# Hit-and-Run or Sit and Wait? Contestability Revisited in a Price Comparison Site Mediated Market

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*The authors would like to acknowledge the considerable assistance of Eleanor Morgan, editor of the *Journal*, and two anonymous referees in revising this paper. Many helpful comments on the paper were also provided by Pascuale Schiraldi and other participants at the ZEW Digital Economy Conference, Mannheim, Germany, October 2011 and the IOS Conference in Boston, Massachusetts, May 2013, especially Felipe Zurita

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**Abstract**

*The price comparison site, with its (near-) zero sunk costs of entry, would appear to approximate the 'almost perfectly contestable market' envisaged by the contestability theorists where 'hit-and-run' entry was conjectured to constrain sellers to zero profit outcomes. We investigate hit-and-run using a unique unbalanced panel of 295 digital camera markets mediated by NexTag.com. We find, however, in line with Farrell (1986)'s prediction, a bifurcation of strategies with low reputation/smaller participants favoring a hit-and-run strategy involving lower entry prices and shorter forays into the market than their high reputation/larger rivals. Furthermore, the former entrants induce a much larger price response from low reputation incumbents reflecting the more intense rivalry for the price-sensitive consumers willing to eschew retailer reputations.*

JEL codes: D4; L1

Key Words: Internet; Contestability; Entry

## I. Introduction

This paper revisits the phenomenon of 'hit-and-run' entry using data from a price comparison site, a setting in which there are (almost) no sunk costs of market entry facilitating ultra-short stay visits [Baye et al (2007)]. Contestability theory [Baumol *et al*. (1982)] postulated that hit-and-run entry was a disciplinary mechanism that would generate competitive market outcomes irrespective of observed market structures. The theory suggested that potential entrants facing no sunk costs of entry and enjoying resource access on equal terms to those of incumbents had an incentive to make temporary visits to markets to undercut profit-earning incumbents, provided the latter were constrained by some positive response lag. It followed that any supra-normal profit industry configuration is unsustainable. Since the mere *threat* of entry is sufficient to generate this outcome, the extensive literature generated by contestability overwhelmingly ignored hit-and-run as a phenomenon, concentrating instead on the robustness of the theory and the testing of its prediction of the irrelevance of actual market structure in low sunk cost markets.[1]

In this paper we suggest that e-commerce, especially the development of the price and product comparison site (PCS), has created conditions that appear to resemble an 'almost perfectly contestable market'[2] more closely than any previously observed elsewhere. However, it is noted that electronic trades are 'experience goods' in the sense that a satisfactory buyer outcome is not assured, with the moral hazard threat from egregious traders creating a reputational barrier to entry, even in the absence of conventional sunk costs. (This is consistent with the widely reported early mover advantages in price and/or market share enjoyed by trusted –i.e. high reputation - e-sellers [Clay *et al*. (2001), Waldfogel and Chen (2006)].) Farrell (1986a) augments the assumptions of the contestability model with reputational heterogeneity. Thus amended, his model overturns contestability's competitive equilibrium outcome and generates a bifurcation of seller strategies, with low-reputation sellers competing for price-sensitive consumers while high-reputation sellers enjoy larger margins from serving the more risk-averse buyers. This, he suggested would generate hit-and-run behaviour among the former sellers with the latter opting for a stable high-price incumbency.

The paper uses a specially-constructed unbalanced panel of daily observations on 295 digital camera models listed on *NexTag,com* over a 134-day period. It finds that seller behaviour apparently resembling hit-and-run is commonplace. However, in line with Farrell's critique of contestability, it appears that seller reputation is a key determinant of both the entry strategy followed and the incumbents' response to entry. The results are suggestive of a clear bifurcation of strategies in line with the Farrell (1986a) predictions. Low-reputation/small sellers opt for transient cut-price visits - behaviour resembling hit-and-run entry - while high-reputation/larger entrants both remain longer and set higher prices. Our exploration of the incumbent price response to entry reinforces this. Incumbents respond to discounted entry with price cuts, but only to entry within their own reputation status group. Similarly, they react to premium price entry with price increases, again only within their own status group. In each case the magnitude of the response is considerably greater for the low-reputation group.

Our results contribute to several strands in the literature. First, they document the existence of an approximation to the hit-and-run phenomenon in an ultra-low sunk cost environment; although as predicted by Farrell and not the contestability theorists, this occurs in merely a segment of the market. Second, more generally, they contribute to the entry literature, particularly that part exploring the impact of new entry on price [Frank and Salkever (1997), Simon (2005), McCann and Vroom (2010)], by examining entry in the absence of almost all of the usual market frictions. Finally, our results also add to the rapidly growing literature on e-markets. Much of that work seeks to explore price and price dispersion [Haynes and Thompson (2008), Ellison and Snyder (2013) and references therein]. By contrast, the role of e-markets in lowering entry costs has been largely ignored. Our results help to reconcile two apparently contradictory stylized facts to emerge from research on e-commerce in general and PCS markets in particular: namely that while reputation commands a significant price premium [Waldfogel and Chen (2006) and references therein] the observed elasticity of demand in such markets is extremely high by comparison with traditional markets [Baye *et al*. (2009), Ellison and Ellison (2009) etc.].

The paper is organized as follows: Section 2 examines the institutional arrangements in a PCS against the theoretical background of a contestable market. Section 3 describes the data collection and sample generation processes it employed and presents some sample characteristics. In Section 4 we present the empirical results of our investigations of *run* and *hit* respectively. First, is a duration analysis for market entry across the panel; and second is an investigation of the price impact of such entry. A conclusion follows.

## II. Entry at a PCS Market: Institutional and Theoretical Background

### PCS Market Characteristics

Price comparison sites such as *NexTag.com* are two-sided markets to which consumers are drawn by the provision of product and seller data and sellers are attracted by access to potential consumers. While there are variants to the PCS business model[3], platforms such as *NexTag.com* offer sellers a free listing and access to enabling software. In exchange, each seller pays a fee-per-click through to their own web site, irrespective of whether a sale is subsequently concluded. The minimum fee, currently 50c to $1, usually varies between product categories in approximate proportion to their average price, and may be unilaterally raised by the PCS in periods of high demand such as the Christmas season. Since the fee is only incurred after a click through, there is in principle no sunk cost associated with entry.

The PCS as gatekeeper may refuse a seller admission; either because of congestion or the latter's poor record in satisfying buyers. Listed sellers are displayed in a uniform format which includes their logo, if any, but is otherwise restricted to informative material; as shown in the screenshot in Figure A1 in Appendix A. The PCS also determines the default ranking of sellers for consumers searching by product, with sellers bidding above the minimum fee being rewarded with a higher rank. Pre-emptive bids are not accepted so a high ranking is always potentially vulnerable to new bidders[4]. Ranking is important since traffic to seller sites declines with position, probably quite sharply[5]. *NexTag.com* reinforces this by providing direct links to the three highest-ranked sellers on its product pages.

Clicks through to the seller's site are not, of course, equivalent to sales. The average PCS conversion rate has been variously estimated at between 50% [Brynjolffson *et al*. (2004) p6] and three to five per cent [Baye *et al*. (2009) p2]. It is unclear whether this varies with price or positional ranking; although traffic generated by advertising on general search engines, probably lowers the merchant's conversion rate[6].

It might be expected that e-retailing, by lowering search costs, would reduce prices and shrink price distributions. However, empirical research from Brynjolffson and Smith (2000) onwards suggested that observed price distributions in e-markets were comparable to those found among traditional bricks and mortar sellers. This was consistent with sellers using randomized pricing strategies, following the classic free-entry models of Varian (1980) and Rosenthal (1980), to exploit uninformed/loyal consumers and thereby avoid Bertrand competition. Unfortunately, these insider-outsider models also generate the prediction that prices *rise* with the number of sellers. By contrast, the empirical evidence is strongly suggestive of a *negative* correlation between number of sellers ($n$) and average price[7].

A second driver of price dispersion is reputation. Uncertainty attaching to payment and delivery, turns otherwise homogeneous products into experience goods, in the sense of Nelson (1970). Farrell (1986a) demonstrated that among sellers of experience goods the provision of a poor quality experience may be the optimal strategy for some market newcomers who lack an established reputation; not least because e-commerce offers considerable scope for seller misrepresentation [Ellison and Ellison (2009)]. Some consumers, in anticipation of such behavior, will rationally shun low-price entrants in favor of higher priced established sellers[8]. Thus the threat of moral hazard behaviour by egregious sellers creates a premium for reputation and a *de facto* barrier to entry. Seller reputation is found to command a price premium in empirical studies [e.g. Clay *et al*. (2001)]. Waldfogel and Chen (2006) suggest this should decline as consumers gain familiarity with Internet shopping, but they in turn report its persistence.

