The Value of Online Seller Reputation: Evidence from a Price Comparison Site

Abstract

This paper examines the value of seller reputation for e-retailers trading via a price comparison site (PCS). E-markets are widely held to accommodate sellers of differing service quality, including some who behave opportunistically. The paper uses a sample of offers on up to 295 digital cameras traded on a leading PCS, over a 134-day period to estimate reputation's price impact. User-generated reputation measures have a significant impact in the expected direction. However, their magnitude is small compared to variables capturing economy-wide reputation. The strength of the reputation signal increased non-monotonically with the number of reviews on which it was based.

JEL Codes: L11, L81, M21 **Key Words: Reputation, Pricing, e-Commerce**

I INTRODUCTION

This paper looks at the value of seller reputation for e-retailers trading via an online price comparison site (PCS). The PCS offers sellers immediate access to buyers without the conventional sunk costs associated with market entry [Haynes and Thompson (2013b)]. However, sellers in e-markets are widely considered to exhibit a heterogeneous quality of service delivery, a characteristic which - following Klein and Leffler (1981) - might be expected to generate a price premium for those with a reputation for good service. In addition to any intrinsic variation in their service competence, in a free-entry market there is a potential moral hazard problem if sellers lacking a reputation premium deliberately opt for a low-quality strategy. The market problem is further compounded if the anticipation of such behaviour produces an adverse selection among low-price sellers. Farrell (1986) showed that under such conditions we might observe a bifurcation of strategies with low/no reputation sellers competing with low prices and established sellers offering a high quality service at a premium price.

The PCS, along with other successful Internet sales platforms such as *e-Bay* and *Tripadvisor*, has sought to address the heterogeneous quality problem by encouraging user-generated feedback on seller performance. The feedback is then aggregated to produce simple summary evaluations for each seller. This paper explores the price impact of such information for a panel of 295 digital cameras, traded on *NexTag.com*, a leading American PCS, over a 134 day period. In general, empirical work on reputation value has used experimental data on platforms such as *e-Bay.* This, as Resnick *et al* (2006) point out, reflects the difficulty of infering a

reputation premium from observational data because of omitted variable problems, particularly variations in the quality and accessibility of sellers' web sites. However, at a PCS all sellers display in a standardized format with entries differing only in price and reputational characteristics, facilitating the study of price determination.

Our paper finds support for the maintained hypothesis – namely, that the seller's star rating impacts its ability to charge a premium price – but our results also suggest that reputation is a multidimensional concept. In particular, we find that outside standing – proxied here by membership of the leading 100 electronics retailers nationwide – and a binary variable distinguishing offerings from *Amazon.*com, the market leader, exert a substantial positive effect on a seller's online pricing. These findings for a PCS complement the much more extensive *e-Bay* literature [Houser and Wooders (2006), Jin and Kato (2006), Waterson and Doyle (2012)] in seeking to quantify the value of reputation in electronic markets.

The paper is organised as follows: Section II examines the role of reputation at a PCS. Section III describes the data. The price impact of reputation is analysed in section IV and a brief conclusion follows.

II Price and Reputation at a PCS

The PCS has become a central part of B2C business with an estimated 45% of US shoppers using this medium by 2010[1]. The PCS business model offers sellers easy - and generally free - entry to the platform's listings but it collects a fee for clicks through ('leads') to the seller's own site. This fee is payable irrespective of whether a sale is made. On a PCS such as *NexTag.com* the required fee or minimum cost-per-click (CPC) varies by product category in approximate proportion to mean price. On some sites it may be raised at times of high demand, such as Xmas. Sellers bidding above the minimum CPC may secure an advantageous position in the site's default category or product rankings; although as this is part of a continuous auction with no pre-emption there is no certainty of a high ranking.

Participation at a PCS requires the merchant to submit price and product data in the form of a unified 'feed' which is then displayed in a standardized format, facilitating easy search by consumers comparing prices and delivery terms online. US consumers enter their zip code to obtain the price after delivery charges and any local taxes. As is typical with a two-sided market, the PCS also provides consumers with additional information, including links to a user-generated product evaluation as well as external product descriptions and evaluations.

[1] http://www.topwebhosts.org/wp/blog/category/shopping-portals/nextag/, visited on 16/8/2012.]

Those trading on markets have always faced some risk that the other party will fail to complete its part of the transaction in a satisfactory manner. It follows that risk-averse buyers will be willing to pay some premium to sellers with a high reputation, that is those sellers who are expected to expedite transactions in an entirely satisfactory manner. Klein and Leffler (1981) showed that such a price premium creates the incentive for sellers to invest in reputation-building activities. However, when remote, impersonal trading on e-markets is compared to face-to-face transacting it seems reasonable to assume that the transaction risk is correspondingly increased. Not least as many of the sanctions associated with inter-personal trade are absent and because removing the need for physical proximity substantially increases the number of potential transactors and so will tend to reduce the average number of interactions between transactor pairs.

In addition to the risk of any accidental failure to meet buyer expectations, there is a risk of sellers deliberately opting for low service quality. Farrell (1986) demonstrates that with free entry and no commitment via reputation some participants may benefit from adopting a low-quality service followed by exit. Since e-markets typically possess much lower (frequently approximately zero) sunk costs than their traditional equivalents [Haynes and Thompson (2013b)] and exit and re-entry under a different name is relatively easy [Ellison and Ellison (2009)], such an outcome appears feasible. Moreover weak branding among e-sellers – and correspondingly low seller identification by consumers – means that instances of low quality may cause

collective reputational damage, in the sense of Tirole (1996)[2], increasing the potential for adverse selection outcomes in the e-marketplace.

Although outright fraud is more or less effectively controlled by the criminal law in most jurisdictions, a range of less-than-scrupulous practices has been observed in e-markets: tardy despatch may be used to economise on inventory or labour costs; products may turn out to be reconditioned items or unofficial imports[3]; and, as Ellison & Ellison (2009) demonstrate, electronic sellers may use 'bait and switch' tactics whereby consumers are enticed to sites by attractive – but ultimately unavailable – offers before being encouraged to accept poorer value deals.

