Rev Ind Organ (2013) 42:1–23
DOI 10.1007/s11151-012-9358-4

Entry and Exit Behavior in the Absence of Sunk Costs: Evidence from a Price Comparison Site

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Published online: 10 August 2012

Abstract This paper explores entry and exit at a price comparison site (PCS) where the sunk costs of participation are effectively zero. We first use an unbalanced panel of 295 products on *NexTag.com* to estimate an error correction model of net entry. Although the results support our characterization of the PCS as a zero sunk cost market in which potential sellers behave as Kirznerian entrepreneurs in responding to opportunities, it is clear the net entry flow involves participants with widely differing behavior. This is investigated by examining exit and re-entry decisions at the seller level, which reveal that size and reputation determine individual responses to market opportunities.

Keywords Zero sunk costs · Entry and exit · Kirznerian entrepreneurs

JEL Classification L81 · M13 · L11

1 Introduction

Digital trading platforms have dramatically reduced the sunk costs of market entry. This is most obviously seen in the case of the free listing price/product comparison site (PCS or 'shopbot'). Here an entrant can both avoid the start-up costs of establishing a physical entity and gain instant access to potential buyers on terms that, in principle, are no different from those enjoyed by incumbents. A new entrant that operates out

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of a personal residence[1] may well be a virtual competitor of a billion dollar retail chain.

The purpose of this paper is to provide an empirical examination of entry and exit at a PCS that is characterized by near-zero sunk costs. PCS sites such as *NexTag.com* list sellers in exchange for click-through fees for the delivery of potential shoppers. The absence of the sunk costs that are normally required to establish a market presence gives seller listings at a PCS a transient quality, as compared to participation in a traditional market. Nonetheless, there is a body of empirical evidence that suggests that prices at a PCS reflect both market structure and the rivalrous conduct of participants, in ways that are comparable to those observed in traditional market[2] settings.

This paper contributes to the literature on net entry that, since Orr (1974), has been premised on the assumption that entry/exit is a disequilibrium reaction to changes in market opportunities. The sluggish response that is generally observed is usually considered a consequence of the deterrent effect of sunk costs. We examine entry in the absence of significant sunk costs. The paper also contributes to the literature on the role of firm heterogeneity in determining the ordering of entry and exit among migrants to the market (Cotterill and Haller 1992; Igami 2011). Here the absence of the resources that are required for market involvement reduces the dimensions of seller heterogeneity, which allows us to focus on the reputation/size effects that appear to perpetuate frictions in e-markets.

The paper uses a unique unbalanced panel of daily observations on 295 digital cameras that are traded on *NexTag.com*. Our data confirm that a PCS experiences very high rates of churn, but the data also suggest that seller size/reputation variation generates differences in pricing and entry behavior, with small/low reputation entrants opting for lower prices and shorter market tenure. We first model net entry using an error correction process. We then use seller-level observations to explore exit/re-entry decisions, evaluating the effects of seller and market characteristics. While sellers behave as Kirznerian entrepreneurs (Kirzner 1973), entering and exiting in response to changes in expected profitability, size and reputational differences reintroduce frictions into the entry and exit of potential sellers.

The paper is structured as follows: Sect. 2 outlines the institutional background, including the economic characteristics of a PCS. The data collection procedure is described in Sect. 3. Section 4 specifies and estimates a model of the net entry process. Section 5 considers the impact of seller heterogeneity on entry and exit decisions with an examination of these decisions at the seller level. A brief conclusion follows.

1 *NexTag* appears to be particularly supportive to smaller sellers and offers a program for sellers with less than 100 products; see Lin and Scholten (2005).

2 It has been argued that the lack of restrictions on entry and low search costs together make the PCS a close approximation to textbook perfect competition. Brynjolfsson et al. (2009) discuss—and ultimately reject—this argument.

2 Entry and Exit at a PCS: Institutional Background and Discussion

2.1 Shopbots as Markets: Institutional Background

Listing a product at a specific PCS is more than merely advertising a willingness to supply. The PCS format—see "Appendix" for a screenshot example—typically provides potential buyers with a complete product description, including user reviews, details of the seller's price and terms of supply, as well as providing the mechanism by which potential buyers can complete their purchase. *NexTag.com* treats each product that is listed as a separate market, supplying historical data on its price evolution, seller participation, and buyer clicks-through, as well as on contemporary price offerings. We follow *NexTag.com* in treating each model as a distinct market.

Notwithstanding the apparent ease of buyer and seller multi-homing, there is abundant supportive evidence that each PCS product operates as a distinct market entity: For example, product pricing at each PCS reflects its particular competitive circumstances, including the number of participating sellers (Baye et al. 2004a; Haynes and Thompson 2008) and the presence of sellers that offer low-price substitutes, such as unofficial imports (Thompson 2009). Price levels show systematic—if modest—variation across shopbots (Lin and Scholten 2005). Similarly, participants' within-PCS shares appear to be substantially determined by within-market price and display position (Baye et al. 2007).

Economists initially conjectured that ultra-low search costs would ensure Bertrand competition and the convergence of PCS prices towards marginal cost. However, the evidence (e.g., Baye et al. 2004a,b) suggests that the dispersion of *posted* prices remains substantial and comparable to what occurs in traditional markets.[3] In part this reflects a price premium for seller reputation in e-markets (Waldfogel and Chen 2006).

Since price rankings are often unstable (Baye et al. 2004b, 2006), it appears that observed price dispersion also results from the pricing strategies of sellers that face a mix of informed and uninformed buyers. Salop and Stiglitz (1977) formalized Stigler (1961) in demonstrating the existence of a dual price equilibrium, with informed buyers getting search-based low prices and uninformed buyers receiving a random mix of low-price and no-search high-price options. Clearing house models (e.g. Varian 1980; Rosenthal 1980; Baye and Morgan 2001; Iyer and Pazgal 2003) predict that sellers will randomly mix low prices (to capture price-sensitive consumers) with high prices (to loyal buyers). Therefore, in addition to seller heterogeneity effects, some observed price variation results from sellers that respond to buyer heterogeneity.

2.2 Seller Participation at a Shopbot

Entry to a PCS differs in two key inter-related ways from entry into conventional product markets: First is the near-complete absence of sunk costs, with their implied

[3] Recent work suggests that the traffic at price comparison sites generally flows towards the cheaper and/or more prominently displayed offerings. If so, the distribution of *transaction* prices could be very different from what is observed for *posted* prices and would almost certainly exhibit lower dispersion.

barriers to entry and exit; and second is the minimal specific resource requirement for participation. These attributes and their implication are considered in turn:

PCS participants pay no up-front fee for a listing and gain access to software that enables them to display their offerings and to monitor interest that is shown by potential buyers. Each entrant needs few resources beyond a web site that is capable of processing sales transactions. While there are inevitable learning costs of using a PCS, the explicit, incremental listing costs for an additional product would appear to be close to zero. Involvement is not entirely free of explicit costs in that participants incur click-through fees irrespective of whether such clicks generate subsequent sales. Since the conversion rate is well below unity,[4] sellers may expect to incur at least some fees prior to any sale, although the cost of these fees per product offered will be small.

