Hit-and-Run or Sit and Wait? Contestability Revisited in a Shopbot Mediated Market

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Abstract

The shopbot appears to approximate to the conditions in which the contestability theorists envisioned hit-and-run entry behavior. We explore this using a unique data set obtained from daily visits to Nextag.com for an unbalanced panel of 295 digital cameras. We find, however, evidence of seller heterogeneity 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.

1. Introduction

Hit-and-run entry is the disciplinary device whose threat contestability theorists [Baumol et al. (1982)] postulated would generate competitive market outcomes irrespective of observed market structures. Like the nuclear sanction during the cold war, the mere existence of a credible hit-and-run threat was considered sufficient to generate the appropriate equilibrium – one exhibiting zero allocative and operational inefficiency – such that any exercise of the threat was redundant. Reflecting this, the substantial literature generated in response to the contestability approach overwhelmingly ignored hit-and-run as a *process.* Instead theorists concentrated on the viability of the assumptions necessary for perfect contestability, while empirical researchers tested the predicted irrelevance of market structure in explaining performance in seemingly contestable markets. After the former poured doubt on the theory's robustness[1] and the latter generally reported significant structural effects[2], contestability discussion largely moved from the academic literature to the policy field, where it has focused the attention of regulators and antitrust authorities on the reduction of entry and exit barriers, not least by promoting access to fixed capital particularly in utilities.

In this paper we revisit hit-and-run entry. We explore the contention that the rise of electronic commerce, especially the development of price and product comparison sites or shopbots, has lowered the sunk costs of market entry such that hit-and-run behavior has ceased to be a mere theoretical curiosity and is descriptive of a retail trading strategy, at least for a subset of sellers. While the impact of electronic markets on price distributions is widely researched in the literature[3], their role in lowering entry costs has been largely ignored. This is perhaps surprising, since the economic logic of a two-sided market[4] requires that the easy access of consumers to sellers is matched by the easy access of sellers to those consumers. To that end shopbots such as *NexTag.com* offer a free listing to sellers, effectively reducing the sunk costs of market entry and exit to zero. Moreover, by requiring all would-be sellers to present via stardardized screenshots, the shopbot clearly neutralizes many of those resource differences between sellers that would, in other settings, constitute barriers to entry. This requirement also gives the new entrant instant access to potential buyers, opening up at least the possibility of profitable sales *before* any incumbent response, thus meeting another key assumption of contestability theory normally violated in real-world markets. Furthermore, it is at least technically feasible for a suitably-priced new entrant to displace any incumbent seller, and empirical evidence suggests that the lowest price seller does indeed capture a disproportionate share of sales [Baye et al (2007)]. In traditional markets, by contrast, the acquisition of sufficient capacity to displace incumbents *before* any incumbent response is frankly unrealistic [Cairns and Mahabir (1988)].

The shopbot-mediated market (SMM), despite displaying an apparently closer approximation to the perfect contestability assumptions than any of the markets used in prior empirical work, falls short in at least one important respect. An environment in which there is perceived consumers' uncertainty about the seller's intention and ability to deliver the product leaves seller reputation as a source of heterogeneity. Farrell (1986) predicted that a combination of zero sunk costs and seller differences in reputation would lead to market segmentation with hit-and-run entry in the low-price, low-reputation segment[5] and stable high-price incumbency in the high-reputation segment. We find considerable support for Farrell's predictions.

The paper uses a specially constructed unbalanced panel of daily observations on 295 digital camera models sold on *NexTag.com* over a 134-day period. It finds that seller reputation is a key determinant of both the entry strategy followed and the price response of incumbents to entry. A duration analysis for SMM entrants reveals that reputation, size and entry at a price premium reduce the hazard of exit. Our data are suggestive of a clear bifurcation of strategies, with low-reputation/small sellers opting for transient cut-price visits while high-reputation/larger entrants remain for longer periods with high-priced offerings. 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 respond to premium price entry with prices increases, again only within their own status group. In each case the magnitude of the response is considerably greater for the low-reputation group.

Taken together our results suggest that, homogeneous product and zero sunk costs of entry notwithstanding, seller heterogeneity effectively partitions shopbot markets. Low-reputation and generally smaller sellers compete for the price-sensitive consumers. Here, in line with Farrell (1986), something approaching hit-and-run entry is observed. By contrast, high-reputation/larger sellers are able to enter for longer periods at higher prices and so (presumably) enjoy higher margins at the expense of more loyal or more risk-averse consumers. Our results help to reconcile two apparently contradictory stylized facts to emerge from previous research on e-commerce in general and shopbot markets in particular: namely that while reputation commands a significant price premium [Waldfogel and Chen (2006) and references therein] the observed elasticity of demand at shopbots is extremely high by comparison with traditional markets [Baye et al.(2007)].