The fear of unsatisfactory behaviour by sellers has been cited as a major cause of the general failure of B2C commerce to generate the Bertrand outcome expected by early analysts [Brynjolffson and Smith (2000)]. Posted[4] price dispersions appear stubbornly persistent in e-markets [Baye *et al*. (2004), Haynes and Thompson (2008)], in large measure because of the price premium enjoyed by early movers [Clay *et al*. (2001)]. Reputation appears to permit these market leaders to enjoy a competitive advantage that typically erodes very slowly [Waldfogel and Chen

[2] Tirole instances wine producers from the same region, say Bordeaux, who have both an individual reputation and a collective reputation. Clearly, the more obscure the former the more consumers depend on the latter.

[3] Unofficial imports frequently arise on e-markets as a result of arbitrage in response to international third degree price discrimination by manufacturers - see Thompson (2010). However, in electronic goods the same model may carry national variants of software, language of instruction etc. rendering unofficial imports inferior to regular supply.

[4] Research by Baye *et al*., (2009) suggests that transactions at a PCS market by volume are heavily concentrated on the cheapest offers. This implies that the distribution of *transaction* prices exhibits much less dispersion than the distribution of *posted* prices.

(2006)], in spite of the contemporaneous growth in consumer experience of electronic trading.

The principal challenge to these early movers comes from platforms or two-sided markets – such as *e-Bay.com* or price comparison sites – where multiple sellers can display directly to potential consumers with each side attracted by the presence of the other[5]. The success of such two-sided markets is widely attributed to their ability to develop credible reputation systems for sellers, using unbiased user-generated feedback (UGF). For example, a substantial body of empirical work suggests that *e-Bay*'s UGF scoring system - described in Lucking-Reiley *et al*. (2007) - is largely effective in rewarding traders judged to be efficient and ethical with a price premium [Houser and Wooders (2005), Jin and Kato (2006), Waterson and Doyle (2012) etc.]. However, recent work - Resnick *et al*. (2006), Cabral and Hortacsu (2010) - is also suggestive of an asymmetric response by consumers to good and bad news on sellers. In particular, negative feedback appears to generate substantially larger absolute effects than does its positive equivalent.

A typical PCS such as *NexTag.com* offers potential buyers at least three types of quality information:

[5] *Amazon.com* is an interesting case in that it enjoyed significant early mover advantages in e-retailing books prior to developing into a wider selling platform hosting other sellers as associates.

First, the PCS operates a UGF system whereby buyers' comments on sellers' delivery performance are recorded, together with buyer evaluations which are aggregated into a one-to-five star rating. Attached to each star rating is the number of reports on which it is based. Although easily accessible, the star rating is not readily transferable to other selling media and therefore might be expected to lock in high star-rated sellers. Sellers with very few posted reports are assigned zero stars.

Second, the site may operate its own reputational assessment; at *NexTag.com* by the award of "trusted seller" status to selected merchants. Although the precise requirements for this award are not made available, holders must meet threshold levels of user satisfaction, deal satisfactorily with complaints and include specific price and product information in their feed. In our data approximately 53% of offers were by merchants with "trusted seller" status, with the proportion rising with the intensity of a seller's use of the site.

The extent to which PCS-assigned designations, such as 'trusted seller', are viewed by buyers as unbiased signals is unclear. Baye and Morgan (2003) explore the effect of the comparable CNet certification on the site *CNet Shopper.com*, but fail to find a statistically significant price premium for certified sellers. This they attribute to mutually offsetting investments in quality - 'red queen' effects - by rival sellers. They suggest that once CNet certification becomes commonplace it can no longer deliver a competitive advantage to its holders.

Finally, to protect its own reputation the site has some incentive to act as gatekeeper and may refuse a listing to sellers with very poor records of service. It is not known how often this occurs.

In addition to listing regular e-sellers, a PCS such as *NexTag.com* may list other selling platforms. In our period *Amazon Marketplace* was the principal example. Here independent sellers could display to buyers clicking on to the *Amazon Marketplace* offer. Thus potential buyers were offered the security of the *Amazon.com* parent as gatekeeper. In the event of *Amazon Marketplace* hosting multiple sellers, the price listed alongside *Amazon Marketplace* in the *NexTag.com* ranking was ordinarily the lowest of these.

III DATA COLLECTION AND SAMPLE

III.I Data collection

Data were obtained from *NexTag.com*, the second ranked PCS in the US with 18.2% of the market in 2010[6]. *NexTag.com* currently receives 13.5m 'unique visitors' per month[7]. The digital camera was selected as product category, being both

[6] http://www.topwebhosts.org/wp/blog/category/shopping-portals/nextag/ , visited on 16/8/2012.]

[7] 'Unique visitor' is the term used by digital platforms to denote separate users, as opposed to volume of traffic. It is determined by cookies placed on the user's machine so strictly it records the number of browsers visiting the site not the number of individuals. See

http://www.ebizmba.com/articles/shopping-websites viewed 9/5/13

representative of the high value-to-weight ratio products prominent on price comparison sites and being usually purchased singly and so not subject to the bulk discounts of, say, books or CDs. A comparison of the listings with industry sources, such as *dpreview.com,* suggested that almost all digital cameras sold in the USA are listed on *Nextag.com* soon after launch.

Two specially written Java programmes were used to extract data from *NexTag.com*'s screen display, which appeared as in Appendix 1. The first took price, product and seller data on a daily basis (at 02.00 EST) between 19th November 2007 and 31st March 2008, an interval chosen to include the Xmas season. The length of the collection run was determined by labour availability. Although the raw data collection was automated, the resulting material required manual cleaning. [Automated data extraction from screenshots is vulnerable to very minor changes in visual display formatting.] The second programme collected product leads data, available on a monthly basis. For each programme, camera models were identified using the unique product code (upc) number – then available on the site – and the sample was updated weekly, allowing the addition of new models and the dropping of some which had ceased to be traded. From the population of listed models, we discarded pre-2006 models (assumed discontinued), those priced below $50 (likely to be unofficially imported or refurbished models), those with very thin markets - here defined as at no time reaching 100 leads per month – bundled kits[8] and models with missing data. This reduced the sample to 295 traded camera models, with up to 134

[8] Where a product is bundled with accessories, say camera lenses, the composition of the bundle is not necessarily constant over time causing shifts in quality that are difficult for the researcher to observe.