Sellers may opt to pay the basic click-through fee, currently 20c to $1 per click on *NexTag.com* according to product category, or bid a higher rate to secure a superior position in the PCS's default listing. Ranking here will reflect both the bid and some additional seller features, but PCSs do not reveal their ranking algorithms. Position, as well as price, appears to be a determinant of the probability of securing a click through to the selling page (Baye et al. 2007).

Newly listing sellers may display on equal terms to established incumbents, but will usually lack any reputational advantage of the latter. As noted above, electronic markets generally display a price premium for reputation, even with an otherwise homogeneous product (Clay et al. 2001; Waldfogel and Chen 2006). Of course, with high frequency data and markets that are defined at the individual product level, most entrants are not complete newcomers, but are already selling related products across the same PCS. These entrants will bring their reputation, including any user-generated feedback record, with them and hence are not necessarily disadvantaged with respect to current sellers of the product.

The corollary to the absence of sunk costs in PCS entry is that the entrant may lack the commitment that normally accompanies market involvement. In consequence of this minimal specific resource requirement, it is conjectured here that the PCS will more obviously provide a forum for pure entrepreneurial activity, in the meaning of Kirzner (1973)[5] than has been observed elsewhere in the entry literature. In general, the existence of sunk costs introduces inertia, not least by creating a strategic threat that may discourage would-be entrants. Therefore absent sunk costs in a PCS setting, it is conjectured that more fluid net entry flows will be observed, with agents' migrating between the reservoir of potential sellers and the market.

There is a potential asymmetry between entry and exit at a PCS. If the sunk costs of entry are close to zero, a positive response from potential entrants to increased profit opportunities appears unexceptional. However, it is less clear why exit should follow any reduction in these opportunities if there are no costs of remaining in the market. Why is it more profitable to withdraw from the market entirely than, for example, to remain listed with a price in excess of marginal cost and at least some non-zero

[4] Estimates of the conversion rate for clicks into sales vary widely. Baye et al. (2004a) report a 50 % conversion rate on *Dealtime.com*, with little variation across retailers; but two more recent estimates have put the conversion rate at 0.05 and 0.03, respectively (Baye et al. 2007, 2009).

[5] That is alertness to profitable opportunities gives rise to arbitrage activity (Caree and Thurik 1999).

probability of sales? Indeed why should each PCS not contain the maximum number of sellers permitted by the site?

Three possible explanations for exit may be advanced: First, if competition at the PCS drives its prices lower than elsewhere, the seller may choose to concentrate upon those more profitable outlets. Second, low PCS prices may discourage re-stocking by sellers and so precipitate exit by those that have exhausted their inventory. Third, we conjecture that while there is no *explicit* resource cost in continuing to list,[6] there may be a negative horizontal externality, particularly for multi-homing sellers that wish to post a uniform price (Lin and Scholten 2005). Adjusting price at one outlet alone may be infeasible, while not posting and thereby maintaining an uncompetitive price may do reputational damage. Therefore we anticipate that exit may be an alternative to local re-pricing.

3 Data: Collection, Characteristics and Sample

3.1 Data: Sources and Collection

NexTag.com, the source of our data, is a leading general merchandise PCS, operating sites in the USA and Europe. The digital camera, which is the product that we selected for our research, is representative of high value-to-bulk goods that are traded on e-markets and carries the advantage of usually being purchased singly and therefore is without the complication of quantity discounts, as might apply to, say, books. *NexTag.com* provides comprehensive data on the pre- and post-tax prices of listing sellers, delivered prices, feedback on seller reputation and model characteristics for each camera listed, as shown in "Appendix". Additional information on price history and monthly "leads"—clicks through to the seller from *NexTag.com*—is available to users for the previous 17 months.

We used a java program to interrogate *NexTag.com* to extract data from the screen display.[7] The program was run daily, at 2:00 a.m. between November 19, 2007, and March 31, 2008. The target sample was updated weekly to allow for new model entry, with models being identified by their unique product code (upc).[8] On average, over 1,000 items were offered daily under the 'digital camera' heading, with over 650 sellers participating at least once. To exclude dormant markets and non-comparable products we dropped cameras that were introduced prior to December 2005 (assumed to be discontinued), accessories, bundled kits, unofficial imports, and refurbished models[9] and those priced below $50, which were also considered likely to be refurbished.

A second program was run to capture the leads data that corresponded to the target sample. In addition, a search of camera industry sites was undertaken to determine the

[6] Of course, if consumer search continues to bring clicks through to higher-priced sellers and their conversion rate falls on account of price, an explicit cost of inertia is generated.

[7] Although collection was automated, screen shot originating data did require some cleaning before use and time costs prohibited more frequent visits.

[8] The upc formerly appeared on *Nextag*'s screen display but is currently not available.

[9] Thompson (2009) explores the impact of parallel imports and refurbished models in Internet-enabled markets.

manufacturer's recommended selling price (MRSP) by upc. We followed the four-fold classification of camera format that is used by *Depreview.com*, which distinguishes compact and sub-compact point-and-shoot models from higher-quality single lens reflex (SLR) and SLR-type models.[10] Non-availability of leads and/or MRSP data and the exclusion of models where leads failed to reach 100 clicks[11] per month on at least one occasion reduced the final sample to 295 models. With entry and exit over the 134-day interval, an unbalanced panel of approximately 26,000 model-day observations was generated.

Scrutiny of the raw data immediately confirms two of our prior conjectures on PCSs: First, these listings are used, at least intermittently, by a large number of sellers; and second, on average each model's listing exhibits very high rates of entry and exit. These findings are considered in turn:

In total 161 different sellers participated in the 295 sample *NexTag.com* camera model markets over the 134-day interval of scrutiny. The average number of sellers per model, on any one day, was approximately 13, with an average of 71 separate sellers participating daily across all markets in the sample. This is consistent with the existence of a substantial reservoir of potential sellers, some of which enter each product market as opportunities arise. Sellers ranged from very large on-line retailers such as *Amazon.com*, which participated in 95 % of the model markets at some time during the investigation, and large specialist electronics retailers to 37 sellers with five products or less.