The paper is organized as follows: Section 2 examines the institutional arrangements for the SMM 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.

2. Contestability at a Shopbot Market: Institutional and Theoretical Background

2.i Shopbot Market Characteristics

Shopbots such as *NexTag.com* have evolved from being mere search engines to become hosts to a two-sided market to which consumers are drawn by the provision of product and seller data and sellers are attracted by access to potential consumers. Sellers receive a free listing and access to enabling software. Sellers pay a flat fee for each click through to the relevant page on their 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 raised by the shopbot in periods of high demand such as the Christmas season.

The shopbot may refuse a seller admission; either because of the latter's poor reputation or because of congestion. The shopbot also determines the ranking of sellers in the default listing for consumers searching by product, with those sellers who bid above the minimum fee being rewarded with a higher rank than those that do not. *NexTag.com* reinforces the role of ranking by providing direct links to the three highest-ranked sellers on its product pages; that is the pages *prior* to those displaying seller listings for searchers by product. Pre-emptive bids are not accepted so a high ranking is always potentially vulnerable to new bidders. Since the shopbot does not publish its ranking algorithm, the weight given to factors other than the bid cannot be determined[6]. Ranking is important since research using shopbot data suggests that the traffic to seller sites falls with position. For example, Baye et al. (2007) report a *ceteris paribus* decline in clicks of 17% per ranking position. They do however note two important caveats: first, there is a large discontinuity between positions one and two in the rankings, with an associated 40% fall in clicks; and second, the positional effect is sensitive to the number of sellers and to any movement between successive screen pages.

Clicks through to the seller's site are not, of course, equivalent to sales. The average conversion rate has been estimated at between 50% [Brynjolffson et al. (2004) p6] and three to five per cent [Baye et al. (2007) p2]. It is unclear whether the conversion rate varies with price or positional ranking. However, it has been suggested that the shopbot practice of generating additional traffic by advertising on general search engines, using products as keywords, and thereby gaining income from the arbitrage between cost-per-click rates lowers the merchant's conversion rate[7] .

It would be expected that price comparison sites, by lowering search costs, would reduce retail prices and shrink price distributions. However, research on pricing behavior in e-markets indicates a number of ambiguities. Early work [reviewed in Brynjolffson and Smith (2000)] suggested that 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 the Bertrand trap of descent to marginal cost pricing. 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 the average price level[8].

Another driver of price dispersion is reputation. Uncertainty attaching to payment and delivery, turns otherwise homogeneous products, such as specified cameras or books, into experience goods, in the sense of Nelson (1970). Empirical research on e-markets [e.g. Clay et al. (2001)] has consistently suggested that reputation commands a (posted) price premium for established sellers such as *Amazon.com.* Waldfofel and Chen (2006) suggest this should decline as consumers gain familiarity with Internet shopping, but they in turn report its persistence. Farrell (1986) demonstrated that providing a poor quality experience may even be the optimal strategy for market newcomers who lack an established reputation. Some consumers who anticipate such behavior will rationally shun low-price entrants in favor of higher priced established sellers[9].

The shopbot, like other institutions of market mediation, functions in part to police seller quality and thus reduce the importance of reputation. It both directly truncates the quality distribution of sellers on its pages, by rejecting applicants it believes to be of very low quality, and operates a consumer feedback-generated measure of seller reputation. Since the shopbot's revenue depends on delivering – and therefore attracting – consumers, it has an incentive to police quality to preserve its own reputation. The extent to which this quality control re-establishes an incentive for reputation building by newcomers is unclear.

Recent evidence [e.g. Ghose and Yao (2006)] suggests that consumer behavior at e-markets, especially shopbots, may be considerably more price sensitive than has been inferred from conclusions about the (posted) price distribution and the reputation premium. Ellison and Ellison (2004), for example, report elasticity estimates of -24 to -40, very much higher than those previously reported for conventional markets. Baye et al (2007) 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 it costs the seller the lowest price position. Dulleck et al. (2008), using Austrian data, find that 69% of offerings, overwhelmingly those with high relative prices, receive no clicks at all in an average week. These recent findings suggest that the received wisdom about e-markets' price distributions may require some modification: First, the price 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.

2.ii How Well do Shopbots Meet the Assumptions for Contestability?

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 than 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 may be compared to the conditions obtaining at a shopbot-mediated market such as *NexTag.com*:

No Sunk Costs Entrants have minimal sunk costs, certainly by comparison with those in other markets that have been studied. The initial decision to become a shopbot affiliate 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 entering additional product markets and larger sellers many offer thousands of separate products via each shopbot. The entrant's only explicit cost is the fee payable on clicks through from the shopbot site. Since the conversion rate per click is likely to be well below unity and to vary with others' pricing strategies, 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 irrecoverable explicit costs of entering a particular product market appear unlikely to be much above the trivial.