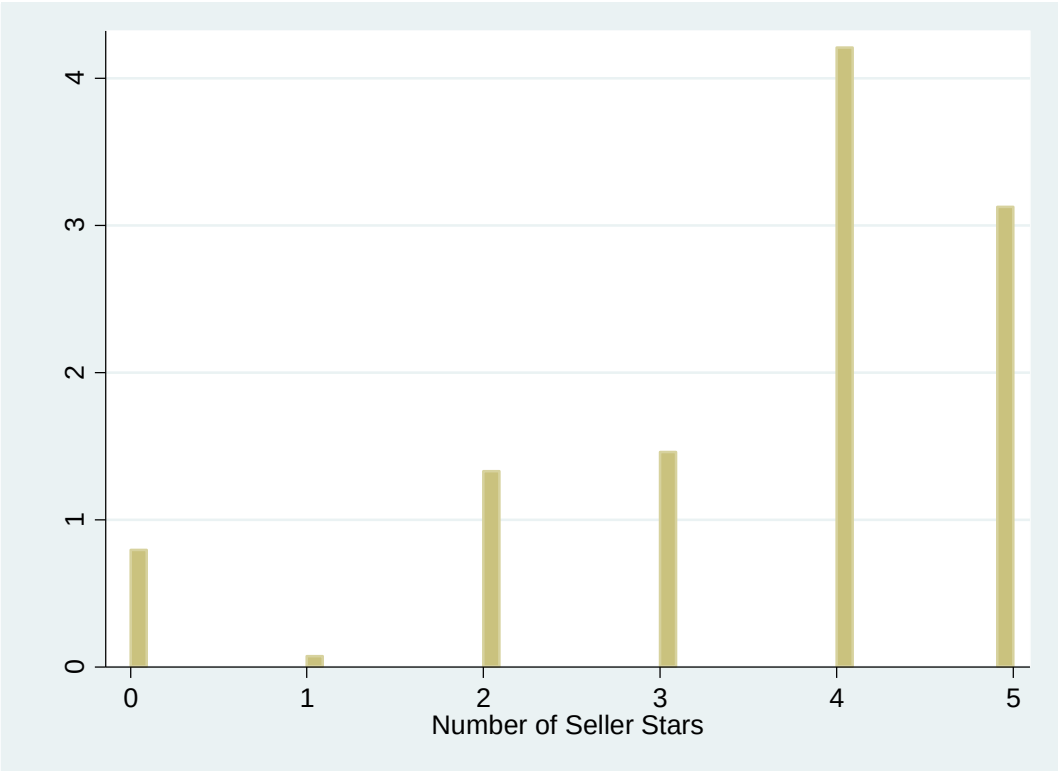
days of market data for each. [Further details of data collection are given in Haynes and Thompson (2013a)]. Additional product data were obtained from *dpreview.com.*

Over the entire 134 day period a total of 161 separate merchants were involved in selling the 295 camera models, with a mean of 16 sellers per model per day. On average, each model attracted 71 sellers over the entire period. However, sellers varied considerably in the intensity of their involvement; from *Amazon.com* which sold 95% of models at some time over the period, to 37 sellers that were involved with five models or less.

NexTag.com aggregates buyer evaluations to provide a star ranking for each seller. These are updated as additional feedback becomes available. Over the entire unbalanced panel of our data there are observations on approximately 360,000 seller-model-days. A histogram of their distribution by stars is given in Figure 1. Whilst the one-to-five rating has an easy interpretation of a user-generated quality-of-service measure and hence might be expected to be a monotonic indicator of reputation, a zero star rating may indicate insufficient data for *NexTag* to form an assessment. The zero star firms are generally newcomers who later develop a quality rating or disappear from listings[9]. Therefore the relationship between 0 and 1-5 stars has some ambiguity: indeed it may be preferable to have zero stars rather than one star, if the latter is an indicator of sustained poor performance.

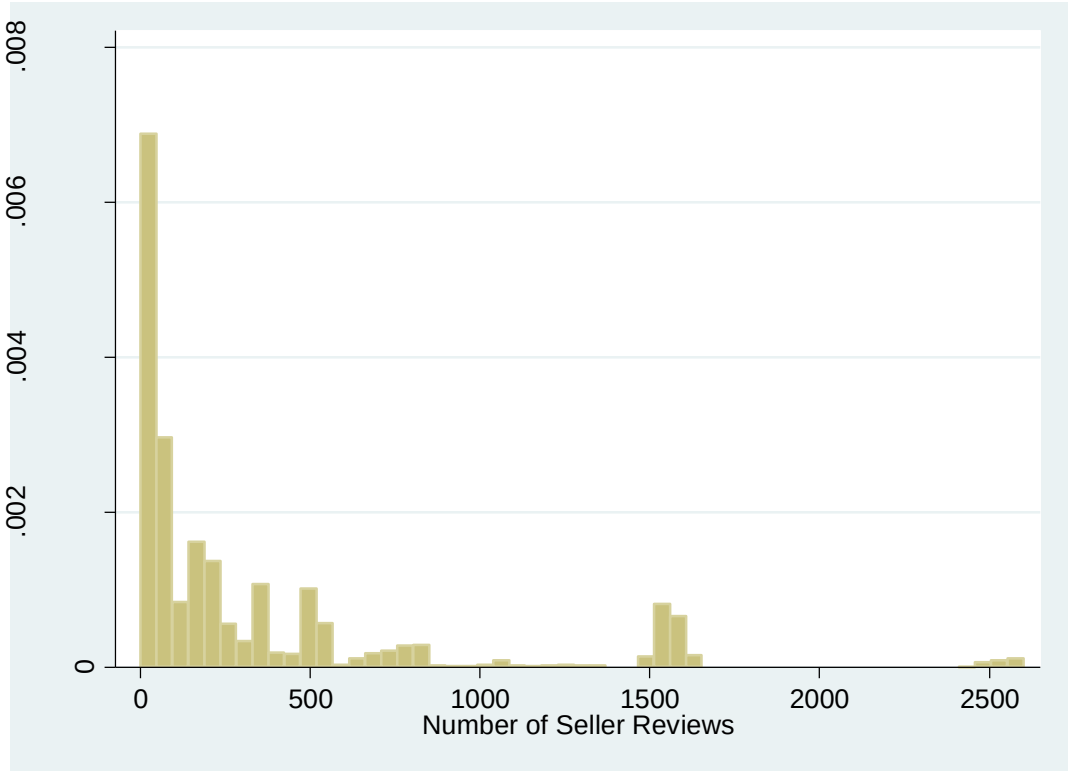
[9] Those sellers who failed to achieve any positive rating in a market over the period of study were excluded from the regression analysis. 33 sellers failed to achieve a positive rating in any particular market. These accounted for 6% of the total seller-model observations.