Across the 295 products the mean numbers of entrants (including re-entrants) and exits (including temporary exits) was each approximately 189 per day. This is equivalent to 0.64 per model per day's inclusion in the sample. Given a daily average of 13 sellers per model, this represents approximately 37 % that leave and are replaced each week. This is a far higher rate of churn than is observed in conventional retail markets, where perhaps 5 to 10 % *per year* would be normal. The daily profile of net entry is shown in Fig. 1.[12]

The data suggest that entry/exit strategies differed across retailers according to size and reputation. For example, if we denote as 'large' those retailers that figured in the *Dealerscope* leading 100 US electronics goods sellers for 2007 and as 'small' those that did not, it seemed that smaller sellers were involved for fewer days but were more likely to make temporary forays into a PCS. Large sellers tended to remain for a longer period. For example, across the sample, if we ignore movements in and out, large sellers were present for a mean of 56 days (median 49), and small sellers were present for a mean of 41 days (median 25).

Since large sellers on average participated in many more markets than smaller sellers, they still accounted for 35.5 % of all entries and 37.3 % of all exits. Both groups tended to engage in temporary entry; although large sellers stayed on average for

[10] An SLR-type model has the appearance of an SLR with the components of a high-end point-and-shoot. In particular it has a viewfinder that displays a digitally generated image, whereas an SLR shows an actual optical image.

[11] A cut-off of 100 leads was used to ensure a sample of actively traded models.

[12] The high variance in net entry, as shown in Fig. 1, was not obviously linked to holiday dates or day-of-the-week effects. More analysis of these data is available from the authors.

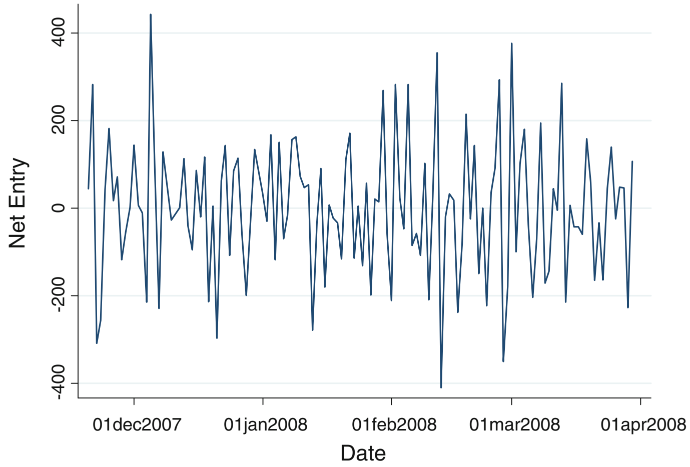

Fig. 1 Daily net entry

Table 1 Comparison of mean entry price differentials[a] of small and large sellers

	Large sellers	Small sellers	z Statistic [*p* value]
Mean	−8.735848	35.15724	−32.3249 [0.000]
SD	88.53022	130.149	
No. of obs.	9,414	16,750	

[a] Previous day's mean price minus entry price

12 continuous days (median six), small sellers averaged nine continuous days stay (median three). Thus a high proportion of small firm entry, in particular, appears to resemble a hit-and-run response to market conditions.

Differences were also apparent in pricing strategy: Subtracting the seller's entry price from the previous day's mean price yields \$35.16 (a 7.7 % discount) for smaller sellers and − \$8.74 (a 1.5 % premium) for their larger rivals. The mean difference is highly significant, as is shown in Table 1. This finding is also suggestive of smaller sellers' temporarily undercutting the prices of incumbent sellers before exiting. By contrast, the larger sellers do not appear to offer price discounts over incumbents, which suggests that they hope to sell on reputation.[13]

Thus scrutiny of the raw data suggests that large and small sellers may be using the PCS in somewhat different ways. Large sellers tended to offer models at higher prices and for a greater proportion of the interval studied. While both large and small sellers exhibit high rates of entry and exit compared to traditional markets, larger sellers' forays into each market tend to last substantially longer than those of the small firms. A broadly similar pattern of pricing and stay length differences was also apparent when sellers were distinguished according to their user-generated star rating on

[13] A multivariate analysis confirmed the smaller discount offered by larger sellers. For example, regressing the discount on a larger seller dummy variable, using the definition given in the text above, with controls for format and a time trend yielded a large-firm coefficient of −0.092 (t = 47.5), which is suggestive of a 9 % lower discount from sellers that are in the leading 100 US electronics retailers.

NexTag.com. Both size and star ratings are dimensions of seller reputation and these effects are explored further in Sect. 4 below.

4 Modeling Net Entry in the Absence of Sunk Costs

The treatment of net entry as a response to market disequilibrium is central to an extensive entry literature extending back via Geroski (1991, 1995) to Orr (1974). The underlying demand and cost conditions are assumed to determine the equilibrium number of firms or “carrying capacity” (Caree and Thurik 1999) that each market can support, with recruits from a pool of potential entrants joining and leaving in response to perceived opportunities. Sunk costs pose two qualifications:

First, in traditional industries the irrecoverable set-up costs act as identifiable barriers to entry (e.g. Geroski and Schwalbach 1991; Fotopoulos and Spence 1999), ensuring that the observed entry/exit response to changing profit opportunities is relatively sluggish (Caree and Thurik 1999). These costs also explain why new entrants are usually much smaller than are average incumbents (Geroski 1995).

Second, the empirical studies typically proxy *expected* profitability by *observed* lagged profitability. This, as Geroski (1995) noted, is a useful device but one that assumes a naïve view of the entry/exit process, since players that enter (exit) will themselves affect profits such that simple expectations are unlikely to be completely fulfilled.

We conjecture that in an environment with abundant potential entrants and an absence of sunk costs the speed of adjustment to equilibrium will far exceed that observed in the more frictional circumstances of traditional markets. Furthermore, while lagged profitability may be a flawed proxy for expected profitability in traditional markets, the absence of sunk costs at a PCS would appear to give it a quasi-contestable character,[14] in the sense that entrants are able to take short-term gains and exit without penalty. Moreover, these opportunities should be generated on a regular basis if, as the literature has suggested, continuous price perturbation occurs.

Here it is assumed that there is a reservoir of potential sellers of product I, some of which enter (leave) that market in response to increases (decreases) in profitable opportunities. Since a count across our sample revealed 161 separate sellers over the period of investigation, this assumption appears benign. Each potential seller is assumed to be aware of its own marginal costs of selling i via a PCS. Potential seller j, anticipating price P_i and marginal cost C_{ij}, is attracted to using the PCS if $P_i - C_{ij} > 0$. This leads us to a basic error correction model with the following form:

$$\begin{aligned}\Delta N_{it} = \beta_1 \Delta PC_{it-1} + \varphi_1 \Delta L_{it} - (1-\alpha)[N_{it-1} - \gamma_1 - \gamma_2 PC_{it-1} \\ -\gamma_3 L_{it-1}] + \varepsilon_{it}\,, \end{aligned} \tag{1}$$

[14] Seller heterogeneity, especially with respect to reputation, clearly prevents the PCS from meeting the assumptions for a perfectly contestable market as in Baumol et al. (1982).

where N is the number of sellers in the market; *PC* is average ratio of price to marginal cost in the market; L is the number of leads, used here as a proxy for sales;[15] and ε_{it} is the usual error term. All variables are in logs.

