0.2303	3.03	0.0823	1.33	0.2492	2.69	0.1008	2.77	0.0958
$BT_2 = BT_4$	17.83	0.0000	20.6	0.0000	17.84	0.0000	20.33	0.0000	20.49	0.0000
$BT_1 = BT_2 = BT_4$	11.69	0.0000	12.24	0.0000	23.72	0.0000	24.65	0.0000	24.74	0.0000

	OLS (6)		SUR (8)		SUR (9)	
Null hypothesis	F	p-value	χ^2	p-value	χ^2	p-value
Q_1 coefficient = Q_2 coefficient	6.20	0.0131	5.67	0.0176	6.33	0.0119
Q_1 coefficient = Q_3 coefficient	12.53	0.0004	10.86	0.0001	13.01	0.0003
Q_1 coefficient = Q_4 coefficient	11.87	0.0006	11.42	0.0008	12.42	0.0004
Q_2 coefficient = Q_3 coefficient	1.25	0.2639	0.90	0.3433	1.35	0.2450
Q_2 coefficient = Q_4 coefficient	1.57	0.2109	1.17	0.2799	1.72	0.1893
Q_3 coefficient = Q_4 coefficient	0.03	0.8568	0.02	0.8866	0.04	0.8425
Coefficients of $Q_1 = Q_2 = Q_3$	6.52	0.0016	5.73	0.0034	13.52	0.0012
Coefficients of $Q_2 = Q_3 = Q_4$	0.95	0.3875	0.69	0.5002	2.07	0.3546
Coefficients of $Q_1 = Q_2 = Q_3 = Q_4$	5.26	0.0014	4.85	0.0024	16.44	0.0009

5.4 More insights from quantile regression

To conserve space, the quantile regression results will only be presented for 512 Mb, as shown in Table 9. There are considerable differences, including differences in sign, in their impact on prices with different degrees of auction prices. At the 0.25 and 0.5 quantiles, the estimate of *SCORE*, surprisingly, turns out to be insignificant; that is, seller reputations do not affect the median and first quartile auction prices. This finding cannot be observed through the conventional OLS regression, and the implication of this outcome is even more interesting. That is, as long as the prices are relatively equal or lower than median prices, buyers are not particularly concerned with seller reputations.

While at the 0.1, 0.75, and 0.9 quantiles, *SCORE* is significantly associated with prices, in particular, at the 0.9 quantile, the estimated coefficient is 0.15, which is more than double as the mean coefficient estimated by the OLS regression. The implication is that when auction prices are far above (or far below) the median prices, bidders are willing to buy and pay more only if sellers establish better reputations. Although *NEGSCORE* does not have any impact on prices according to the OLS estimation, it seems no longer to be true in quantile regression, especially, at the 0.1 and 0.9 quantiles, where the estimated coefficients of *NEGSCORE* are statistically significant at –3.45 and –9.10, respectively. For prices in the tails of the distribution, bidders are particularly sensitive to negative scores and negative scores have a much greater effect than (positive) scores do. The coefficient estimates of *OPBID* and *OPBIDONE* from the 0.1 to 0.9 quantiles fall gradually from 0.84 to 0.14 and from 2022 to 219, respectively, implying the influences of the opening bid as well as an opening bid at $NT1 decrease as auction prices increase.

Although the mean coefficient estimates of BT_1, BT_2 and BT_4, respectively, are 265, 125, and 300, there are wide variations in coefficient estimates in different quantiles. For instance, the estimates of BT_1 and BT_4 increase steadily, ranging from 121 to 350 and from 181 to 354, respectively, but BT_3 has a significant positive correlation with auction prices at the 0.1 and 0.25 quantiles only, and its impact falls gradually. The insignificant impact of quantity supply on prices at the 0.5 quantile, contrary to the OLS result, indicates a strong demand for median prices of the iPod shuffle.

Table 9 Coefficient estimates of the quantile regression and OLS estimation for 512 Mb

Model	0.1	0.25	0.5	0.75	0.9	OLS
SCORE	0.02**	0.01	0.04	0.06***	0.15***	0.06**
	(2.33)	(0.47)	(1.36)	(3.24)	(7.46)	(2.43)
NEGSCORE	–3.45*	1.91	1.87	7.37	–9.10*	5.98
	(–1.70)	(0.57)	(0.26)	(1.64)	(–1.74)	(1.02)
BIDS	1.20**	6.31***	5.69***	7.28***	6.82***	5.87***
	(2.22)	(6.41)	(3.58)	(4.59)	(2.99)	(4.49)
OPBID	0.84***	0.46***	0.20***	0.19***	0.14***	0.20***
	(94.24)	(31.95)	(7.18)	(5.39)	(2.74)	(8.65)
OPBIDONE	2021.65***	937.63***	301.70***	295.04***	219.05*	331.32***
	(128.16)	(32.95)	(4.59)	(3.74)	(1.92)	(6.22)
BT_1	120.52***	163.70***	250.82***	271.41***	349.72***	264.62***
	(7.42)	(6.66)	(5.92)	(6.71)	(6.76)	(7.80)
BT_2	18.33	78.52***	141.06***	142.79***	96.22*	124.81***
	(1.27)	(3.58)	(3.76)	(3.93)	(1.93)	(4.14)