Figure 1. Distribution of Seller Stars



The seller ratings are based on a highly variable number of user reports. The distribution of these is summarised in Figure 2. This shows the expected skew, with an extended right tail consistent with a small number of sellers receiving a very high number of reviews.

Figure 2. Distribution of Seller Reviews



Although *NexTag.com* does not provide the precise algorithm used to determine "trusted seller" status, the PCS indicates that e-retailers need to have achieved a satisfactory star rating and to provide stipulated price and product information in the feed, together with a contact phone number. They are also required to identify refurbished/unofficial import products and to deal promptly with any complaints. Overall, 52.7% of the seller-model-day observations corresponded to sellers with trusted status; although among the regularly listed merchants the proportion was very much higher. Across the entire sample the correlation between star rating and trusted status was 0.455, with the star rating varying between 2 and 5 with a mean of 4.20. This compares to a mean star rating of 2.93 for sellers without trusted status. Trusted sellers also posted a much higher average number of reviews (545.7) than their non-trusted counterparts (117.7).

Consumers are not limited to site-specific reputation indicators and some sellers at a PCS will have brands reflecting their bricks and mortar business or other online sales. This we proxied by distinguishing the larger national sellers from their smaller rivals, with the former being those featuring on the contemporary *Dealerscope Top 100* sellers of electronics goods in the USA. Some 31 (19%) of the sellers in our sample met this definition, but these accounted for 43% of our product-seller-days. As an alternative size measure we employed the average number of products [*Average Product Count]* listed by the seller in the data set.

IV THE MODEL

The purpose of the paper is to estimate the value of UGF reputation to sellers in terms of a mean price premium. Here seller reputation is treated as a goods characteristic since uncertainty over seller performance turns product offerings into experience goods. Of course, in e-markets there is also price dispersion about the mean if sellers behave strategically. A substantial theoretical literature suggests that at least some of this behaviour has its origins in seller/consumer variations in reputation/search costs.

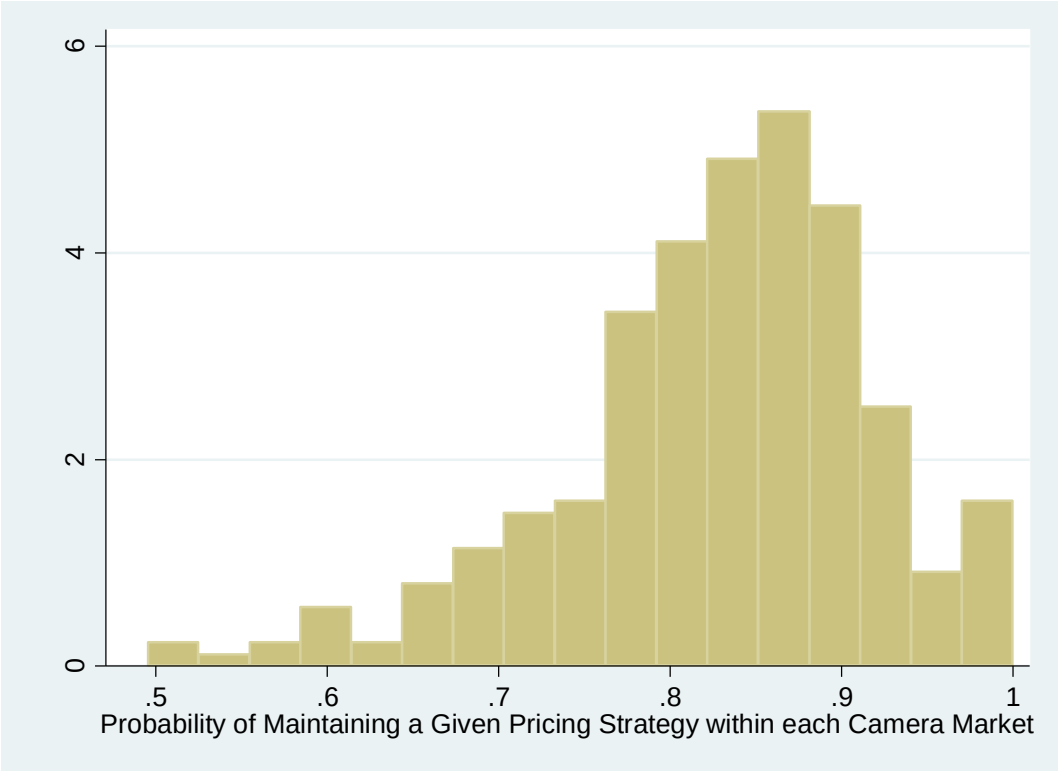
Rosenthal (1980) and Varian (1980) initially showed how buyer heterogeneity could produce a mixed-strategy equilibrium with sellers shifting between high prices (to exploit loyal consumers) and low prices (to steal sales). Stahl (1989) generated a

mixed-strategy equilibrium where consumers differ in search costs and sellers choose between posting low prices to attract informed buyers and posting high ones to secure good margins from reluctant searchers. These models appear largely plausible in the context of a PCS; although they possess two weaknesses in the present context:

First, the models share the prediction that prices *rise* with the number of sellers (as the expected gain from a price cut falls). This hypothesis is generally unsupported by the available evidence on e-markets [see Haynes and Thompson (2008) and references therein].

Second, any examination of the pricing behaviour of the sellers in our dataset suggests these generally adopt a consistent high or low price policy and this is maintained across different model markets. For example, if we categorize a seller's price as 'high' or 'low' according to whether its first entry for model *i* is above or at or below the mean for all sellers that day, then 85% of subsequent prices offered by the same seller for the same model fall into the same category. This is illustrated in Figure 3 which charts the probability of maintaining the initial pricing strategy.

Figure 3. The Distribution of a Seller's Pricing Strategy



Reputational differences between sellers may shape the choice of behaviour. For example, Farrell (1986) shows how introducing reputational diversity into an otherwise perfectly contestable market generates a bifurcation of behaviour; with low-reputation sellers opting for low-price visits to the market, comparable to hit-and-run tactics of perfect contestability, while high-price sellers remain to exploit their higher reputation. Moreover, low-reputation sellers may employ obfuscation and name changes to counteract their weaknesses [Ellison and Ellison (2009)].