Thus, within the model the current change in the number of sellers is determined by the lagged changes in average PC and leads, together with an adjustment the magnitude of which depends on the deviation of prior period N_{it-1} from its equilibrium value. Error correcting behavior requires that the coefficient on the error-correction term is negative. Thus, ceteris paribus, if the number of sellers is above its long-run predicted level, ΔN_{it} will be negative in order to move it back towards its long-run equilibrium value, and vice versa. Provided that the variables co-integrate, all terms in the error correction model are stationary, such that standard critical values of t and F distributions apply. We generate our baseline estimating equation by expanding the square bracketed term to get:

$$\begin{aligned}\Delta N_{it} = \beta_0 + \beta_1 \Delta PC_{it-1} + \phi_1 \Delta L_{it} - (1-\alpha)N_{it-1} + (1-\alpha)\gamma_2 PC_{it-1} \\ +(1-\alpha)\gamma_3 L_{it-1} + \varepsilon_{it}\,, \qquad (2)\end{aligned}$$

where $\beta_0 = (1-\alpha)\gamma_1$. Since, the variables are in logs, the short-run elasticities are given by the coefficients β_1 and ϕ_1. The long-run parameters are derived from the coefficients on the lagged levels variables and the adjustment coefficient in the usual way.

Having estimated the basic model, we perform some further experiments with the data to explore market adjustment and entry deterrence: First, since *inactive* PCS membership appears to carry no explicit resource costs, we allow for the possibility of asymmetric behavior between market expansion and market contraction. We use a decrease in the (lagged) number of sellers to make the distinction between a growing, stagnant and declining market.[16] We then estimate separate adjustment parameters to compare the respective rates of expansion and contraction in response to changes in expected profitability.[17]

Second, the parity in exposure across a PCS, where every seller is allocated a standardized display, coexists with considerable heterogeneity in size and reputation among participants. We examine this by looking at the entry deterrence effect of the PCS presence of *Amazon* as a seller. We augment the baseline model with variables

[15] The number of leads is widely used as a quantity proxy in shopbot research; see Baye et al. (2009).

[16] For a robustness check, we also used the change in the number of leads to classify a market. The general pattern of results did not change. These results are available from the authors.

[17] Iyer and Pazgal (2003) present a model of seller participation at a PCS, in which sellers opt either to join it, and follow a mixed strategy of randomized pricing, or to target loyal (thus price insensitive) customers outside. In the present context their model has two serious disadvantages: First, while it derives an optimal number of inside participants, this comes at the cost of endogenizing the "reach" of the market in terms of the participants' characteristics. Among other things this treats the PCS as a single market rather than a gatekeeper to k product markets, each with its distinctive circumstances, as in our research. Second, as with other insider-outsider models its force depends on average prices within the PCS *increasing* with the number of sellers. This contradicts the empirical evidence, which overwhelmingly suggests that prices *fall* with n (Baye et al. 2004a; Haynes and Thompson 2008), and references therein).

Table 2 Summary statistics

	Mean	Median	SD	Min	Max	No. of obs.
Price	433.606	249.89	842.214	64.99	9,999.99	26,357
MRSP	520.700	300	890.542	79.99	8,000	26,357
PC	1.59518	1.5791	0.2617	0.572894	3.131641	26,357
Sellers	12.6320	12	7.1052	1	39	26,357
Leads	371.185	158	656.618	0	10,500	26,357

that alternatively denote *Amazon* entry/exit or presence and re-estimate after adjusting the seller number to remove *Amazon*.[18]

Third, recognizing that retailing SLRs will involve high price/low volume trades in comparison with selling the other camera formats, we estimate the baseline model separately for SLR cameras and the rest. In the event an F-test rejected any net entry behavior differences across the two submarkets.

4.1 Net Entry: Sample Characteristics

Weekly revisions to the sample generated an unbalanced panel, but Table 2 provides summary statistics, across markets and time, for the 295 models in our net entry sample. *NexTag* provides both net and tax-inclusive prices and the price inclusive of shipping costs. We used the net price in our analysis. The right skewness of the price variable reflects the small number of high-quality SLR cameras among the larger numbers of compact and ultra-compact point-and-shoot models.

The marginal cost (C) to the retailer is directly unobservable. However, the manufacturer's recommended selling price (MRSP) was collected, and C was assumed to be $0.5 \times$ MRSP.[19] From this we constructed a daily measure (PC) of profitability as the ratio of net price to C.[20] Unit profit (as measured by net profit minus C) appeared to be greater on the high-quality/low-volume models than on the cheaper, high-volume models. Thus using the industry's own classification of camera types, the average unit profits for compact ($86.26) and subcompact ($90.45) models were similar but each was considerably less than that of the (high-quality) SLR models ($629.31).

The number of sellers listed per model ranged from one to 39, with a mean of approximately 13. Inclusion in the sample required that a model experienced a period of active trading, taken to be a minimum of 100 leads in a single month. Inevitably not

18 This includes both *Amazon* and *Amazon Mall*, the arrangement whereby independent retailers sell via the *Amazon* platform.

19 This followed consultations with retail industry sources. Of course, marginal cost to the retailer could fall over the period of our investigation, but this was not expected to be a frequent problem: First, the length of our investigation (134) days is relatively short; and, second, while cuts in MRSP do sometimes occur, the manufacturers generally prefer to replace models with newer versions incorporating improved features.

20 We used a ratio rather than the price-cost margin since in a small number of cases price was below marginal cost; an unsurprising outcome in that inventory considerations sometimes generate deep discounting.

all models sustained this level of demand over the period of inquiry, so that the range of leads ran between zero and 10,500, with a mean of approximately 356.[21]

4.2 Results

Prior to running the error correction model, we explored the time series characteristics of the data and tested for stationarity. After confirmation of the satisfactory time series properties of the data,[22] the error correction model was estimated and the results are reported in Table 3. In all equations, the error term is free from autocorrelation and heteroskedasticity, and an F-test on the joint significance of the regressors is overwhelmingly significant.[23]

The results from the baseline model are given in column (1). All of the principal parameter estimates are significant with the expected signs'.[24] The two variables that are assumed to determine the expected gain from market membership—average (lagged) PC and (lagged) sales, as proxied by leads—each have a positive and significant effect on the number of sellers in a camera market. This supports our conjecture that inward and outward movement at the PCS responds systematically to profit opportunities.