Recent evidence [e.g. Ghose and Yao (2007), Ellison and Ellison (2009)] suggests that consumer behaviour at e-markets, especially PCS-enabled ones, may be considerably more price sensitive than has been inferred from their (posted) price distributions. Baye *et al*. (2009) find that in an illustrative 10-seller market the lowest-priced seller secures an average 45% of the clicks through and the lowest three take 79%. They also report a price elasticity of -3 for sellers outside the lowest three, rising to -9 if a price hike costs the seller the lowest price position. Dulleck *et al*. (2008) find that 69% of offerings, overwhelmingly those with high relative prices, receive no weekly clicks at all. These findings suggest that the received wisdom about e-markets' price distributions may require some modification: First, the distribution *weighted by sales* may be very different to the *posted* price distribution and will probably display less dispersion. Second, they suggest that a low-price entry strategy may be an effective means of capturing market share from incumbents.

**How Far does a PCS Meet the Assumptions for Contestability?**

Elsewhere Haynes & Thompson (2013) show that rates of entry and exit at a PCS market are overwhelmingly greater than at a traditional bricks and mortar retail context. They estimate an error correction model which confirms that net entry flows are sensitive to market opportunities, to a far greater degree than would be expected in a conventional entry setting where sunk costs generate sluggish reactions. Building on from these findings, the present paper explores whether the (near) complete absence of sunk costs is sufficient to allow hit-and-run entry to act as a disciplinary device as the contestability theorists postulated.

Following Baumol *et al*. (1982) the requirements for a perfectly contestable market may be summarized briefly:

1. There are no sunk costs associated with entry or exit. (*No Sunk Costs*)
2. Incumbents can respond to entry but only after a lag, such that hit-and-run entrants can exit with their profits intact. (*Incumbent's Response Lag*)
3. All current and potential market participants have access to the same technology/resource. (*Same Resources*)

These assumptions have proved unrealistic when compared to entry conditions in conventional markets – see Geroski (1995) – but might appear to be a closer approximation to the conditions obtaining at a PCS platform such as *NexTag.com*:

*No Sunk Costs* The initial decision to list at a PCS requires an upfront deposit, currently \$150-\$200 at most shopbots. This is subsequently exhausted by incurring the specified fee for clicks. There is no fee for adding additional products; larger sellers many offer hundreds of separate products via each shopbot. The entrant's only explicit cost is the click-through fee. Since the conversion rate, as noted above, is well below unity, some sunk element is introduced. However, as the fee is small, both absolutely and in relation to price, and entry can be reversed at any time without additional expenditure, the explicit sunk costs of entering a particular product market appear unlikely to be much above the trivial.

Sellers using a PCS clearly incur learning costs, particularly in preparing the "product feed" or input file. However, these costs should not be replicated when the retailer offers additional products or re-enters following a temporary exit. Most sellers in our sample offer multiple products and make frequent reversals of entry/exit decisions.

*Incumbent's Response Lag.* It seems likely that PCS participants, able to keep rivals' prices under continuous observation, can respond much more quickly to entry than incumbents in traditional markets[9]; although *NexTag.com* suggests uploading may take up to 24 hours for amended offers and up to 48 hours for new listings. Moreover, since click data by product is normally issued to listing sellers on a daily basis, there may be some delay in incumbents gauging the effect of entry and determining an appropriate response. We take this to constitute a response lag in the sense of Baumol *et al*. (1982).

*Same Resources.* The standardized listing format ensures that all participating sellers present a similar display to potential buyers. Each seller is provided with the software required to monitor and amend their offerings[10]. Listing merely requires the seller's possession of a widely available, low-cost[11] selling technology. Of course, established sellers may have a variety of underlying supply side advantages, including perhaps superior logistics, bulk discounts and - in the case of authorized dealers - earlier access to new models, but in principle newcomers can sell a homogeneous product in an identical way. Sellers are distinguished by display position but, as noted above, this depends primarily on the seller's bid.

An implication of the contestability assumptions is that entry is *total* in that the entrant's output can completely – even if temporarily - replace that of the incumbent. This is highly unrealistic in most industries where newcomers are typically much smaller than incumbents [Geroski (1995)], reflecting the costs and time involved in making capital investments [Cairns and Mahabir (1988)]. At a PCS there are no such constraints. As indicated above, the limited available evidence suggests that the lowest priced seller does capture a disproportionate share of sales.

Therefore it is conjectured that the key source of seller heterogeneity is reputation. If the role of reputation is sufficiently diminished by PCS intermediation, then entrants will represent a total threat to incumbents and hit-and-run entry will affect all market participants. However, where incumbents retain a reputational advantage with at least some potential consumers, hit-and-run entry will have a restricted effect. In particular, following Farrell (1986a), it is conjectured that the market will be segmented with hit-and-run entry effective in the low-price segment, where consumers are either less risk-averse or otherwise more price-sensitive, and largely ineffective in the retailer brand-dominated higher price segment.

Finally, it should be noted that exit might be considered a puzzle in a market where there are apparently no costs to remaining. Unless inventory is exhausted – in which case exit is required to forestall costly unanswerable clicks through - why leave if there is any non-zero probability of a sale? While this paper is exploring hit-and-run behaviour, the literature considers numerous strategic pricing considerations – see Baye et al (2007) – some of which suggest at least partial explanations:

First, sellers multi-home across platforms but normally post a single price; meaning that a seller undercut in market A may prefer to withdraw rather than cut price to market B as well. Second, posting a non-competitive price may deliver reputational damage for avowed low-price retailers. Third, Baye et al (2007) point to the danger of e-retailers being "stuck-in-the-middle", where they neither enjoy the sales volume of the cheapest nor the margins of those selling only to their most loyal customers. Fourth, early withdrawal by price cutters may forestall incumbent retaliation with the accompanying threat to everyone's margins. Lastly, e-retailers suffer if their prices are predictable - and hence easily undercut - by rivals. Frequent entry and exit enhance uncertainty and make behaviour less predictable .

## Sample and Data

*NexTag.com* is a typical general merchandise PCS being particularly strong in high value-to-weight products such as consumer electronics. The digital camera was selected as the product for analysis; since its purchase is typically a discrete event, thus avoiding any multiple purchase discounts that impact, say, book buying. *NexTag* provides buyers and sellers with daily updated data on the pre- and post-tax prices of listing sellers, delivered prices, feedback on seller reputation and limited information on model characteristics for each camera listed. Unless an alternative is specified by the user, the default ranking of sellers is determined by the PCS, as illustrated in Appendix A. Additional information available includes a diagram of the product's price history and a histogram showing the number of leads – or clicks through to seller – on a monthly basis for a period up to 17 months.

A Java program was written to extract data from the *NexTag.com* screen display. The program was run daily[12] (at 2.00am EST) between November 19th 2007 and March 31st 2008, an interval chosen to include the Xmas season. A separate program was used to extract data on the level of leads or clicks through, which were available on a monthly basis. The target sample was updated weekly to allow for the entry of new models, each identified by its unique product code (upc)[13]. Excluded were pre-2006 models, assumed to be discontinued, cameras bundled with complementary products and models posting prices below $50 to reduce the likelihood of including refurbished or misreported items. Further exclusions for the non-availability of leads data and thin markets, here defined as cases where the number of leads never reached 100 per month, reduced the final sample to 295 models[14].

In addition, information was collected on the month and year in which the camera was introduced to the market and the format group to which it belonged (compact, ultra-compact, SLR or SLR-type). PCS data are sometimes contaminated by different treatments of taxes and shipping. However, *NexTag.com* provides both net and post-sales tax prices and the price inclusive of shipping costs[15]. We used the net price in a zero tax state in our analysis[16].

Scrutiny of the raw data immediately confirms two of our prior conjectures on PCSs: first, these markets are used, at least intermittently, by large numbers of sellers; and second, PCSs exhibit very high rates of entry and exit. These findings are considered in turn:

The data confirmed the general accessibility of PCSs to sellers. In total 161 different sellers participated in the 295 sample *NexTag.com* camera model markets over a maximum of a 134 day interval of scrutiny. The average individual market on any day listed 16 sellers, with a mean of 71 separate sellers participating daily across all model markets in the sample. This is consistent with the existence of a substantial reservoir of potential entrants ready to join as opportunities arise. Sellers ranged from large general and/or on-line retailers such as *Amazon.com*, who participated in 95% of the sample markets at some stage, to the 37 sellers who participated in five markets or less during the period investigated.