Faced with such a profusion of possible strategic behaviours linked to reputation and search costs, we adopt a reduced form approach in the spirit of the hedonic pricing

literature [Rosen(1974)] which models price as a function of product characteristics[10]. Here seller reputation is treated as a vertical characteristic since uncertainty over seller performance turns product offerings into experience goods. The other quality attributes are assumed here to be unchanging over the 134 day period of our investigation. In recognition of the multidimensional nature of seller reputation, we include *Seller Stars,* initially as a scaled 0-5 variable and *Trusted Seller,* a binary variable distinguishing sellers awarded trusted seller status by *NexTag.com.* It would be expected that reputation also resides in factors beyond the PCS, hence we include *Top100,* a binary variable denoting membership of the *Dealerscope Top 100* electronics goods retailers.

Additional control variables were added as follows: research elsewhere [e.g. Baye *et al*. (2004), Haynes and Thompson (2008)] suggests that pricing at a PCS is sensitive to the number of rivals selling the same product with *Sellers* here expected to impact price negatively. Rapid innovation by digital camera makers was expected to reduce the attraction of any specific model soon after its introduction, so a quadratic time trend in *Age* since initial launch was included.

Visitors to a PCS such as *NexTag.com* may opt to search by price or may retain the site's own default listing. Since - low search costs notwithstanding - ranking appears to be a major determinant of buyer leads [Baye *et al*. 2009] some sellers may seek e-visibility by bidding above the minimum CPC to secure a high ranking in the

[10] That is our objective is to value reputational increments at the mean. An investigation of the price effects of following alternative strategies represents a substantially more complex task. In a companion paper [Haynes and Thompson (2013)] we explore the contention of Farrell (1986) that reputation determines exit and pricing strategies.

default listing. Such bids are unobservable, but membership of the top three sellers in each product's ranking (*Top Rank*), which also entailed they alone being listed on the initial product page, is here used as a proxy for above-minimum bids.

On *a priori* grounds it might be expected that since paying a CPC premium and offering a low price are alternative methods of achieving prominence, they are simple substitutes and *Top Rank* would have a negative impact on the price discount. Armstrong and Zhou (2011), however, show that in a market with heterogeneous buyers and sequential search the reward for prominence depends on the relative proportion of high-search cost to low-search cost consumers. High-search cost buyers (who pay a higher price) are more likely to search (and buy) from the most prominent sites. Therefore in the absence of more detailed information on buyers, the sign of *Top Rank* is ambiguous.

Finally, industry sources classify cameras into four categories - *Compact, Sub-compact, SLR-type* and *SLR* - by structure and sophistication of the product. Category dummies were included to allow for the possibilities that buyers of the more complex, more expensive, models used information differently to consumers buying simpler point-and-shoot products. In our sample the four formats were represented as shown in Table 1.

Table 1. Number of Cameras in the Sample, Split by Format Type

Format Type	Number of Cameras
Compact	116
Ultra-Compact	97
SLR	52
SLR-Type	30

Our dependent variable is the discount on the posted price over the manufacturer's recommended selling price (MRSP), that is Ln(MRSP)-Ln(P). The MRSP is widely employed in US industries, including electronics and automobiles (the "sticker price") as an introductory price and (legal) device to assist smaller retailers in avoiding price wars[11]. Hedonic price estimation [e.g. Thompson (2009)] suggests that for electronics goods it is set with regard to each model's characteristics compared to those of its competitors. This gives a basic estimating equation:

$$\text{Ln(MRSP)-Ln(P)} = f[i, t, \textit{Seller Stars}, \textit{Trusted Seller}, \textit{Number of Sellers}, \textit{Top100}, \textit{Top Rank}, \textit{Age}, \textit{Age}^2, \textit{Format Dummies}] \quad \ldots(1)$$

Having estimated the basic model, we perform some further experiments with the data. As indicated above, the number of observations used to generate the star ratings varies substantially by product and time. Following Resnick *et al*. (2006) and

[11] *NexTag.com* provides a graphical price history for each model. This overwhelmingly indicates that trading starts from the neighbourhood of the MRSP and quickly falls.

Cabral and Hortacsu (2010) it was assumed that the number of observations was an indicator of signal strength; although it was not evident that such a relationship would be linear. Accordingly, alternative representations of the strength of signal were generated and entered in the price equation. First we include an additional interaction term constructed by interacting product stars with the number of product reviews, *Seller Stars*Number of Reviews*. If consumers use the number of reviews to assess the reliability of a product rating then a negative coefficient on this will pick up the reinforcing effect. Second, we multiply the seller star variable by a weighted response variable constructed from a ranking of the number of seller reviews[12].

The parity in seller exposure across a PCS, where every merchant is allocated a standardized display, coexists with considerable heterogeneity in size and experience among participants. We examine this by looking at the effect of Amazon, the market leader, as a seller. We augment the baseline model with a dummy variable equal to one if the seller is Amazon.

Summary statistics of our continuous variables are given in Table 2, where it can be seen that on average sellers offered camera models at a 19% discount on MRSP. It may also be noted that on rare occasions the discount was negative, an outcome consistent with the Waterson and Doyle (2012) finding of a premium for some newly-

[12] To construct the weighted-response variable we ranked the number of product reviews on a monthly basis from the highest to the lowest number of reviews. The largest number of reviews in any given month was given a weighting of one and the remaining number of reviews were ranked relative to this number. The product stars variable was then multiplied by this constructed 'weight'. So for example, a 5 star product with the highest number of reviews in a month would still record a value of 5 stars whereas a 5 star product with a lower number of reviews would record a slightly lower star value.

released electronics goods. It is also clear that sellers varied hugely in the intensity of their use of the PCS, with the average product count varying from one to 629 items.

Table 2. Summary Statistics

	Mean	S.D.	Min	Max	No. of Obs
Average Net Price ($)	404.88	663.8705	60.81	9999.99	336,882
MRSP ($)	500.6125	726.3422	79.99	8000	336,882
Discount Measure ($)	95.7325	155.5968	-1999.99	549.01	336,882
Seller Stars	3.8303	1.0965	0	5	336,882
Number of Seller Reviews	365.5588	517.206	0	2600	336,882
Number of Sellers	16.2425	7.4024	1	39	336,882
Average product count	193.7601	177.558	1	629	336,882
Age (days)	269.4498	188.0079	1	1126	336,882

V RESULTS

The results from equation (1) are given in column (1) in Table 3. Seller Stars, has a significant negative impact on the discount on the manufacturer's recommended selling price. In other words, sellers with a higher seller rating sell at a lower discount than those with a lower seller rating. However, the size of the coefficient is modest,

implying that the possession of an additional star, on a scale of zero to five, reduces the discount by less than 1% of the mean value.