Firms deciding to use a shopbot clearly incur learning costs, particularly in preparing the “product feed” or input file specifying transaction terms. However, these costs should not be replicated when the retailer offers additional products or exits and then re-enters the original market. Most sellers in our data, described below, appear to offer multiple products and to make frequent reversals of entry/exit decisions.

Incumbent’s Response Lag. Contestability requires that incumbents react with a lag to entry, such that the entrant enjoys some period of positive profits. It seems likely that shopbot sellers, with their low menu costs and ability to keep one another’s prices under continuous observation, can respond more quickly than incumbents in traditional markets[10]; although *NexTag.com* suggests uploading may take up to 24 hours for amended offers and 48 hours for new listings[11]. Moreover, since click data by product is normally issued to listing sellers on a daily basis, there is likely to be some delay in incumbents gauging the effect of entry and determining an appropriate response. Given the short average duration of spells at the shopbot market revealed in our data – see below – we take these delays to constitute a response lag in the sense of Baumol et al. (1982).

Same Resources. The standardized shopbot listing format requires that all participating sellers display to potential buyers in a similar manner. Shopbots also provide each seller with the software required to monitor and amend their offerings, even if they require product feed to be supplied in a standardized form[12]. Listing on most shopbots does require the seller's possession of electronic selling technology, but this is widely available at a low cost[13]. Of course, established sellers may have 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 willingness to pay for clicks through.

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)], generally reflecting the costs and time involved in making substantial capital investments [Cairns and Mahabir (1988)], and even successful entrants tend to acquire market share quite slowly. At a shopbot market, however, there is no such constraint on the displacement of an incumbent's sales by those of a suitably priced newcomer. As indicated above, the limited available evidence in electronic retail markets suggests that the lowest priced seller does capture a highly disproportionate share of sales.

Therefore it is conjectured that the key resource issue comes down to reputation. If the role of reputation is sufficiently diminished by shopbot intermediation then entrants will represent a total threat to incumbents and hit-and-run entry will affect all market participants. If established sellers retain an early mover advantage with at least some proportion of potential consumers, it may be expected that hit-and-run entry will have a more restricted effect. In particular, following Farrell (1986), 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 may be a consequence of sellers multi-homing across electronic markets. Since few sellers operate multiple prices across such markets, a seller matching a price cut at shopbot A would ordinarily make a comparable cut at B. If that is an unattractive option, the seller may face a choice of maintaining an uncompetitive price at A or withdrawing from that market. There are no explicit costs of an inactive shopbot listing, but an uncompetitive price quote may be damaging to a seller’s standing. In such circumstances it is possible that exit is preferred to a passive presence.

3. Sample and Data

NexTag.com is a typical general merchandise price comparison site which lists a wide range of goods and services but is particularly strong in high value-to-weight products such as consumer electronics. We selected the digital camera as the product category for analysis; since purchase here is typically a discrete event, thus avoiding any multiple purchase discount issues that impact decisions on, for example, CD or book choice. *NexTag* provides buyers and sellers with continuously 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. While an alternative listing may be specified by the user, the default ranking of sellers for those searching by product model is determined by the shopbot and displayed on the screen as illustrated in Figure A1 in the Appendix. 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 the previous 17 months.

A Java program was written to interrogate *NexTag.com* and extract data from the screen display. The program was run daily[14] (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)[15]. Excluded were pre-2006 models, assumed to be discontinued, kits where the camera came bundled with (possibly varying) 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[16].

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). Shopbot 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[17]. We used the net price in a zero tax state in our analysis[18].

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

The raw data confirmed the general accessibility of SMMs 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 membership of a camera model on any one day averaged 12 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 each product market as opportunities arise. Sellers ranged in coverage 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[19] averaged 176 per day. Given an average of 12 sellers per market, this is equivalent to 37% leaving and being replaced each day, 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 sellers 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’ perceptions of their and others’ past 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 pricing strategy. Subtracting the entrant's price from the previous day's mean price 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]. By contrast with their smaller rivals, the larger entrants do not appear to offer price discounts over incumbents. 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]

4. An Empirical Analysis of Hit and Run

4.1 A Duration Analysis of Entry

A hit-and-run strategy is taken to involve entry below the incumbent price followed by exit upon the incumbent's 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. Note that these are reduced form estimates of the equilibrium outcomes in the entry price game.