Ordinarily, the inclusion of price- and quantity-related variables in a single estimating equation would raise endogeneity concerns. However, here it will be recalled that leads is the total clicks received across all sellers in the preceding month and as such is uncontaminated by subsequent changes in the number of participants. Similarly, daily decisions on entry and exit are related to the previous day's price-cost ratio. An examination of the coefficients in the baseline model suggests that a one per cent increase in the PC ratio leads to an immediate 0.34 % increase in seller numbers, with a long-run multiplier of 0.624. The short-run (long-) leads effect is statistically significant but of much smaller magnitude 0.0035 (0.1776).

The error correction coefficient is negative and significant, as expected. Its magnitude indicates that about 3 % of any disequilibrium is corrected each day. This confirms our conjecture that PCS markets adjust far more quickly than do their traditional counterparts. For example, where Caree and Thurik (1999) reported 40 % adjustment per *year* in traditional retail markets our model suggests an equivalent adjustment time of 11–12 days.

[21] Only six cameras saw their number of leads fall to zero over the period of inquiry.

[22] A discussion of the time series properties of the variables used here was included in earlier versions of the paper but is omitted for space reasons.

[23] We run separate regressions for SLR cameras and for all other cameras and performed a Chow Test. The resulting test statistic was 2.161, which is insignificant at the 1 % level and confirms that a pooled model is the most appropriate.

[24] We initially included 295 camera model dummy variables; however, these were jointly insignificant at the 1 % level (F test = 1.05 p = 0.2795). An F test on the joint significance of the time dummy variables was overwhelmingly significant. As expected, we found a positive and significant coefficient on the day before (U.S.) Thanksgiving (0.130 $p = 0.000$), Thanksgiving (0.148 $p = 0.000$), and the day after Thanksgiving ("Black Friday") 0.1397 $p = 0.000$). The size of the coefficient decreased immediately after this period.

Table 3 Determinants of net entry: error correction model estimates

	(1)	(2)†	(3)†	(4)†
Intercept	0.0382024	0.0187598	0.0170467	0.0164745
	(0.007577)***	(0.0064626)***	(0.0065297)***	(0.0064882)**
ΔPC_{it-1}	0.3400177	0.7469086	0.7461898	0.5865962
	(0.058211)***	(0.0670335)***	(0.0670881)***	(0.0650681)***
ΔL	0.0034599	0.0034121	0.0033183	0.0030192
	(0.0010898)***	(0.0008637)***	(0.000863)***	(0.0008547)***
N_{it-1}	−0.0331096	−0.0316156	−0.0318015	−0.0394207
	(0.002833)***	(0.0024785)***	(0.0024821)***	(0.0026784)
N_{it-1}∗Increasing				−0.0014724
				(0.0009607)
N_{it-1}∗Decreasing				0.0261805
				(0.0009679)***
PC_{it-1}	0.0207135	0.0468176	0.0466467	0.0493778
	(0.0067747)***	(0.0077073)***	(0.0077107)***	(0.0075999)**
L_{it-1}	0.0058809	0.0057719	0.0055886	0.0048533
	(0.0010633)***	(0.000901)***	(0.0009078)***	(0.000901)***
Amazon_Entry		−0.0159369		
		(0.0065437)**		
Amazon_Exit		0.0188012		
		(0.0072581)***		
Amazon_Presence			−0.0409229	−0.0413651
			(0.0113488)***	(0.0025648)***
Ultra-compact	−0.004558	−0.0057371	−0.0058879	−0.0053593
	(0.0024526)*	(0.002917)*	(0.00291)*	(0.0028698)*
SLR	−0.0020898	−0.0014446	−0.0015106	−0.0001085
	(0.0028826)	(0.003156)	(0.0031495)	(0.0031107)
SLR-type	−0.0017246	−0.0007481	−0.000172	0.0005112
	(0.003593)	(0.0036013)	(0.0035779)	(0.003535)
Time dummies	Yes	Yes	Yes	Yes
F test	26.26	32.81	35.54	54.45
[*p* value]	[0.000]	[0.000]	[0.0000]	[0.0000]
No. of observations	26,357	26,357	26,357	26,357

Robust standard errors are given in parentheses below the estimated coefficients: *** $p<0.01$; ** $p<0.05$; * $p<0.1$. † Indicates that the number of sellers *excludes Amazon* and *Amazon Mall*

As a robustness check, the model was re-estimated using the minimum price to construct the unit profit measure and again under alternative assumptions about marginal cost as a fraction of MRSP. The results were not materially affected. Of course, an omitted source of PC variation using our approach will be within-period reductions, if any, in the wholesale price to sellers. However, the relatively short duration of our investigation, coupled with the brief life cycle of camera models, should keep this to a minimum.

It is well-established that early-mover advantages have been found to be surprisingly persistent in electronic markets. Initial market leaders typically enjoy a price premium and/or enjoy a disproportionate share of sales (Waldfogel and Chen 2006; Clay et al. 2001). It was conjectured that the presence of such a market leader would discourage participation by other sellers, either because the leader takes a disproportionate share of the price insensitive consumers or because of a leader-follower effect in which the lesser brands perceive a lower residual demand. The raw data were consistent with an *Amazon* entry deterrence effect, with mean market membership significantly lower—by 1.45 participants ($z = 14.76$).

To investigate the entry-deterrence effect of the market leader, separate *Amazon* entry/exit dummies were created where *Amazon* entered/exited between $t-2$ and $t-1$ and, alternatively, an *Amazon* presence dummy was defined for markets with *Amazon* present at $t-1$. The error correction model was then re-estimated after removing *Amazon* (and *Amazon Mall*) from the seller count to avoid drawing tautological inferences. (This does mean that net entry is being assessed across a smaller set of sellers and ones that are on average considerably smaller/lower reputation.) It can be seen in Column (2) that the entry (exit) of *Amazon* has a significant negative (positive) impact on the number of non-*Amazon* participants.

The specification with an *Amazon* presence variable confirms the significant negative effect, with the market leader's displacing non-*Amazon* participants. This is indicative of a modest strategic entry barrier, although the consequences may be greater, given smaller/low reputation sellers' lower prices. Omitting *Amazon* (and *Amazon Mall)* from the seller count substantially increases the size of the PC coefficients. This suggests that smaller/low reputation retailers are more price sensitive in their entry/exit behavior than is the market leader. Taken together with the entry deterrence effect, this result is suggestive of a bifurcation of market participants into one or more dominant players and a competitive fringe, with the latter acting as Kirznerian entrepreneurs.

It was noted above that inactive sellers at a PCS, unlike their counterparts in traditional markets, do not appear to face explicit costs of continuing market membership, although posting an uncompetitive price may generate reputation damage. In consequence of this lack of explicit costs, it was conjectured that the incentive to exit from the PCS may be smaller, which gives rise to an asymmetry in adjustment. Column (4) reports the results of re-estimating the model with additional interaction terms that distinguish increasing and decreasing numbers of participants. The positive additive effect for N_{it-1}***Decreasing** in Column (4) is consistent with an asymmetric adjustment that involves slower exit than entry, as hypothesized.