Table 3. Price Discount Regressions

	(1)	(2)	(3)	(4)
Number of Seller Stars	-0.007962	-0.004985	-0.004034	-0.00977
	(0.001804)***	(0.001922)***	(0.001930)***	(0.001845)***
Trusted Seller	0.012457			0.02439
	(0.004909)**			(0.005276)***
Prop. of Trusted Sellers < 25%		-0.100137	-0.087973	
		(0.026721)***	(0.025575)***	
Number of Sellers	0.002460	0.002209	0.002107	
	(0.001304)*	(0.001301)*	(0.001299)*	
No. of Sellers excluding Amazon				0.001951
				(0.001334)
Top100	-0.081922	-0.078079	-0.072040	-0.076491
	(0.005162)***	(0.005083)***	(0.004843)***	(0.004848)***
Top Rank	-0.017423	-0.015645	-0.015278	-0.009535
	(0.004380)***	(0.004037)***	(0.003998)***	(0.003722)***
Amazon			-0.043093	
			(0.009852)***	
Age	0.000642	0.000649	0.000651	0.000656
	(0.000142)***	(0.000141)***	(0.000141)***	(0.000138)***
Age Squared	-0.00000018	-0.00000018	-0.00000018	-0.00000017
	(0.00000019)	(0.00000019)	(0.00000019)	(0.00000018)
Ultra-compact	0.021935	0.022529	0.022635	0.026478

	(0.018593)	(0.018552)	(0.018518)	(0.018517)
SLR	-0.076490	-0.07760	-0.077742	-0.083171
	(0.038247)**	(0.038066)**	(0.037998)**	(0.039109)**
SLR-type	-0.053285	-0.053220	-0.053500	-0.055286
	(0.02041)***	(0.020371)***	(0.020346)***	(0.020821)***
F-Test	20.17	20.13	19.83	20.25
[p value]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
No. of Observations	336,882	336,882	336,882	314,777

Notes: All regressions include time dummies. The dependent variable is the log of the discount on the manufacturer's recommended selling price (MRSP). Columns (1) to (3) report the results for the full sample. Colum (4) reports the results excluding Amazon. Robust standard errors, clustered by camera, are given in parentheses. *** p=0.01, ** p=0.05, * p=0.1

Turning to the other variables, being a seller in the Top100 listing of electronics retailers has a significant negative effect on the product discount. This result supports previous findings that larger (and correspondingly better-known) sellers tend to price higher than small sellers [see for example Haynes and Thompson (2008)][13]. The size and significance of the coefficient is consistent with a substantial reputational benefit being enjoyed by these major retailers. The positioning of a seller in the top three sellers ranked on a page also has a significant negative effect on the discount on the MRSP. This suggests that paying a higher fee per click to

[13] To verify this finding, we alternatively use the average number of products sold by each seller as a measure of size. In this instance, the resulting coefficient is -0.0001157 (0.00002)*** in our basic estimating equation, which confirms our finding that larger sellers discount less than smaller sellers. Of course, it is likely that sellers with a substantial bricks-and-mortar selling presence use on-line outlets in a different way to pure play e-retailers: not least to promote sales in their stores.

gain e-visibility – i.e. paying more to advertise the seller's offer – represents an alternative strategy to price discounting in garnering sales, an expected outcome.

In contrast, the number of sellers has a weakly significant positive effect on the discount on the MRSP. This result confirms the findings of previous studies on electronically-mediated markets that indicate that price falls with the number of sellers, presumably reflecting keener competition.

The age and age squared variables have their expected signs and indicate that the discount on the MRSP increases over the life cycle of the model. This is consistent with the observation of price falls for high-tech goods of recent origin, reported elsewhere in the literature [e.g. Gandal (1994)]. Finally, SLR and SLR-type camera models display smaller discounts than cheaper point-and-shoot models. This is entirely consistent with high quality – and therefore relatively expensive – models selling in much lower volumes than their more basic equivalents.

Rather surprisingly, the trusted seller status variable attracts a positive significant coefficient which implies that trusted sellers offer a higher discount than those without such a status. Since Baye & Morgan (2003) find that CNet status (similar to our Trusted Seller status) attracts a price premium only in markets where it is a relatively scarce attribute, we constructed a variable that was equal to one if the seller had trusted seller status and less than 25% of their rivals in the same market on the same day also had that status. These results are presented in column (2).

The resulting negative and significant coefficient supports Baye and Morgan's finding that a price premium is observed by sellers with trusted status only in markets where such sellers are relatively scarce.

As an additional reputation variable, we also included a dummy variable for Amazon, the market leader among e-sellers in our sample. The results, in column (3), show an additional price premium effect for Amazon. The final column in Table 3 reports the results excluding Amazon from the sample and modifying the number of sellers accordingly. The resulting coefficients are similar to the full sample results presented in column (1).

Additional Experiments with the Data

We re-estimated equation (1) with the addition of a term constructed by interacting the seller star rating with the number of seller reviews. The results, in column (1) in Table 4, show that the addition of this interaction term increases the size of the coefficient on the seller star variable, however the interaction term itself is insignificant. To examine this effect in more detail, we split the interaction term at the median value[14] of seller reviews. The results are shown in column (2). A Wald test of the equality of the coefficients is highly significant (F=19.37 [p=0.000]). The results suggest that the reinforcing effect of seller reviews is positive and significant for sellers with less than the 139 reported seller reviews. This means that sellers with a

[14] The median value of seller reviews is 139.

low number of reviews are more likely to discount. In column (3) our basic model is re-estimated after weighting the number of stars by the number of reviews on which each is based. Comparing column (3) with the estimates in Table 3 confirms that the size of the discount falls with the perceived strength of the UGF signal. As expected, the number of reviews does appear to have some impact on the value of online reputation.