Entrants (including re-entrants) averaged 188 per day and exits[17] averaged 176 per day. Given an average of 16 sellers per market, this is equivalent to 27% leaving and being replaced each week[18], a far higher rate of churn than observed in conventional markets.

The average duration of completed spells is 8.68 days and the median is 4 days. The Kaplan-Meier function showing the proportion of surviving entries is given in Figure 1 and exhibits substantial early attrition.

**[Insert Figure 1 here]**

When entry duration was compared by size or by reputation it was apparent that larger/high-reputation entrants remained in the market for longer than their smaller and/or low-reputation rivals. For example, denoting as “large” those retailers which figured in the *Dealerscope* leading 100 US electronics goods sellers for 2007 and as “small” those that did not, it appeared that smaller retailers had a mean stay of 7 continuous days (median 3), while large sellers averaged 11 continuous days stay (median 5). Examining duration length by seller reputation produces a similar result. Reputation, of course, is a multidimensional concept reflecting consumers’ past experience of - and anticipated future interactions with - the seller. Here we measure seller reputation by the number of seller stars listed in the user-generated feedback displayed for consumers on *Nextag*.com. A seller possessing a “high” reputation was defined as one who was awarded four or more stars, while “low” reputation was defined by less than four stars. High-reputation sellers stayed on average for 11 continuous days (median 6), while low-reputation sellers averaged 6 continuous days (median 3).

Plotting the Kaplan-Maier survival functions confirms the more rapid exit among smaller and low-reputation entrants, with a log-rank test [p=0.000] rejecting the null hypothesis of a common survivor function in each case. The functions according to reputation are shown for illustrative purposes in Figure 2.

**[Insert Figure 2 here]**

Differences were also apparent in the pricing strategy of different entrants. Subtracting the entrant's price from the mean price of incumbent suppliers present the previous day yields -$7.72 for large entrants (median $3.19) and $38.68 (median $23.18) for their smaller rivals. The mean difference is highly significant [t=-30.772; p=0.0000]. In contrast to their smaller rivals, larger entrants do not appear to offer price discounts over incumbent suppliers. The relevant figures for low- and high-reputation entrants is $38.39 (median $22.65) and $4.74 (median $6.96) respectively. Again, the mean difference is highly significant [t=-22.778; p=0.0000].

A comparison of the duration of market membership confirms that low-priced entrants exit earlier. Discounted retailers stayed on average for 7 continuous days (median 3); while non-discounted sellers averaged 12 continuous days stay (median 5). Figure 3 shows the survival functions by pricing strategy. Once again, a log-rank test [p=0.000] clearly rejects the null hypothesis that the survivor functions of the two groups are the same.

**[Insert Figure 3 here]**

## III. An Empirical Analysis of Hit and Run

### A Duration Analysis of Entry

A hit-and-run strategy is taken to involve entry below the incumbent price followed by subsequent exit upon the incumbent's price response. To explore this we investigate the impact of entry pricing strategy on the exit hazard, having controlled for underlying characteristics such as size and reputation. Specifically, we postulate a conditional probability for new market entrants of the form:

$$p(Exit)_t = f[E, S, M_t, P] \qquad \ldots(1)$$

Where E is a vector of entry characteristics, including the entrant's relative price on entry, S represents seller characteristics capturing reputation and seller size effects; whilst $M_t$ is a vector of time varying market characteristics. Finally, P is a vector of product characteristics, including camera format and age[19].

The entrant vector includes a binary variable **Discount** for entrants pricing below the incumbents' mean price and which are therefore assumed to "hit" the latter. **Relative Price** is the entrant's price relative to the mean price of the remaining sellers in that model's market on that day. Also included is the entrant's time-varying **Position** in the default seller listing in each model's market on each day, the number of **Co-entrants** on the day of entry and a count of the number of **Products** each entrant listed on NexTag.com at the start of our data collection period. Aspects of reputation are captured by the number of seller **Stars** listed in the user-generated feedback displayed by the shopbot at the time of entry and **Authorized** dealer status; whilst **Large** sellers are distinguished by membership of *Dealerscope*'s top 100 electronics retailers. To capture our expectation of greater exit in more congested markets the number of **Sellers** and the (log of) market size (**Lmarket_size**) were included. Following prior research on shopbots (e.g. Baye *et al*, 2004), market size is captured by the number of leads – or clicks through to sellers - relative to the number of sellers. The product characteristics vector included quadratic terms in age since launch (**Age**, **Agesq**), to control for life cycle effects, and binary variables (**SLR, SLR-type, Compact, Ultra-compact**) to denote the four recognized product formats. The summary statistics for the period averages of the continuous variables are given in Table 1.

**[Insert Table 1 here]**

The duration of entry is explored using the Cox proportional hazard model. This model allows a flexible form for the underlying baseline hazard compared to parametric models. It can also easily accommodate right censoring[20] which is a feature in our data. Applying the Cox proportional hazard model, the conditional hazard rate $\lambda_0(t)$ faced by the *j*'th retailer is proportional to the baseline hazard that all retailers face, modified by regressors $x_j$:

$$\lambda(t \mid x_j) = \lambda_0(t)\phi(x_j\beta_j) \qquad \ldots(2)$$

We assume an underlying exponential form [i.e. $\phi(x_j\beta_j)$=exp( $(x_j\beta_j)$ ] and also extend the model to include time-varying regressors. There are two potentially endogenous variables in the regression: discounted entry (**Discount**) and **Relative Price**. As an instrument for the **Discount** variable we use predicted values from a probit regression of discounted entry on seller reputation variables[21], after the approach of Vella and Verbeck (1999)[22], and re-estimate the hazard function using bootstrapped standard errors. Finding a suitable instrument for the **Relative Price** proved intractable so we estimated the model with and without this variable.

The results from the Cox proportional hazard model are reported in Table 2. For ease of interpretation, the hazard ratios are reported rather than the coefficients themselves. Columns (1) and (2) show the results for equation (2) with and without the **Relative Price** variable respectively. Columns (3) and (4) show the results after the **Discount** variable has been instrumented and the reputation variables have been excluded from the regression, again with and without the **Relative Price** variable. It is immediately apparent that **Discount** entrants experience a substantially larger exit rate than non-discounters and that this effect is highly significant (for example, z=12.78 in Column (1))[23]. The estimated effect is even larger for the instrumented results in Columns (3) and (4). This confirms the observation from the raw data that discounters tend to have shorter market tenure than their higher-priced rivals.

Obtaining high e-visibility by out-bidding rivals for ranking position is an obvious substitute for price-cutting as an entry strategy and one that also directly impacts the seller's profit margin. In the event **Position** did raise the hazard, but by a relatively small amount with merely borderline significance.[24] The average number of **Products** also increased the hazard slightly indicating that more intensive users of the price comparison site are more likely to exit early from the market. This could be the result of entry/re-entry costs being lower, given the fee structure of the PCS, for larger/more intensive users. By contrast, bigger and higher reputation entrants display much lower hazard rates. The **Large** entrant, S**eller Stars** and **Authorized** dealer variables, each capturing aspects of reputation, generate hazard ratios well below unity with high levels of significance.

**[Insert Table 2 & 3 about here]**

Turning to the market characteristics, **Relative Price**, attracts a significant positive coefficient indicating many discounters exit even before the market has fully adjusted to their entry. Posting low prices – whether on entry or later - is therefore associated with higher hazard rates among entrants, as might be expected with a hit-and-run approach. Any congestion effects, as captured by **Lmarket_size** and the number of **Sellers** are very small. Among the control variables, the number **o**f **Co-entrants** attracts a negative coefficient, consistent with a common supply side stimulus, while the **Age** variables are completely insignificant. The format variables are also largely insignificant. As shown, the removal of the **Relative Price** variable from the estimating equation and the instrumentation of the **Discount** variable does not materially affect the pattern of results.

In order to assess Farrell's prediction that ultra-low sunk costs coupled with reputational differences will lead to a bifurcation of entry strategies, we constructed an interaction term between the seller star and the discounted entry variables. The results from this estimation are reported in Table 3. As shown, the hazard is significantly higher for low reputation, discounted sellers[25]. While the mean tenure for all entrants to the PCS is relatively short, the entrant's hazard falls with the reputation of the seller, as would be expected where more established retailers enter to cater for brand-loyal consumers.