Finally, we split the sample into SLR and all-other format subsamples and re-estimated the baseline model. An F test across the two estimations did not support a conjecture of there being significant differences in net entry behavior between the two submarkets.

5 Further Analysis: The Determinants of Exit and Re-entry

The preceding analysis reported that ultra-low sunk costs in a PCS have substantially reduced the frictions that are associated with market participation, which has encouraged rapid net entry flows in response to profit opportunities. Two factors suggested that this was an incomplete story: First was the asymmetry between entry and exit at a PCS, given that posting an uncompetitive price appears to generate no *explicit* costs; and second was the continuing role of seller size/reputation. In a traditional setting, resource differences among firms create unequal opportunities, which determine their order of entry/exit to and from different markets (Waterson 1981; Cotterill and Haller 1992). In consequence, we investigated the *seller level* determinants of movement in and out of PCS markets.

At the seller level it is easier to examine exits than entry decisions since the set of,potential exiters at time t + 1 is unambiguously defined by the incumbents at t, while the set of potential entrants is difficult to determine. We first investigate the determinants of the incumbent's response to entry, using multinomial and ordered logit analysis. However, recognizing that the exit decision is frequently short-lived—therefore that temporary withdrawal might itself be part of the response to a rival's entry—we then investigate the *re-entry* decision for those sellers that have recently terminated their listing of product j at the PCS.

5.1 Incumbent Response to Entry: Ignore, Fight or Flight?

Incumbent sellers that experience a changed environment as a consequence of the entry of a newcomer may react in one of at least three ways: first, do nothing (**no response**); second, remain listed but **reduce price**; or third, **exit** the PCS, at least temporarily, in accordance with the basic net entry model. The previous analysis has suggested that this response is conditioned by seller-specific characteristics as well as market and product factors. That is:

$$p[Response_h] = f(M_{it}, S_{jt}, X_i) \tag{3}$$

for $h = 1, \ldots, 3$ responses, where M_{it} is a vector of market characteristics; and S_{jt} and X_i are vectors of seller and product characteristics, respectively.

We conjecture that since high reputation sellers are more likely to post a premium price, ceteris paribus these face a lower threat from entry—itself more likely from low reputation rivals – than those who compete primarily on price. Therefore high reputation sellers are less likely to respond by either **exit** or, especially, a **price cut**. Reputation is a complex phenomenon, but in electronic markets it clearly relates to the buyer's confidence in the seller delivering as required. Since both user-feedback ranking and overall visibility of the retailer are likely to affect reputation, we include **seller stars**[25] and **large** size (as proxied by *Dealerscope 100* membership) as elements of the S vector.

Sellers vary with respect to the extent of their use of the PCS and it is conjectured that some economies of scope benefits, in terms of lower costs of adjusting/posting offers, accrue to more intensive users. **Products**, a count of the number of models

[25] *NexTag.com* encourages user feedback on seller performance. The results are then aggregated to provide a score on a zero-to-five star scale, using half-star gradations.

that each seller listed on *NexTag.com* at the start of our data collection, is included to capture any such effect, with the expectation that by lowering adjustment costs it has a positive impact on the probabilities of exit and price cutting.

Market characteristics included were the log of the number of leads in the prior month (**leads**) and the price-cost ratio (**PC**). Following the net entry model it was anticipated that challenged incumbents will be more reluctant to exit high-demand markets and hence more inclined to adopt a defensive lower-price strategy. Therefore the **leads** variable was expected to reduce **exit** but increase the probability of a **price-cut** response to entry. Similarly, the probability of **exit** was expected to fall with unit profit while the same variable indicated the scope for price cutting. Finally, it was expected that entry by market leader *Amazon.com* (**Amazon**) would stimulate **exit** but—since it was unlikely to be undercutting existing prices—generate no significant price cutting.

Equation (3) was first estimated as a multinomial logit model, treating **price cut** and **exit** as alternatives to **no response**, and then as an ordered logit in which **exit** was considered a more drastic alternative to **price** cut. Equation (3) was first estimated across the entire sample and then re-estimated separately for non-SLR and SLR formats. Finally, it was noted that seller-level estimation that used electronically collected data was potentially vulnerable to outlier problems. Accordingly, we re-estimated the models after winsorizing the first and last percentiles.

The marginal effects from the multinomial logit regression are reported in Table 4. The full sample and both the subsamples yielded very similar sets of coefficients, but since a likelihood ratio test supported heterogeneous behavior, we report the latter.[26] The seller-level analysis confirms the role for expected profitability, with each of the coefficients statistically significant in the expected direction. Both **leads** and **PC** reduce the probability of exit whilst increasing the likelihood of a price cut. More intensive users of the PCS were more likely to respond to entry, either by exit or a price cut. The presence of *Amazon.com* increased the likelihood of incumbent exit but did not appear to affect the probability of a price response.

Turning to the variables of interest, we find that seller size and reputation are major determinants of the response to entry. Large incumbents are very much less likely to cut prices or, especially, to exit in response to entry. Reputation (**seller stars)** strongly affects the exit decision, but not the price-cut decision. That is, sellers with a high reputation that is specific to the PCS are less likely to exit, but neither more nor less likely to lower prices in response to entry. The highly significant positive coefficient on **products**, for both responses, confirms our conjecture that the more intensive users of the PCS are more likely to react, consistent with their having lower adjustment costs. These results are largely confirmed when using an ordered logit model as reported in Table 5.[27]

Separate estimation of the model by format submarket suggested very minor behavioral differences: A higher price ratio decreased the probability of exit in the face of new entry for both groups; but while non-SLRs experienced a corresponding rise in

[26] The full sample results are available from the authors.

[27] Winsorizing the data left the results materially unaffected.