Table 4. Price Discount Regressions using Alternate Seller Review Measures

	(1)	(2)	(3)
Number of Seller Stars	-0.015154	-0.016159	
	(0.002208)***	(0.002153)***	
Seller Stars*Number of Reviews	0.0000057		
	(0.0000053)		
Seller Stars*Number of Reviews		0.000084	
(<median)		(0.000018)***	
Seller Stars*Number of Reviews		0.0000078	
(>median)		(0.0000053)	
Weighted Seller Stars			-0.017904
			(0.003429)***
Prop. of Trusted Sellers < 25%	-0.098710	-0.104237	-0.106338
	(0.025925)***	(0.02649)***	(0.026756)***
Number of Sellers	0.002223	0.00223	0.002169
	(0.001299)*	(0.001300)*	(0.001303)*
Top100	-0.091008	-0.092527	-0.072648
	(0.005378)***	(0.005329)***	(0.005056)***
Top Rank	-0.014638	-0.014663	-0.015240

	(0.003967)***	(0.003966)***	(0.004019)***
Age	0.000658	0.0006609	0.000657
	(0.000141)***	(0.000141)***	(0.000142)***
Age Squared	-0.00000018	-0.00000019	-0.00000019
	(0.00000019)	(0.00000019)	(0.00000019)
Ultra-compact	0.024327	0.02395	0.022781
	(0.018516)	(0.018539)	(0.018586)
SLR	-0.078649	-0.080812	-0.080584
	(0.038183)**	(0.038273)**	(0.038125)**
SLR-type	-0.053144	-0.053616	-0.054643
	(0.020268)***	(0.020370)***	(0.020331)***
F-Test	20.23	20.98	19.24
[p value]	[0.0000]	[0.0000]	[0.0000]
No. of Observations	336,882	336,882	336,882

Notes: All regressions include time dummies. The dependent variable is the log of the discount on the manufacturer's recommended selling price (MRSP). Robust standard errors, clustered by camera, are given in parentheses. *** p=0.01, ** p=0.05, * p=0.1

Table 5 reports the results of further estimations using alternative measures of the seller's star rating variables. While the one-to-five rating appears a plausible monotonic quality measure, the zero star rating applies largely to newcomers and therefore may be a poor quality signal. To investigate this we first replaced those zeroes covering observations on sellers with no current reviews with the rating the seller subsequently achieved. This is to allow for the fact that the pricing strategy it adopted prior to the rating may have affected its subsequent rating. As shown in

column (3), the coefficient on the *Constructed Seller Stars* variable is negative and significant and only marginally different from that reported in column (1) in Table 3.

Second, we then excluded those observations where the seller rating was zero and re-ran the regression using the slightly smaller sample of observations. These results are given in column (2) in Table 5. The coefficient on seller stars is almost identical to that in column (1) and again, very similar to that reported in column (1) in Table 3.

Finally, we include as an alternative measure of UGF reputation, the average rating for a seller across *all* of its digital camera products on a particular day. This would be a more appropriate measure if consumers take into account the overall performance of a particular seller across its product offerings in determining which e-tailer to purchase from. These results are presented in column (3). The resulting coefficient is negative and significant and is very similar to the results based on the seller's rating in only one market.

Table 5. Price Discount Regressions using Alternate Seller Stars Measures

	(1)	(2)	(3)
Constructed Seller Stars	-0.006986		
	(0.002172)***		
Positive Seller Stars only		-0.006958	
		(0.002189)***	
Average Number of Seller Stars			-0.006451

			(0.001962)***
Prop. of Trusted Sellers < 25%	-0.099444	-0.098855	-0.099273
	(0.02672)***	(0.026718)***	(0.026711)***
Number of Sellers	0.002218	0.002302	0.002218
	(0.001301)*	(0.001304)*	(0.001301)*
Top100	-0.078936	-0.078071	-0.078573
	(0.005092)***	(0.005132)***	(0.005086)***
Top Rank	-0.01568	-0.015821	-0.015659
	(0.004040)***	(0.004070)***	(0.004036)***
Age	0.000648	0.000648	0.000649
	(0.000141)***	(0.000142)***	(0.000141)***
Age Squared	-0.00000018	-0.00000018	-0.00000018
	(0.00000019)	(0.00000019)	(0.00000019)
Ultra-compact	0.022448	0.022296	0.022443
	(0.018549)	(0.018582)	(0.018551)
SLR	-0.077607	-0.078037	-0.077436
	(0.038056)**	(0.038163)**	(0.038047)**
SLR-type	-0.053347	-0.053694	-0.053211
	(0.020355)***	(0.020425)***	(0.020354)***
F-Test	20.22	22.51	20.15
[p value]	[0.0000]	[0.0000]	[0.0000]
No. of Observations	336,882	332,538	336,882

Notes: All regressions include time dummies. The dependent variable is the log of the discount on the manufacturer's recommended selling price (MRSP). Robust standard errors, clustered by camera, are given in parentheses. *** p=0.01, ** p=0.05, * p=0.1

Finally, recognising that the discount-star quality effect might not be monotonic, we also investigated how the discount varied according to the number of stars obtained. We therefore re-estimated the basic equation using separate dummy variables for each of the recorded seller star categories. These results, reported in Table 6, confirm the premium enjoyed by sellers with three or more stars over their two-star or less rivals. However, the estimated discount-star relationship was not monotonic. In part this appeared to reflect the correlations between trusted seller status, possession of four or five stars and a Top 100 position. The results are also consistent with a phenomenon observed elsewhere in e-markets that the absolute value of the marginal reputation effect is higher for adverse news than it is for positive news [Resnick et al. (2006), Cabral and Hortacsu (2010)]. If so, it may be that escaping possession of a two-star reputation or less – i.e. having a reputation for indifferent/poor treatment of clients - is more important than enhancing a reputation deemed satisfactory or above.

Table 6. Price Discount Regression Split by Seller Star Category

3 Seller Stars	-0.044013
	(0.007188)***
4 Seller Stars	-0.032799
	(0.00696)***
5 Seller Stars	-0.02927
	(0.007118)***
Prop. of Trusted Sellers < 25%	-0.098929
	(0.026704)***

Number of Sellers	0.002197
	(0.002197)*
Top100	-0.074289
	(0.00499)***
Top Rank	-0.015371
	(0.004009)***
Age	0.00065
	(0.00014)***
Age Squared	-0.00000018
	(0.00000019)
Ultra-compact	0.022554
	(0.018520)
SLR	-0.077286
	(0.037874)**
SLR-type	-0.053233
	(0.020373)***
F-Test	20.95
[p value]	[0.0000]
No. of Observations	336,882

Notes: All regressions include time dummies. The dependent variable is the log of the discount on the manufacturer's recommended selling price (MRSP). Robust standard errors, clustered by camera, are given in parentheses. *** p=0.01, ** p=0.05, * p=0.1

VI CONCLUSIONS

This paper has examined the value of seller reputation on the pricing of digital cameras at a price comparison site. Observational research on reputation effects at e-sellers usually suffers from an omitted variables problem insofar as selling sites

differ in their visual appeal and ease of use. We are able to use the uniform presentation opportunity offered to sellers at a PCS to circumvent this difficulty. The paper finds evidence that user-generated measures of seller reputation do impact price; although the coefficients – while statistically significant – are relatively small. This finding corroborates those for other selling platforms, most obviously e-Bay, where highly rated sellers have been consistently found to enjoy a small premium. Reputation is, of course, a multidimensional concept and here the seller's overall prominence, proxied by membership of the leading 100 electronics goods sellers, appears to exert a substantially larger impact on price, when compared to the platform-specific measure. Similarly, market leader *Amazon.com* enjoys a larger premium still.