**Measuring the Hit: Estimating the Price Impact of Entry**

We next explore the price response of incumbents to different entry strategies and differences in the intensity of entry. The observed high rates of entry and exit, coupled with the rapid reactions permitted by e-trading, generate events at a much higher frequency than is observed in studying traditional markets. Observations at intervals longer than a day involve conflating the effects of multiple events. Accordingly we use a simple regression framework to compare mean responses on a daily basis, with the empirical design:

$$\Delta \log P_t^* = a + bE_{t-1} + cX_{t-1} + e_t \qquad \ldots(3)$$

Where $\Delta \log P^*_t$ denotes the change in the log of the mean price of suppliers present at *t-1* and *t*, i.e. excluding that of new entrants at *t-1*. $\Delta \log P_t^*$ is alternatively calculated for all incumbents and for those whose characteristics coincide with and contrast with those of the corresponding entrant. **E** is a vector of characteristics describing the entrants, if any, at *t-1*. **X** denotes exit at *t-1* and *e* is an error term.

Incumbent sellers have three possible reactions to market entry: change price, exit or do nothing[26]. The more the market inclines to full contestability the more we might expect incumbents that wish to retain sales to reduce prices in the face of low-price entry. Moreover, if low prices dominate reputation we might expect this to hold whatever the correspondence between the entrant's reputation and that of the incumbent(s). Conversely, if reputation segments the market, as Farrell (1986a) predicted, we would expect the price effects of entry to be primarily restricted to the relevant market segment. Research on conventional markets also suggests a price cut response to entry is particularly associated with low reputation/new incumbents[27]

It is immediately clear that **entry** lowers the mean price of surviving incumbents, with **multiple entry** having a significant additional effect. Table 4 shows the impact of *any* **entry** at *t-1* on the mean price of the continuing incumbents: i.e. firms other than entrants present at both *t-1* and *t*[28]. It is also apparent that incumbents do not respond uniformly. When incumbents are split, as before, by their star rating, the impact on low-reputation incumbents is approximately six times that of their high-reputation rivals; with a large additional multi-entry effect confined to the former.

If we split the entrants into high and low reputation, the results in Table 5 confirm that entry by low-reputation sellers (**Low_Rep_Entry**) has a substantial and highly significant impact on low-reputation incumbents. By contrast, high-reputation entrants (**High_Rep_Entry**) reduce the price of high reputation incumbents but by a much smaller proportion.

**[Insert Tables 4 and 5 here]**

Table 6 divides entrants into discounters (**Discounted Entry**) and non-discounters (**Non-discounted Entry**), according to their price relative to the average at the time of entry. A discounter is defined as an entrant pricing below the incumbents' mean price. Here an even sharper picture emerges with incumbents reacting to discounted entry with significant price cuts and non-discounted entry with significant price *increases*. Again the negative effects are much stronger for low-reputation sellers, reinforcing the result that competition on price is keener among low-reputation sellers. Table 7 repeats the exercise by e-visibility, splitting the entrants according to whether or not they are placed in the top three places (**Top3 Entry**) in the *NexTag.com* default listing. This confirms that ranking matters, with **Top3** entrants having a much greater impact on *all* incumbents than their lower ranked rivals. Again the effect appears to be much greater for the low-reputation incumbents.

**[Insert Tables 6 and 7 here]**

In Table 8 the high and low reputation and discounted and non-discounted pricing strategies are used to distinguish four categories of entrant, whose separate effects on incumbent prices are reported. It is apparent that **Discounted Entry** has a strong negative effect on incumbents' prices; **Non-discounted Entry** serves as a signal to raise prices. Moreover, while these effects are symmetric across the sample as a whole, they turn out to be confined to incumbents of the same reputation category: for example, discounted entry by low reputation sellers reduces the mean price of other low reputation sellers by almost two percent, whilst leaving the prices of high reputation sellers effectively unchanged. **Discounted Entry** by high reputation sellers similarly reduces incumbent prices only in the high reputation market segment and then to a much smaller extent. Our results may be contrasted with research on traditional markets, where entry by low reputation sellers typically produces a price response which is largely confined to low reputation/new incumbents in, for example, pharmaceuticals [Frank and Salkever (1997)], magazines [Simon (2005)] and hotels [McCann and Vroom (2010) ].

**[Insert Table 8 here]**

Finally, in Table 9 the three pairs of entrant characteristics are combined to yield eight entrant types, whose separate impacts on incumbents are then assessed. The results confirm that the price effects of entry are very largely specific to sellers in the reputation category of the entrant. The effect of the superior electronic exposure enjoyed by the top three serves largely to increase the absolute value of the respective same category coefficients, generally by the equivalent of one to two percentage points. Whether this is indicative of limited search of rivals' prices by sellers or their anticipation of such behaviour by potential buyers cannot be determined. The overall pattern of coefficients is remarkably robust with one exception, namely that high reputation non-discounted entrants exercise a small negative effect on low-reputation sellers. This appears to be a consequence of entry by a single market leader.

**[Insert Table 9 here]**

It is clear that the intra-segment price effects of entry are highly significant if modest in size. Their magnitude should be set against three caveats: first, average profit margins are already comparatively small for sellers using PCS markets, particularly in the low-reputation segment; second, since the price effect relates strictly to *remaining* incumbents it ignores any displacement of higher-priced sellers arising as a consequence of entry; and third, ours is necessarily a short-term analysis and it ignores any dynamic processes affecting pricing.

## Further Experiments with the Data

It has been seen that sellers vary in their entry strategies with some – usually low-reputation and/or smaller sellers - tending to opt for shorter duration spells in the market than others, usually their high-reputation and/or larger rivals. Since the sellers typically face one another across multiple product markets within the same PCS, it appears likely that some learning occurs allowing incumbents to predict whether entrants pose a temporary or more permanent threat. To explore this we classify each of the sellers in the sample as "temporary" or "permanent" according to whether their average completed duration is above or below the sample mean. If hit-and-run pricing is largely confined to low-reputation/smaller sellers, as we observe, we conjecture that paradoxically the *price* impact of entry will be greatest for those entrants perceived to be temporary. This is explored in Table 10, where it can be seen that entry by short-term visitors (**Temporary Entry**) does induce price cutting, consistent with it being overwhelmingly by low reputation incumbents. This reinforces our finding of a bifurcated market.

**[Insert Table 10 here]**

In addition to investigating the average incumbent response to entry, we also examined the response by the lowest-priced incumbent only. If consumers use a price ranking default when searching, the lowest-price incumbent might be expected to respond to being undercut, if only by dropping her price slightly below the entrant's. In the event the price cut for the lowest incumbent alone was insignificant.

Since the mean price in a market will be affected by the distribution of high and low reputation seller in that market, we also located the entrant's nearest competitor in that market, and also the nearest competitor by reputation-type. We obtained a negative but insignificant price response from that incumbent but with a larger absolute magnitude reported for the low reputation entrants[29]. Thus, our previous results using the mean response from incumbents of the same reputation-type supports the notion that it is not just the closest incumbent who is responding to entry by dropping their price. The distribution of responses across all incumbents may be an interesting avenue for future research.

Finally, we investigated whether the institutional property of the payments mechanism at the shopbot may have generated involuntary exits and re-entries with implications for the analysis. Newcomers whose initial deposit of $100-$150 is exhausted by consumers' clicks and who fail to renew it can be temporarily excluded. We reclassified exits as a continuing presence where exit was reversed a day later with no difference in the terms of supply. This made no material difference to our results.

## V. Conclusions

We have presented results suggesting that in PCS-mediated markets something resembling hit-and-run entry is a real phenomenon and not merely a theoretical curiosity. The absence of sunk costs combined with a format which constrains all sellers to present in a similar way facilitates a much higher rate of entry and exit than has been observed in conventional markets. However, seller heterogeneity, particularly with regard to reputation, prevents shopbot markets meeting the full assumptions [Baumol *et al*. (1982)] for perfect contestability. In line with the theoretical prediction of Farrell (1986), we find that reputational differences among sellers produce an effective bifurcation of the market, with both entry strategies and incumbent responses to entry depending on the seller's status. Smaller and/or low-reputation sellers typically make brief visits to the market generally offering prices below the current mean. This draws an immediate price response from incumbent sellers. However, this response appears entirely confined to other low-reputation/smaller sellers. High reputation and/or larger sellers are unaffected. By contrast, entry by larger/high-reputation sellers tends to be longer-lasting and to be associated with pricing above the existing mean. It is thus among the no/low reputation and/or smaller sellers that something approximating to hit-and-run behavior is observed.

High reputation/larger sellers entering with a price below the mean also trigger a significant immediate price fall, but this is restricted to other sellers of a similar status. It is typically much smaller than that observed among low-reputation/smaller incumbents when joined by a similar entrant. This is consistent with a relatively reduced role for price competition in this segment of the market.