Table 4 Response to entry: multinomial logit estimates

	Compact, ultra-compact and SLR-type cameras			SLR cameras		
	(1) No response	(2) Price cut	(3) Exit	(1) No response	(2) Price cut	(3) Exit
PC	0.0342164	0.0034804	−0.0376966	0.0029966	0.0215122	−0.0245086
	(0.0028339)***	(0.0016415)**	(0.0024051)***	(0.0047234)	(0.0030268)***	(0.0037849)***
Leads	−0.0039226	0.0068821	−0.0029595	−0.0060291	0.0095536	−0.0035244
	(0.0007054)***	(0.0004636)***	(0.0005608)***	(0.0016518)***	(0.0010878)***	(0.0013051)***
Amazon	−0.0508827	−0.0051141	0.0559968	−0.0292107	0.007126	0.0220847
	(0.0035926)***	(0.001956)**	(0.0032499)***	(0.0112221)***	(0.0072597)	(0.0092824)**
Large	0.040635	−0.0122649	−0.02837	0.0509616	−0.0191694	−0.0317922
	(0.0018992)***	(0.0012835)***	(0.0015471)***	(0.0040899)***	(0.00283)***	(0.0031925)***
Seller stars	0.0277367	0.0018604	−0.0295969	0.0307389	−0.0017469	−0.0289918
	(0.0007882)***	(0.0005191)***	(0.0006305)***	(0.0017878)***	(0.0011499)	(0.0014362)***
Products	−0.0002217	0.0001372	0.0000845	−0.0001347	0.0001227	0.0000119
	(0.0000046)***	(0.0000032)***	(0.0000035)***	(0.0000103)***	(0.0000075)***	(0.0000074)
Ultra-compact	0.0028334	0.0006816	−0.0035151			
	(0.001762)	(0.0011339)	(0.001421)**			
SLR-type	0.0012183	−0.0028396	0.0016213			
	(0.00245)	(0.0014887)*	(0.0020394)			
Wald-test	6232.63	6232.63	6232.63	957.40	957.40	957.40
[*p* value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
No. of obs.	158,101	158,101	158,101	31,387	31,387	31,387

Robust standard errors are given in parentheses below the estimated coefficients: *** $p<0.01$; ** $p<0.05$; * $p<0.1$

Table 5 Response to entry: ordered logit estimates

	Compact, ultra-compact and SLR-type cameras			SLR cameras		
	(1) No response	(2) Price cut	(3) Exit	(1) No response	(2) Price cut	(3) Exit
PC	0.0355016	−0.0117594	−0.0237421	0.0064117	−0.0024334	−0.0039783
	(0.0028111)***	(0.0009288)***	(0.0018936)***	(0.0046858)	(0.0017717)***	(0.0029153)
Leads	−0.0028677	0.0009499	0.0019178	−0.0050136	0.0019028	0.0031108
	(0.0006999)***	(0.0002329)***	(0.0004673)***	(0.0016254)***	(0.000623)***	(0.0010045)***
Amazon	−0.0549302	0.0173988	0.0375314	−0.0294155	0.0108998	0.0185156
	(0.0037075)***	(0.001122)***	(0.0026062)***	(0.0112022)***	(0.0040539)***	(0.0071592)***
Large	0.0443984	−0.0146035	−0.0297948	0.0546985	−0.0207386	−0.0339599
	(0.0019623)***	(0.0006531)**	(0.0013341)***	(0.0042772)***	(0.0016643)**	(0.0027077)***
Seller stars	0.0324484	−0.0107481	−0.0217002	0.0348421	−0.0132233	−0.0216187
	(0.0008053)***	(0.0002662)***	(0.0005712)***	(0.0018674)***	(0.0007086)***	(0.0012468)***
Products	−0.0002233	0.000074	0.0001494	−0.0001457	0.0000553	0.0000904
	(0.0000044)***	(0.0000017)***	(0.0000030)***	(0.0000101)***	(0.0000042)***	(0.0000062)***
Ultra-compact	0.0030631	−0.0010148	−0.0020483			
	(0.0017562)*	(0.0005819)*	(0.0011745)*			
SLR-type	0.001488	−0.0004922	−0.0009958			
	(0.0024398)	(0.0008077)	(0.0016321)			
Wald-test	4349.73	4349.73	4349.73	545.14	545.14	545.14
[*p* value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
No. of obs.	158,101	158,101	158,101	31,387	31,387	31,387

Robust standard errors are given in parentheses below the estimated coefficients: *** $p<0.01$; ** $p<0.05$; * $p<0.1$

the probability of a doing nothing and/or lowering price, in the SLR segment the PC effect was significant for price cutting alone. The impact of Amazon was generally larger outside the SLR set

The results have some similarities to those of Igami (2011) study of Japanese supermarkets, which finds that large entrants affect large incumbents while leaving small rivals at worst unaffected. However, whereas the supermarket industry exhibits product differentiation in the service available—full shop versus convenience—sellers at a PCS offer the same goods but are differentiated by reputation. The restricted effect of entry on price also mirrors Stranger and Greenstein (2008) findings on the early ISP market, where established incumbents were able to enjoy a price premium over their new challengers.

5.2 Determinants of Re-entry

The raw data indicated that although sellers frequently withdrew their products from listing following a rival's entry, they were quite likely to re-list the same model after a relatively short interval: 64 % re-entered within one week of exit. At a PCS, unlike a bricks-and-mortar retail market, short-term exit carries no obvious costs. To investigate this further, we set out to determine how far this reversal of the entry decision reflected some change in market circumstances and whether it varied according to seller reputation and size.[28] Hence, we estimated the following logit model of re-entry:

$$p[Re\text{-}entry_{jit}] = f(\Delta Sellers_{it}, \Delta PC_{it}, \Delta Leads_{it}, Amazon_t, S_{jt}, X_i), \quad (4)$$

where *Re-entry* is equal to one if the seller decides to re-enter within seven days of exiting the PCS. **Sellers**, **PC** and **Leads** are as defined before, with Δ**PC** being the difference between the exit and day-prior-to-re-entry values for re-entries and day 7 values for the rest. Δ**Leads** is the difference between Leads prior to exit and its subsequent value. **Amazon** is a dummy variable that is equal to one if *Amazon* was present at time t; S_{jt} is a vector of seller characteristics, and X_i is a vector of product characteristics.

Table 6 reports the re-entry model estimated across the entire sample[29] and suggests that seller-specific characteristics dominate market factors in the re-entry decision. **Large** and **seller stars** reputation variables each exert a highly significant negative effect on rapid re-entry, while the **products** variable carries a highly significant positive effect. These results reinforce our earlier findings: Short-run visits to the market tend to be associated with smaller and/or low reputation retailers. This suggests that these firms display greater flexibility in pursuit of price-sensitive consumers. Similarly, more intensive users of the PCS, as indicated by product count, make more frequent adjustments.

[28] Some temporary withdrawals no doubt reflect operational considerations such as the temporary exhaustion of inventory or the exhaustion of clicks credit at the PCS.

[29] The coefficient sets for the non-SLR and SLR submarkets showed a similar pattern, but the numerically-dominated SLR coefficients were less precisely estimated and generally insignificant. No Amazon deterrent effect was present in the SLR subset. These results are available from the authors.