Our finding of a statistically significant but relatively modest premium for user-generated reputation must be qualified in at least three ways: First, competition for electronics goods such as digital cameras has driven down profit margins to the extent that we might expect to observe relatively small effects at the mean. Second, we observe price offers but not sales. Thus we do not know the extent to which reputation delivers substantial *ceteris paribus* benefits via sales volumes. Finally, research on PCS trading[15] suggests that the *ranking* of prices has a major effect in determining sales volumes. If so, having the lowest price for a particular product may be more important than the size of that price difference.

[15] For example, Baye *et al*. (2009) report a major discontinuity between the sales of the cheapest and second cheapest offerings at a PCS.

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Appendix

Figure A1. Nextag Screen Output

NexTag Comparison Shopping

Products Mortgage Travel Degrees Real Estate more

NexTag Search

Sign In | My Lists

Most Popular | Top Brands | Rebates | Price Drops | List Central | My Lists

All Categories : Electronics : Digital Cameras : Canon

Have One to Sell?

Canon PowerShot SD870 8.0MP Digital Camera Silver

8MP - 3.8x Optical Zoom - SD/MMC Memory Card - 3in.

From the very first glance, the smooth shape and bold lines of the stylish PowerShot SD870 IS Digital ELPH signal that this is no ordinary camera. With 8.0 megapixels of resolution, an Optical Image Stabilizer and 3.8x more ...

Part #: 2340B001 / A1276693
Sellers Found: 20
Available Since: Aug 29, 2007
Lowest Price: $238.00

Average Rating: ★★★★☆ (126 user ratings)

+ Add to Shopping List | Set Price Alert

Price History Aug/06 to NexTag

Compare Prices | Write Product Review | Price History

Zip: 03104 change

Seller	Seller Ratings	Description	Price	+Tax & Shipping	TruePrice
ABE'S OF MAINE	Trusted Seller ★★★★☆ 2649 Seller Reviews	In Stock	$243.95	Tax: $0.00 Ship: $2.90	$246.85 Go to Store
17StreetPhoto	Trusted Seller ★★★★★ 79 Seller Reviews	In Stock Canon USA-Authorized Dealer!	$238.00	Tax: $0.00 Ship: $10.49	$248.49 Go to Store
newegg	Trusted Seller ★★★★☆ 518 Seller Reviews	In Stock Special savings w/ 8GB SD card combo, en	$259.99	Tax: $0.00 Ship: $10.27	$270.26 Go to Store
circuit city	Trusted Seller ★★★☆☆ 168 Seller Reviews	In Stock Save up to $70 instantly on digital came	$249.99	Tax: $0.00 Ship: Free	$249.99 Go to Store
ClickForDigital	Trusted Seller ★★★★☆ 223 Seller Reviews	In Stock	$247.00	Tax: $0.00 Ship: Free	$247.00 Go to Store
B&H Photo-Video	Trusted Seller ★★★★★ 1707 Seller Reviews	In Stock Click for our special KIT OFFERS	$244.95	Tax: $0.00 Ship: $6.85	$251.80 Go to Store
JR.com	Trusted Seller ★★★★☆ 1623 Seller Reviews	In Stock	$249.88	Tax: $0.00 Ship: $6.95	$256.83 Go to Store
amazon.com Marketplace	★★★☆☆ 11 Seller Reviews	In Stock	$240.00	Tax: $0.00 Ship: See Site	See Site Go to Store
PCConnection	Trusted Seller ★★★★★ 310 Seller Reviews	In Stock	$299.95	Tax: $0.00 Ship: Free	$299.95 Go to Store
mwave	Trusted Seller ★★★★☆ 413 Seller Reviews	In Stock	$324.64	Tax: $0.00 Ship: $6.00	$330.64 Go to Store
DigitalMEGAStore	Trusted Seller ★★★★★ 444 Seller Reviews	In Stock	$249.00	Tax: $0.00 Ship: Free	$249.00 Go to Store
iBuyDigital.com	Trusted Seller ★★★★☆ 921 Seller Reviews	In Stock	$250.95	Tax: $0.00 Ship: Free	$250.95 Go to Store
US CAMERA	★★★★☆ 171 Seller Reviews	In Stock	$246.00	Tax: $0.00 Ship: Free	$246.00 Go to Store
lenovo	Rate This Seller	In Stock	$369.99	Tax: $0.00 Ship: Free	$369.99 Go to Store
Datavision	★★★☆☆ 58 Seller Reviews	In Stock	$249.00	Tax: $0.00 Ship: $9.94	$258.94 Go to Store
PowerMax	Rate This Seller	In Stock	$279.00	Tax: $0.00 Ship: See Site	See Site Go to Store
Vann's	Trusted Seller ★★★★★ 420 Seller Reviews	In Stock Free Ground Shipping	$279.97	Tax: $0.00 Ship: Free	$279.97 Go to Store
amazon.com	Trusted Seller ★★★★☆ 84 Seller Reviews	In Stock	$249.99	Tax: $0.00 Ship: Free	$249.99 Go to Store
TriState Camera	★★★★☆ 324 Seller Reviews	In Stock	$238.00	Tax: $0.00 Ship: $5.99	Best Value* $243.99 Go to Store
BOOMj.com Store	★★★☆☆ 4 Seller Reviews	In Stock	$252.64	Tax: $0.00 Ship: $6.63	$259.27 Go to Store

The NexTag shopping search engine has prices from name brand stores all over the web. Compare prices for computers, electronics, books, CDs, movies, office products and video games. Become a seller yourself today!

*The Best Value designator is given to the lowest price for an item in new condition from a highly rated NexTag seller. To be highly rated, a NexTag Seller must have at least 10 reviews and an average of four or more stars.

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