Entry at prices above the existing mean produces a significant average price increase among incumbents. This holds for both segments of the market; although the proportionate effect is greater among low-reputation/smaller sellers where it is also less frequent. Again there are generally no cross-segment effects. Why high-priced entry functions as a signal in this respect is not entirely clear; although there are parallels in other markets with frequent price changes, most obviously in the literature on Edgeworth cycles in gasoline markets [Doyle *et al*. (2010)].

An interesting feature of PCS markets is that sellers can buy e-visibility by bidding above the minimum fee-per-click. It was noted that this may be a rational strategy where restricted consumer search implies disproportionate traffic to the most visible sellers in the shopbot's default ranking, as Baye *et al*, (2009) report. We find that additional e-visibility, defined by membership of the three highest ranked sellers changes the size but not the direction of the price effect. Again the effect is very much larger for the low-reputation/smaller sellers.

Our results help to reconcile two stylized facts of e-markets: first, that price competition is much fiercer here than in a traditional market setting; and second, that reputation continues to command a significant price premium. They suggest a bifurcation of the market into a low-reputation-low-price segment, where sellers compete for price-sensitive (and less risk-averse) consumers and a high-reputation-high-price segment for more risk-averse consumers. In the former segment something approaching the hit-and-run behavior predicted by contestability theorists is observed as entrants, often newcomers with little or no reputation, make temporary market visits with low-price offerings.

Among the unresolved issues of PCS market operation is the role of voluntary exit. If market presence only becomes costly when consumers click through to the seller's site, why do sellers withdraw so quickly? Three possible explanations are suggested: First, low-price/smaller sellers typically possess a modest inventory and exit once this becomes exhausted. Second, some sellers finding themselves under-cut by segment rivals and making correspondingly few sales, withdraw to avoid either being perceived as high-price or having to make a price cut that - given multi-homing – affects their profits elsewhere. Third, that in part exit reflects some underlying recognition of the need to avoid descent into a pure Bertrand outcome. That is, it is part of some variant of a randomized pricing strategy extended to include zero product offerings. These conjectures require further research.

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## Appendix A

**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/08 (c) NexTag

400, 350, 300, 250, 200

Sep Nov Jan Mar May Jul Sep

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 78 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 US1CAMERA.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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Table A1. *Duration of entrants' participation: Cox proportional hazard model including time varying regressors*

| | *(1)* | *(2)* | *(3)* | *(4)* |
|---|---|---|---|---|
| Minimum Price Entry | 1.4065 | 1.4370 | | |
| | (0.0240)*** | (0.0241)*** | | |
| Minimum Price Low Reputation Entry | | | 1.6100 | 1.6448 |
| | | | (0.0293)*** | (0.0294)*** |
| Minimum Price High Reputation Entry | | | 0.9373 | 0.9482 |
| | | | (0.0328)* | (0.0331) |
| Seller Position | 1.0024 | 1.0024 | 1.0023 | 1.0023 |
| | (0 .0012)** | (0 .0012)** | (0 .0012)* | (0 .0012)* |
| Number of Co-entrants | 0 .9354 | 0 .9353 | 0 .9355 | 0 .9354 |
| | (0 .0039)*** | (0 .0039)*** | (0 .0039)*** | (0 .0039)*** |
| Products | 1.0016 | 1.0016 | 1.0015 | 1.0015 |
| | (0.0001) *** | (0.0001) *** | (0.0001) *** | (0.0001) *** |
| Top 100 | 0.7588 | 0.7529 | 0.7759 | 0.7709 |
| | (0 .0115)*** | (0 .0114)*** | (0 .0120)*** | (0 .0119)*** |
| Seller Stars | 0.9288 | 0.9299 | 0.9489 | 0.9504 |
| | (0 .0046)*** | (0 .0046)*** | (0 .0048)*** | (0 .0048)*** |
| Authorised Dealer | 0.9193 | 0.9173 | 0.9308 | 0.9291 |
| | (0 .0294)*** | (0 .0291)*** | (0 .0299)** | (0 .0297)** |
| Number of Sellers | 0.9972 | 0.9974 | 0.9960 | 0.9962 |
| | (0 .0011)** | (0 .0011)** | (0 .0011)*** | (0 .0011)*** |
| Log of Market Size | 1.0100 | 1.0115 | 1.0073 | 1.0089 |
| | (0.0064) | (0.0064)* | (0.0063) | (0.0063)* |
| Relative Price | 1.0004 | | 1.0003 | |
| | (0 .0001)*** | | (0 .0001)*** | |
| Age | 1.0002 | 1.0001 | 1.0001 | 1.0001 |
| | (0.0001)* | (0.0001) | (0.0001) | (0.0001) |
| Age-squared | 0.9999 | 0.9999 | 0.9999 | 0.9999 |
| | (0.0000)** | (0.0000)** | (0.0000)** | (0.0000)* |
| SLR | 0.9813 | 0.9986 | 0.9906 | 0.9999 |
| | (0.0238) | (0.0241) | (0.0237) | (0.0240) |
| Compact | 0.9805 | 0.9798 | 0.9864 | 0.9860 |
| | (0 .0208) | (0.0208) | (0.0206) | (0.0205) |
| Ultra-compact | 0.9891 | 0.9888 | 0.9901 | 0.9899 |
| | (0.0214) | (0.0214) | (0.0211) | (0.0211) |
| Wald test | 4196.24 | 4123.90 | 4847.05 | 4813.34 |
| [p-value] | [0.000] | [0.000] | [0.000] | [0.000] |
| Number of Entrants | 22,079 | 22,079 | 22,079 | 22,079 |
| Number of Observations | 187,757 | 187,757 | 187,757 | 187,757 |

*Notes:* Robust standard errors are given in parentheses below the estimated coefficients in columns (1) and (2). Bootstrapped standard errors are given in parentheses below the estimated coefficients in columns (3) and (4): *** p<0.01, ** p<0.05, * p<0.1.