BT_3	68.13***	74.86***	52.42	16.32	–15.07	23.90
	(4.80)	(3.38)	(1.43)	(0.48)	(–0.36)	(0.82)
BT_4	180.87***	245.17***	317.20***	336.00***	354.17***	299.86***
	(10.01)	(8.35)	(6.68)	(8.14)	(6.56)	(7.95)
SHIPPING	–0.03	–0.17	–0.18	–0.35	–0.31	–0.24
	(–0.39)	(–1.14)	(–0.70)	(–1.46)	(–1.07)	(–1.19)
BONUS	23.00	63.48***	126.04***	108.15***	91.81**	94.70***
	(1.49)	(2.65)	(3.08)	(2.82)	(2.15)	(2.90)
VOLUME	–3.16*	–5.60**	–6.87	–11.06**	–3.46	–9.71**
	(–1.81)	(–2.00)	(–1.44)	(–2.39)	(–0.62)	(–2.56)
MONTH	7.13	–3.51	2.15	–7.87	–3.83	2.66
	(1.32)	(–0.43)	(0.16)	(–2.93)	(–0.22)	(0.24)
LENGTH	2.92**	4.60**	5.19	4.85	–2.58	7.08**
	(2.10)	(2.15)	(1.41)	(1.39)	(–0.53)	(2.41)
EXPERIENCED	–16.53*	24.52*	23.86	–3.57	13.56	8.07
	(–1.80)	(1.73)	(1.00)	(–0.16)	(0.48)	(0.42)
Constant	383.06***	1395.72***	2107.86***	2293.59***	2511.42***	2141.67***
	(14.27)	(29.61)	(24.25)	(23.74)	(18.86)	(30.65)
Pseudo R^2	0.3143	0.2120	0.2219	0.2698	0.2383	0.3482[#]
N	466	466	466	466	466	466

Notes: 1. *t*-values are in parentheses and # denotes R-square.

2. ***, ** and * indicate the significance level of 1%, 5% and 10%, respectively.

6. Conclusions

Recently, there has been a growing interest by economists in research into the determinants of the prices in Internet auctions. Despite a consensus on the significant impact of seller reputations on auction prices, the major difference is that the influence of reputations on prices varies substantially, depending on price levels. This paper contributes to the literature by offering significant empirical evidence using Taiwanese Internet auction data for the iPod shuffle. In addition, this paper applies the OLS and SUR estimations and, in particular, quantile regression in order to study the influences of seller reputations and other auction characteristics on auction prices.

Consistent with previous studies, our study reveals that the influence of seller reputations on auction prices is significant, irrespective of the assumptions of the linear and non-linear relationship with price. Nevertheless, there are considerable differences in their impact on prices with different degrees of auction prices; for instance, at the 0.25 and 0.5 quantiles, seller reputations do not have an impact on auction prices. The similar finding of the insignificant impact of negative scores on prices also corresponds to some of the earlier literature. Moreover, BIN, and other auction characteristics (for example, opening bid, length of auction) do significantly contribute to auction prices.

Finally, our findings clearly emphasize the importance of incorporating a non-linear setting of seller reputations and applying quantile regression when analyzing the influence of seller reputation on auction prices. Failure to consider the non-linear setting of seller reputation would have led us to overestimate the impact of reputations on prices, because marginal returns to an incremental increase in reputation declines rapidly for sellers who have more than 15 scores. Our future research aims to include unsuccessful auctions and compare auction behaviors cross countries (for example, Taiwan versus Japan).

Appendix

Table A.1 Definition of variables

Variable	Description
PRICE	the highest winning bid
*RATIO**	ratio of positive scores to the sum of positive and negative scores
SCORE	positive scores minus negative scores
*POSCORE**	positive scores
NEGSCORE	negative scores
*NEUSCORE**	neutral scores
NEGDUMMY	dummy variable = 1, if a seller has negative scores
*TRANSACTION**	number of all transactions, including repeat buyers
BIDS	number of bids
BIDDERS	number of bidders
OPBID	opening bid set by sellers
SHIPPING	cost for shipping and handling or $NT50 if not specified
VOLUME	number of the iPod shuffle sold on the same day
LENGTH	number of days that an item is sold in an auction
Q_0	dummy variable = 1, if a seller has *zero* score
Q_1 (1st quartile)	dummy variable = 1, if a seller has scores between 1 and 14
Q_2 (2nd quartile)	dummy variable = 1, if a seller has scores between 15 and 42
Q_3 (3rd quartile)	dummy variable = 1, if a seller has scores between 43 and 115
Q_4 (4th quartile)	dummy variable = 1, if a seller has scores between 116 and 4982
SIZE	dummy variable = 1, if capacity is 1 Gb
OPBIDONE	dummy variable = 1, if opening bid = $NT1
BIN (Buy It Now)	dummy variable = 1, if auction ended with 'Buy It Now'
BT_0 (bidding type 0)	dummy variable = 1, if one bid until the end of an auction
BT_1 (bidding type 1)	dummy variable = 1, if one bid and is ended with a BIN price
BT_2 (bidding type 2)	dummy variable = 1, if one bid and opening bid equals a BIN price
BT_3 (bidding type 3)	dummy variable = 1, if many bids until the end of bidding
BT_4 (bidding type 4)	dummy variable = 1, if many bids and is ended with a BIN price
BONUS	dummy variable = 1, if scratch resistant protector, and others
WEEKEND	dummy variable = 1, if auction ended on Saturday or Sunday
EXPERIENCED	dummy variable = 1, if sellers who sell two iPod shuffles or more
MONTH	time dummy = 0, if auction ended in October 2005;
	= 1, if auction ended in November 2005;
	= 2, if auction ended in December 2005

Note: Variables with asterisk are not included in the regression analysis.

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