Table 6 Determinants of re-entry: logit estimates

Change sellers	−0.0020854
	(0.0083315)
Change PC	0.7033423
	(0.4154896)*
Change leads	0.0773255
	(0.0305957)**
Amazon	−0.1463324
	(0.0424461)***
Seller stars	−0.2013267
	(0.0118287)***
Large	−0.2373626
	(0.0388977)***
Products	0.0031296
	(0.0001381)***
Ultra-compact	0.0043229
	(0.0411815)
SLR	0.1770873
	(0.0550959)***
SLR-type	0.0871398
	(0.0563004)
Wald-test	986.92
[p value]	[0.000]
No. of obs.	14,161

Robust standard errors are given in parentheses below the estimated coefficients: *** $p<0.01$; ** $p<0.05$; * $p<0.1$

The market variables attract the expected signs, but only **leads**, **Amazon**, and (marginally) **PC** are significant.[30] Re-entry is more likely for higher demand models, whilst the presence of *Amazon.com* reduced the likelihood of re-entry. This latter result confirms our findings from the error correction model in which the presence of *Amazon.com* was found to have a modest strategic entry barrier effect.[31]

6 Conclusion

This paper has presented the results of an investigation of entry and exit behavior at a PCS: a platform without the sunk costs that inhibit entry in traditional markets. It was conjectured that ultra-low sunk costs and standardized access would create

[30] The 7-day interval used in this seller-level analysis contrasts with the daily frequency data used to estimate the error correction model. Therefore the weaker impact of the change in the profit margin and seller number variables is not surprising.

[31] Winsorising the data, so as to reduce the impact of outliers, made no material difference to the results. These results are available from the authors.

an arena in which sellers operate as Kirznerian entrepreneurs: entering and leaving in response to arbitrage opportunities. However, in common with sellers on other e-markets, PCS users are still differentiated by reputation. This was expected to create systematic differences in strategic behavior between highly rated/larger retailers and their lowly rated/ unrated/smaller rivals. To investigate this, we used a specially constructed unbalanced panel of 295 camera models that were traded on *NexTag.com* to investigate entry and exit.

We first examined net entry, estimating an error correction model, which followed the literature in assuming that sellers act in response to changes in expected profitability. The error correction model was well-determined with all of the principal change and levels variables and the adjustment coefficient being statistically significant with the anticipated signs. Our analysis confirmed that sellers made forays, often of a short duration, from a reservoir of potential entrants into the PCS market, with such movements acting as an equilibrating force.

The magnitude of the adjustment parameter confirmed our conjecture that the number of participants adjusts much more rapidly to changes in profit opportunities than do the equivalent in bricks and mortars retailing or other traditional markets. However, there appeared to be an asymmetry between inward and outward movement, with more rapid adjustment during expansions than contractions. This probably reflects the absence of explicit costs associated with continuing PCS participation, certainly by comparison with traditional markets.

It was clear that there is considerable seller heterogeneity across the set of potential market participants, particularly with respect to size and reputation. It appeared that large sellers were more likely to enter at or above the prevailing mean price and, having entered, to remain for longer periods. Re-estimating after controls for the presence of the market leader *Amazon.com* indicated a significant negative affect of Amazon on the number of market participants. Since this exceeded the displacement effect it was suggestive of an entry deterrence effect. Furthermore, excluding *Amazon.com* from the data suggested the existence of even more fluid market adjustment among the remaining sellers.

In recognition of the persistence of seller heterogeneity, even at a PCS, the incumbents' exit and re-entry responses to entry were then examined at the seller level. Exit and price-cutting were treated as possible incumbent reactions to entry and alternatives to ignoring the threat and doing nothing at all. In the event, larger sellers and those with a strong user-generated reputation were much less likely to react to entry, particularly to react by exiting the market. However, exit and price adjustment each increased with the seller's intensity of use of the PCS, which is consistent with economies of scope that reduce adjustment costs to participants.

Our findings at the seller level confirmed the conjecture derived from the raw data that larger/high reputation sellers differ from smaller/low reputation sellers in the way that they use a PCS. Not only are the formers' spells in the PCS market of longer duration, but they appear less likely to be ended by a rival's entry. Similarly, these sellers seem less likely to respond to entry with price cuts. These results are consistent with a bifurcation of strategies with smaller/lower reputation sellers' competing more vigorously on price and larger/higher reputation sellers' seeking to harvest a visibility premium.

Noting that many exiters returned to the PCS listing within a relatively short time, the paper finally looked at the determinants of the re-entry decision. Here we found that having once exited the PCS market, higher reputation/larger firms were less likely to make a quick re-entry than were their lower-reputation/smaller counterparts. The more intensive users of the PCS, as indicated by their count of listed models were, unsurprisingly, more likely to relist within one week.

Overall our results are supportive of the traditional view of entry/exit as an arbitrage mechanism. The absence of sunk cost frictions accelerates the net flow of sellers between the PCS and the pool of potential entrants. It is clear that within the entry flows there are sellers that employ systematic differences in strategy. There appears to be more rapid inward and outward movement among low reputation/smaller sellers, who compete primarily on price, than among their high reputation/larger rivals. Further research is needed to determine how far the former's low-price short-stay forays correspond to the hit-and-run entry mechanism that has been conceived by contestability theory. Not least in determining the success of these short-stay visitors is the capture of a significant share of sales.

Acknowledgments The authors would like to thank two anonymous referees and particularly Larry White for his encouragement and many helpful suggestions over several drafts of this paper. We are also indebted to Victor Porcar for programming assistance and Sourafel Girma, Tim Lloyd, Paul Simpson, Peter Wright, seminar participants at Sheffield and Nottingham universities, and delegates at the Istanbul EARIE Conference 2010, especially Jose Matta, for helpful comments on this research.

Appendix

See Fig. 2.

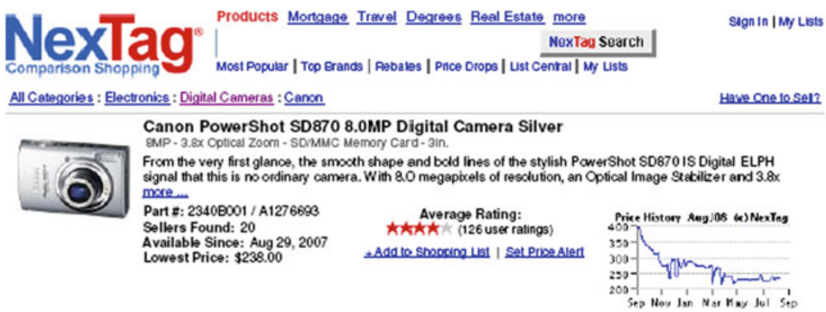

Fig. 2 Nextag screen output

Compare Prices | Write Product Review | Price History

Zip: 03104 change

Seller	Seller Ratings	Description	Price	+Tax & Shipping	TruePrice
ABE'S OF MAINE Since 1979	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.com	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
PC Connection	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 USCAMERA.COM	★★★★ 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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Fig. 2 continued

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