**Figure 1.** Kaplan-Meier Survival Function Estimate

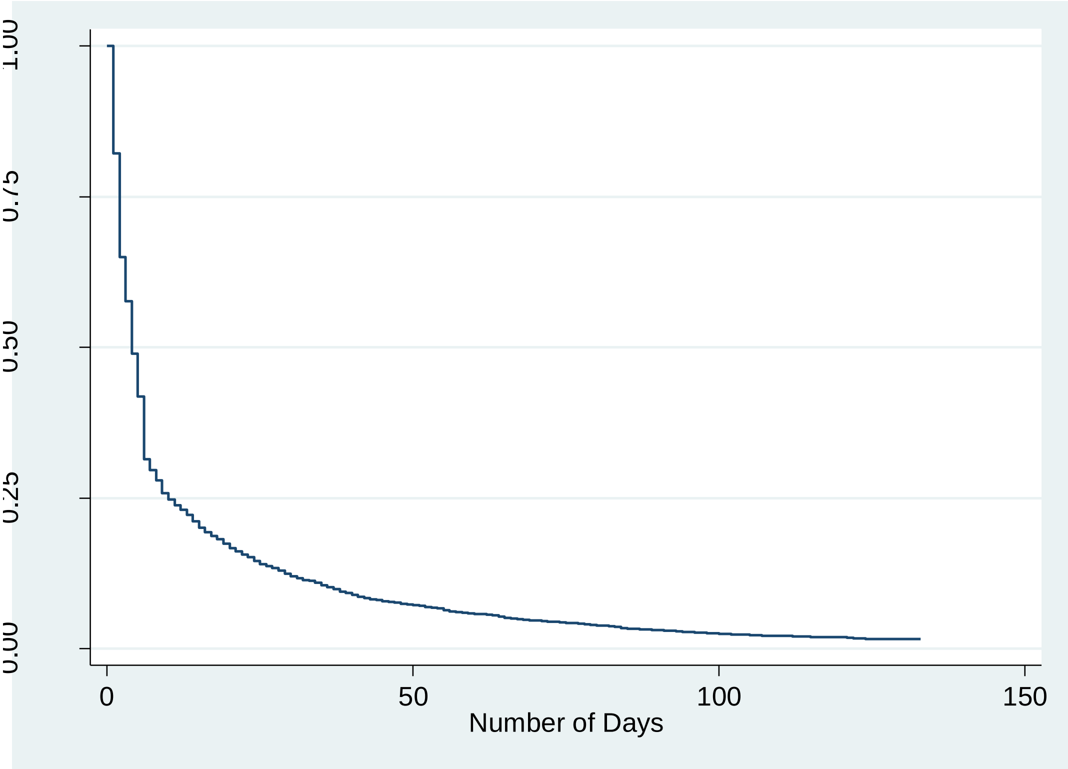

**Figure 2.** Kaplan-Meier Survival Function Estimate by Seller Reputation

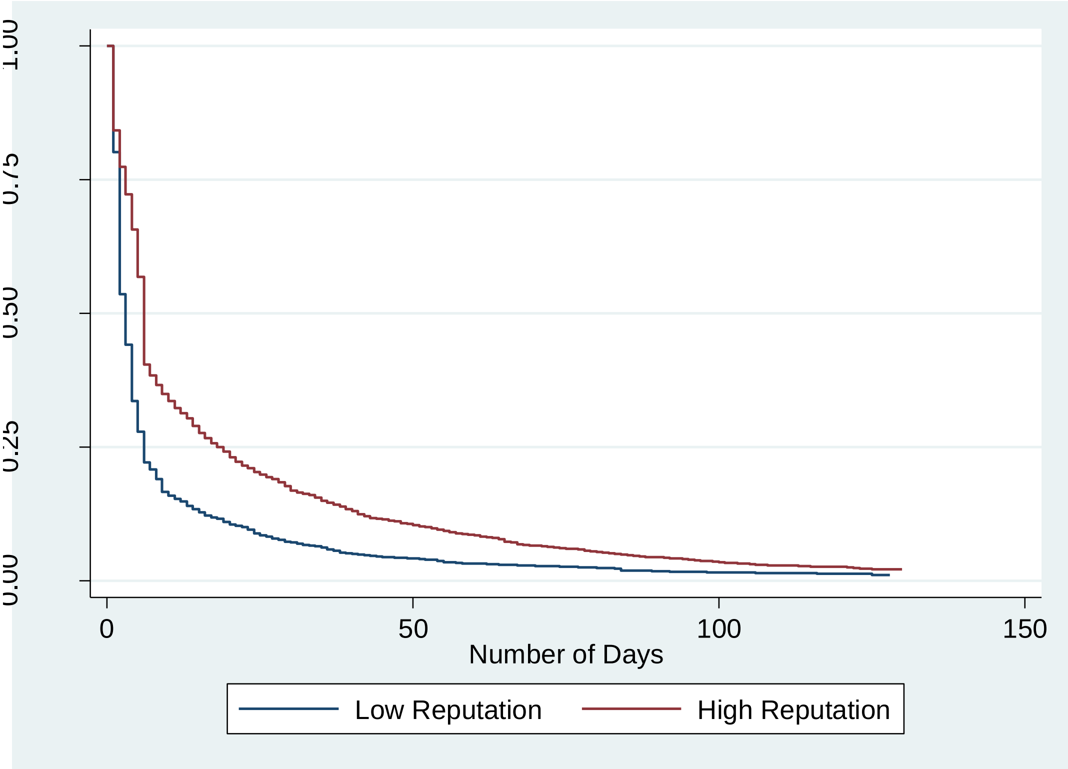

**Figure 3.** Kaplan-Meier Survival Function Estimate by Entry Price Strategy

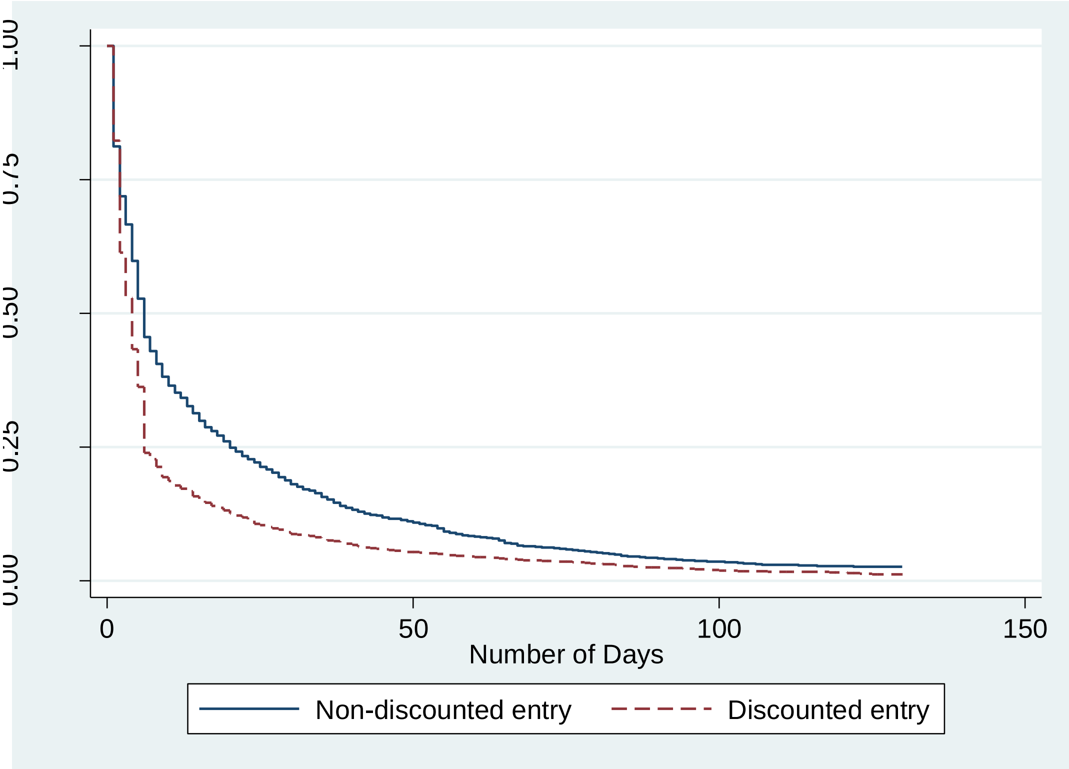

**TABLE 1**

*Summary statistics*

| | *Mean* | *Median* | *S.D.* | *No. of Obs.* |
|---|---|---|---|---|
| Sellers | 16.26 | 16 | 7.28 | 187,757 |
| Leads | 473.18 | 208 | 731.41 | 187,757 |
| Market Size | 0.135 | 0.06 | 0.32 | 187,757 |
| Co-entrants | 1.05 | 1 | 1.491 | 187,757 |
| Age (days) | 268 | 220 | 180.26 | 187,757 |
| Entrant's position | 8.68 | 7 | 6.29 | 187,757 |
| Seller Stars | 3.42 | 4 | 1.47 | 187,757 |
| Product Count | 164.25 | 124.99 | 141.01 | 187,757 |
| Entrant's relative price at exit | 3.185 | 5.675 | 101.273 | 187,757 |

## TABLE 2

*Duration of entrants' participation: Cox proportional hazard model including time varying regressors*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Discounted Entry | 1.24043<br>(0.0205)*** | 1.2737<br>(0.0203)*** | | |
| Discounted Entry: Instrumented | | | 1.8253<br>(0.0873)*** | 1.9575<br>(0.1058)*** |
| Seller Position | 1.0024<br>(0 .0012)** | 1.0024<br>(0 .0012)** | 1.0028<br>(0 .0012)** | 1.0029<br>(0 .0013)** |
| Number of Co-entrants | 0 .9363<br>(0 .0039)*** | 0 .9363<br>(0 .0039)*** | 0 .9355<br>(0 .0036)*** | 0 .9353<br>(0 .0038)*** |
| Products | 1.0017<br>(0.0001) *** | 1.0017<br>(0.0001) *** | 1.0015<br>(0.0001) *** | 1.0015<br>(0.0001) *** |
| Top 100 | 0.7336<br>(0 .0109)*** | 0.7282<br>(0 .0108)*** | | |
| Seller Stars | 0.9117<br>(0 .0045)*** | 0.9113<br>(0 .0045)*** | | |
| Authorised Dealer | 0.8631<br>(0 .0283)*** | 0.8563<br>(0 .0279)*** | | |
| Number of Sellers | 0.9943<br>(0 .0011)*** | 0.9942<br>(0 .0011)*** | 0.9948<br>(0 .0012)*** | 0.9947<br>(0 .0012)*** |
| Log of Market Size | 1.0059<br>(0 .0063) | 1.0075<br>(0 .0064) | 1.0118<br>(0 .0064)* | 1.0149<br>(0 .0069)** |
| Relative Price | 1.0004<br>(0 .0001)*** | | 1.0007<br>(0 .0001)*** | |
| Age | 1.0002<br>(0.0001)* | 1.0001<br>(0.0001) | 1.0003<br>(0 .0001)*** | 1.0002<br>(0 .0001)** |
| Age-squared | 0.9999<br>(0.0000)** | 0.9999<br>(0.0000) | 0.9999<br>(0.0000)*** | 0.9999<br>(0.0000)** |
| SLR | 0.9677<br>(0.0237) | 0.9846<br>(0 .0241) | 0.9260<br>(0.0263)*** | 0.9524<br>(0.0229)** |
| Compact | 0.9783<br>(0 .0209) | 0.9775<br>(0 .0209) | 0.9603<br>(0 .0217)* | 0.9577<br>(0 .0212)* |
| Ultra-compact | 0.9931<br>(0.0216) | 0.9928<br>(0.0217) | 0.9840<br>(0 .0230) | 0.9839<br>(0 .0233) |
| Wald test | 3642.14 | 3530.05 | 2054.25 | 1617.44 |
| [p-value] | [0.000] | [0.000] | [0.000] | [0.000] |
| Number of Entrants | 22,079 | 22,079 | 22,079 | 22,079 |
| Number of Observations | 187,757 | 187,757 | 187,757 | 187,757 |

*Notes:* Robust standard errors are given in parentheses below the estimated coefficients in columns (1) and (2). Bootstrapped standard errors are given in parentheses below the estimated coefficients in columns (3) and (4): *** p<0.01, ** p<0.05, * p<0.1.

**TABLE 3**

*Duration of entrants' participation: Cox proportional hazard model* including time varying regressors, split by entrant's reputation

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Discounted Low Reputation Entry | 1.6332 | 1.6729 | | |
| | (0.0329)*** | (0.0328)*** | | |
| Discounted High Reputation Entry | 0.94107 | 0.9584 | | |
| | (0.0189)*** | (0.0189)*** | | |
| Discounted Low Rep Entry: Instrumented | | | 2.1577 | 2.1957 |
| | | | (0.1268)*** | (0.0952)*** |
| Discounted High Rep Entry: Instrumented | | | 0.8777 | 0.8807 |
| | | | (0.0347)*** | (0.0275)*** |
| Seller Position | 1.0027 | 1.0027 | 1.0025 | 1.0025 |
| | (0 .0012)** | (0 .0012)** | (0 .0013)** | (0 .0012)** |
| Number of Co-entrants | 0 .9368 | 0 .9368 | 0 .9356 | 0 .9354 |
| | (0 .0040)*** | (0 .0040)*** | (0 .0034)*** | (0 .0041)*** |
| Products | 1.0014 | 1.0014 | 1.0015 | 1.0015 |
| | (0.0001) *** | (0.0001) *** | (0.0001) *** | (0.0001) *** |
| Top 100 | 0.7746 | 0.7702 | | |
| | (0 .0120)*** | (0 .0119)*** | | |
| Seller Stars | 0.9990 | 0.9999 | | |
| | (0 .0061) | (0 .0061) | | |
| Authorised Dealer | 0.9252 | 0.9196 | | |
| | (0.0334)** | (0 .0331)** | | |
| Number of Sellers | 0.9945 | 0.9945 | 0.9946 | 0.9945 |
| | (0 .0011)*** | (0 .0011)*** | (0 .0012)*** | (0 .0013)*** |
| Log of Market Size | 1.0031 | 1.0043 | 1.0069 | 1.0102 |
| | (0 .0062) | (0 .0062) | (0 .0061) | (0 .0069) |
| Relative Price | 1.0003 | | 1.0007 | |
| | (0 .0000)*** | | (0 .0001)*** | |
| Age | 1.0001 | 1.0001 | 1.0002 | 1.0002 |
| | (0.0001) | (0.0001) | (0 .0001)** | (0 .0001)* |
| Age-squared | 0.9999 | 0.9999 | 0.9999 | 0.9999 |
| | (0.0000)* | (0.0000) | (0.0000)*** | (0.0000) |
| SLR | 0.9786 | 0.9927 | 0.9654 | 0.9960 |
| | (0.0239) | (0.0240) | (0.0237) | (0.0247) |
| Compact | 0.9801 | 0.9794 | 0.9647 | 0.9623 |
| | (0 .0207) | (0 .0207) | (0 .0211)* | (0 .0186)** |
| Ultra-compact | 0.9810 | 0.9806 | 0.9882 | 0.9888 |
| | (0 .0212) | (0 .0212) | (0 .0214) | (0 .0188) |
| Wald test | 4585.81 | 4504.30 | 1921.29 | 2810.55 |
| [p-value] | [0.000] | [0.000] | [0.000] | [0.000] |
| Number of Entrants | 22,079 | 22,079 | 22,079 | 22,079 |
| Number of Observations | 187,757 | 187,757 | 187,757 | 187,757 |

*Notes:* Robust standard errors are given in parentheses below the estimated coefficients in columns (1) and (2). Bootstrapped standard errors are given in parentheses below the estimated coefficients in columns (3) and (4): *** p<0.01, ** p<0.05, * p<0.1.

## TABLE 4

*Effect of entry on change in incumbents' price*

| | *All Incumbents* | *All Incumbents* | *Low Reputation* | *Low Reputation* | *High Reputation* | *High Reputation* |
|---|---|---|---|---|---|---|
| | *(a1)* | *(a2)* | *(b1)* | *(b2)* | *(c1)* | *(c2)* |
| $Entry_{t-1}$ | -0.0035 | | -0.0053 | | -0.0009 | |
| | (6.42)*** | | (6.02)*** | | (1.63) | |
| $Entry_{t-1}$: Instrumented | | -0.0159 | | -0.0236 | | -0.0042 |
| | | (6.29)*** | | (5.80)*** | | (1.67)* |
| Multiple $Entry_{t-1}$ | -0.0046 | | -0.0066 | | -0.0007 | |
| | (6.22)*** | | (5.65)*** | | (0.98) | |
| Multiple $Entry_{t-1}$: Instrumented | | -0.0204 | | -0.0292 | | -0.0036 |
| | | (5.64)*** | | (5.44)*** | | (1.06) |
| $Exit_{t-1}$ | 0.0034 | 0.0034 | 0.0060 | 0.0060 | 0.0005 | 0.0005 |
| | (7.02)*** | (7.09)*** | (7.66)*** | (7.60)*** | (1.06) | (1.08) |
| No. of Observations | 30,070 | 30,070 | 27,149 | 27,149 | 29,310 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**TABLE 5**

*Effect of entry on change in incumbents' price, split by entrants' reputation*

| | *All Incumbents* *(a)* | *Low Reputation* *(b)* | *High Reputation* *(c)* |
|---|---|---|---|
| Low_Rep_Entry$_{t-1}$ | -0.0038 | -0.0076 | 0 .0003 |
| | (5.00)*** | (6.25)*** | (0.40) |
| High_Rep_Entry$_{t-1}$ | -0.0033 | -0.0033 | -0.0020 |
| | (4.61)*** | (2.86)** | (2.80)*** |
| Multiple Entry$_{t-1}$ | -0.0046 | -0.0069 | -0.0006 |
| | (6.24)*** | (5.82)*** | (0.83) |
| Exit$_{t-1}$ | 0.0034 | 0.0060 | 0.0005 |
| | (7.01)*** | (7.64)*** | (1.06) |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**TABLE 6**

*Effect of discounted and non-discounted entry on change in incumbents' price*

| | *All Incumbents* *(a)* | *Low Reputation* *(b)* | *High Reputation* *(c)* |
|---|---|---|---|
| Discounted $Entry_{t-1}$ | -0.0086 | -0.0110 | -0.0037 |
| | (12.87)*** | (10.33)*** | (5.45)*** |
| Non-discounted $Entry_{t-1}$ | 0.0044 | 0.0042 | 0.0033 |
| | (5.42)*** | (3.25)*** | (4.11)*** |
| Multiple $Entry_{t-1}$ | -0.0049 | -0.0070 | -0.0009 |
| | (6.74)*** | (6.01)*** | (1.27) |
| $Exit_{t-1}$ | 0.0034 | 0.0060 | 0.0005 |
| | (7.02)*** | ( 7.62)*** | (1.05) |
| | | | |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**TABLE 7**

*Effect of entry into top 3 and outside top 3 position*

| | *All Incumbents* *(a)* | *Low Reputation* *(b)* | *High Reputation* *(c)* |
|---|---|---|---|
| Top3 $Entry_{t-1}$ | -0.0056 | -0.0080 | -0.0017 |
| | (6.26)*** | (5.40)*** | (1.82)* |
| Outside Top3 $Entry_{t-1}$ | -0.0027 | -0.0044 | -0.0006 |
| | (4.35)*** | (4.44)*** | (0.98) |
| Multiple $Entry_{t-1}$ | -0.0046 | -0.0066 | -0.0007 |
| | (6.23) *** | (5.65)*** | (0.98) |
| $Exit_{t-1}$ | 0 .0034 | 0.0060 | 0.0005 |
| | (6.91)*** | (7.58)*** | (1.02) |
| | | | |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## TABLE 8

*Effect of entry on change in incumbents' price, split by entrants' reputation & pricing strategy*

| | *All Incumbents (a)* | *Low Reputation (b)* | *High Reputation (c)* |
|---|---|---|---|
| Low_Rep_Disc_Entry$_{t-1}$ | -0.0083 | -0.0193 | 0.0015 |
| | (7.71)*** | (11.27)*** | (1.37) |
| Low_Rep_Non-Disc_ Entry$_{t-1}$ | 0.0085 | 0.0156 | 0 .0010 |
| | (6.23)*** | ( 7.06)*** | (0.71) |
| High_Rep_Disc_Entry$_{t-1}$ | -0.0072 | -0.0019 | -0.0075 |
| | (7.31)*** | (1.19) | (7.64)*** |
| High_Rep_Non-Disc_Entry$_{t-1}$ | 0.0039 | -0.0034 | 0.0066 |
| | (3.27)*** | (1.28) | (5.56)*** |
| Multiple Entry$_{t-1}$ | -0.0042 | -0.0065 | -0.0004 |
| | (5.75)*** | (5.62)*** | (0.56) |
| Exit$_{t-1}$ | 0.0031 | 0.0057 | 0.0004 |
| | (6.52)*** | (7.31)*** | (0.85) |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes: Time* dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

## TABLE 9

*Effect of entry on incumbents' price, split by entrants' reputation, pricing and positioning strategy*

| | *All Incumbents (a)* | *Low Reputation (b)* | *High Reputation (c)* |
|---|---|---|---|
| Low_Disc_Top3_Entry$_{t-1}$ | -0.0157 | -0.0294 | 0.0022 |
| | (10.43)*** | (12.05)*** | (1.42) |
| Low_Non-Disc_Top3_ Entry$_{t-1}$ | 0.0132 | 0.0235 | 0.0000 |
| | (6.15)*** | (6.52)*** | (0.10) |
| Low_Disc_Out_Top3_ Entry$_{t-1}$ | -0.0072 | -0.0166 | -0.0003 |
| | (6.85)*** | (10.13)*** | (0.25) |
| Low_Non-Disc_Out_Top3_ Entry$_{t-1}$ | 0.0033 | 0.0110 | -0.0001 |
| | (2.43)** | (5.10)*** | (0.40) |
| High_Disc_Top3_Entry$_{t-1}$ | -0.0110 | -0.0022 | -0.0122 |
| | (7.06) *** | (0.86) | (7.75)*** |
| High_Non-Disc_Top3_ Entry$_{t-1}$ | 0.0031 | -0.0081 | 0.0067 |
| | (1.62) | (2.54)** | (3.50)*** |
| High_Disc_Out_Top3_ Entry$_{t-1}$ | -0.0063 | -0.0031 | -0.0056 |
| | (6.06) *** | (1.24) | (5.39)*** |
| High_Non-Disc_Out_Top3_ Entry$_{t-1}$ | 0.0033 | -0.0021 | 0.0059 |
| | (2.71)*** | (1.05) | (4.78)*** |
| Multiple Entry$_{t-1}$ | -0.0050 | -0.0078 | -0.0006 |
| | (6.79)*** | (6.68)*** | (0.83) |
| Exit$_{t-1}$ | 0.0033 | 0.0060 | 0.0004 |
| | (6.86)*** | (7.69)*** | (0.90) |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

**TABLE 10**

Effect of temporary and long-term entry on change in incumbents' price

| | *All Incumbents (a)* | *Low Reputation (b)* | *High Reputation (c)* |
|---|---|---|---|
| Temporary Entry$_{t-1}$ | -0.0050 | -0.0081 | -0.0003 |
| | (7.24)*** | (7.21)*** | (0.48) |
| Long-term Entry$_{t-1}$ | -0.0010 | -0.0019 | 0 .0002 |
| | (1.24) | (1.52) | ( 0.30) |
| Multiple Entry$_{t-1}$ | -0.0034 | -0.0045 | -0.0003 |
| | (4.74)*** | (3.93)*** | (0.47) |
| Exit$_{t-1}$ | 0.0032 | 0.0058 | 0.0005 |
| | (6.54)*** | (7.41)*** | (1.07) |
| No. of Observations | 30,070 | 27,149 | 29,310 |

*Notes:* Time dummies included. t-statistics appear in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] The robustness issue is debated by *inter alia* Weitzman (1983), Shepherd (1984) and Farrell (1986b) and the empirical predictions are examined in Morrison and Winston (1987), Hurdle *et al*. (1989) and references therein.

[2] The term employed by both Baumol *et al* (1982) and Farrell (1986b).

[3] Some PCS platforms charge a monthly listing fee. Clearly, on those sites – unlike *NexTag.com* – there is an obvious sunk cost of market entry.

[4] Since the shopbot does not publish its ranking algorithm, the weight given to factors other than the bid cannot be determined.

[5] For example, Baye *et al*. (2009) report a *ceteris paribus* decline in clicks of 17% per ranking position, with a 40% discontinuity between positions one and two. Their results are sensitive to the number of sellers with further discontinuities at the ends of pages.

[6] It has been suggested that attracting interest in this way inflates clicks for the top-ranked sellers in the listing but correspondingly lowers their conversion rates: see http://www.mobile-o.com/docs/Top-Vertical-Search-Sites.html viewed on 30th Oct. 2008.

[7] Baye and Morgan (2001) pose an insider-outsider model in which entry reduces the proportion of uninformed buyers thus encouraging sellers to pursue the more price sensitive consumers and so generating a predicted negative relationship between price and *n*. This is achieved by introducing entry costs which, in reality, appear trivial in many e-markets.

[8] This type of low quality hit-and-run entry in e-markets may be favored by the ease of exit and subsequent name change which reduces the incentive to build reputations [Ellison and Ellison (2009)].

[9] Empirical evidence across e-commerce – reviewed in OFT (2007) - suggests both a much more frequent and smaller price adjustments than occurs in traditional markets.

[10] Specific software to generate and transfer product feed data via FTP is available for as little as $25.

[11] Some shopbots, such as *Shopper.com,* obviate this requirement by providing small sellers with *storefront* services which provide them with a selling site in exchange for commission.

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

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

[14] We used a cut-off of 100 leads since we were interested in studying behaviour in active markets.

[15]We chose a tax free zip code in New Hampshire.

[16] We also repeated all of the analysis using final prices including shipping costs. This did not materially affect our results.

[17] This is the number of exits for which we have a record of their entry.

[18] This is calculated by dividing the average number of entrants/exits by day by the average number of seller-product observations and then multiplying by seven to arrive at a weekly figure.

[19] Our duration analysis necessarily takes product, seller and market characteristics as exogenous or at least pre-determined. No doubt at a finer – but unobservable – level of disaggregation potential entrants and incumbents are exploring their conjectures about one another's behaviour. Thus our duration analysis of the determinants of exit are strictly reduced form estimates, More complex interactions are explored on the pricing side below.

[20] Some entrants survive beyond the end of our sample period.

[21] The probability of discounted entry is determined by seller-specific characteristics, which themselves determine the duration of a seller's visit, resulting in a simultaneity problem.  In an earlier paper (see Haynes and Thompson 2013), we found that seller-specific characteristics dominate market factors in

the entry decision. The coefficients in the probit regression are all individually significant at the one percent level.

[22] Vella and Verbeek (1999) show that this type of IV estimator generates results similar to Heckman's (1978, 1979) endogeneity bias corrected OLS estimator. All of the seller reputation variables used as regressors in the discounted entry probit estimation were significant at the 1% level or above.

[23] If we look at sellers who enter at or below the previous period's minimum price then that hazard is even higher. The proportion of entrants entering at or below the previous period minimum price is approximately 27% of the total number of entries taking place. The results from this estimation are included in Table A1 in the Appendix.

[24] A similar result was obtained when membership of the top three sellers in the default ranking was used instead.

[25] A Chi-squared test on the difference between the high and low reputation coefficients is highly significant.

[26] These decisions have been modelled as a joint decision process in earlier work by Haynes and Thompson (2013).

[27] Frank and Salkever (1997) report that entry by generic pharmaceuticals stimulates price cuts among other generic sellers but price *increases* among branded sellers while Simon (2005) finds entry into a magazine segment triggers price cuts among the more recently-founded titles. McCann and Vroom (2010) report broadly similar findings for hotels.

[28] Since entry is potentially endogenous, we re-estimate equation (3) after instrumenting entry. As in the duration model, we use predicted values from a probit regression of entry on seller reputation variables as an instrument. Since the instrumented variables do not alter the pattern of our results, for space reasons, we have not reported the instrumented results for Tables 4 through to 9. These results are available from the authors.

[29] These results are available from the authors.