The entrant vector includes a binary variable **Discount** for entrants pricing below the incumbents' mean and which are therefore assumed to "hit" the latter. **Discount_exit** is the entrant's price relative to the mean on the day prior to the entrant's disappearance. Also included is the entrant's **Position** in the default seller listing and the number of **Co-entrants** on the day of entry. 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 sellers relative to the total number of 'leads' or 'clicks' through to purchase. 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 further 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.

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. It is immediately apparent that **Discount** entrants experience a substantially larger exit rate than non-discounters and that this effect is highly significant (z=18.37)[21]. 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 rate, but by a relatively small amount with merely borderline significance[22]. By contrast, bigger and higher reputation entrants display much lower hazard rates. The **Large** entrant, Seller **Stars** and **Authorized** dealer variables, each capturing aspects of reputation, generate hazard ratios well below unity with high levels of significance.

[Insert Table 2 here]

Turing to the market characteristics at the time of exit, **Discount_exit**, a binary variable denoting entrants whose price remains below the mean, attracts a significant positive coefficient indicating many discounters exit even before the market has fully adjusted to their entry. Congestion effects, as captured by **Lmarket_size** and the number of **Sellers** are not apparent and the latter even exhibits a positive coefficient[23]. Among the control variables, the number **of Co-entrants** attracts a negative coefficient, consistent with a common supply side stimulus, while the **Age** variables are completely insignificant. The SLR stands out among the four formats suggesting entrants to this, the highest price segment of the camera market, have lower hazard rates perhaps reflecting the thinner markets for specialist models.

Taken as a whole, the duration analysis is consistent with Farrell's prediction that ultra-low sunk costs coupled with reputational differences will lead to a bifurcation of entry strategies. Posting low prices – whether on entry or later - is associated with higher hazard rates among entrants, as might be expected with a hit-and-run approach. By contrast, the entrant's hazard appears to fall with the reputation and size of the seller, as would be expected where more established retailers enter to cater for brand-loyal consumers.

4.2 Measuring the Hit: Estimating the Price Impact of Entry

We next explore the reaction of incumbents to entry by examining their price response to different entry strategies and differences in the intensity of entry, using 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. Again, note these are reduced form estimates of the equilibrium outcomes in the entry price game.

Incumbent sellers have three possible reactions to market entry: change price, exit or do nothing. The more the market inclines to full contestability the more we might expect incumbents that wish to hold on to a non-trivial market share will need 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 (1986) 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[24]

Table 3 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 *t-1* and *t*. It is immediately clear that entry lowers incumbent prices, with multiple entry having a significant additional effect. It is also apparent that the entry effect is not equally felt across incumbents. When the latter are split, as before, by the feedback-generated 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 4 confirm that entry by low-reputation sellers has a substantial and highly significant impact on low-reputation incumbents. By contrast, high-reputation entrants reduce the price of high reputation incumbents but by a much smaller proportion.

[Insert Tables 3 and 4 here]

Table 5 divides entrants into discounters and non-discounters, according to their price relative to the seller average at the time of entry. An entrant is defined as a discounter if they price below the incumbents' mean price and are therefore assumed to "hit" the latter. 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, further suggesting that competition on price is keener among low-reputation sellers.

Table 6 repeats the exercise by e-visibility, splitting the entrants according to whether or not they are placed in the top three places in the *NexTag.com* default listing. This confirms that ranking matters, with Top3 entrants having a much greater impact on *all* incumbents than non-Top3 rivals. However, again the effect appears to be much greater for the low-reputation incumbents.

[Insert Tables 5 and 6 here]

In Table 7 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 7 here]

Finally, in Table 8 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 8 here]

It is clear that the intra-segment price effects of entry are highly significant; even though their magnitude appears modest. For example, even in the most competitive case of multiple entry by low-reputation, Top3, discounters the impact on the other low-reputation incumbents' mean price is little over three percent. However, this must be set against three caveats: first, average profit margins are already comparatively small for sellers using shopbot markets, particularly in the low-reputation segment, with prices typically well below manufacturer's recommended levels; 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 shopbot, 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 9, where it can be seen that entry by short-term visitors does induce price cutting, consistent with it being overwhelmingly by low reputation incumbents. This reinforces our finding of a bifurcated market.

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 alone was insignificant. Similarly, when we attempted to locate the entrant's nearest competitor in format and reputation we obtained a negative but insignificant price response, with larger absolute magnitude for the low reputation entrants. Again this was insignificant at the individual incumbent level[25]. 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.

[Insert Table 9 here]

5. Conclusions

We have presented results suggesting that in shopbot-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. (2008)].

An interesting feature of shopbot 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, (2007) 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 shopbot 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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[1] See for example Weitzman (1983) and Shepherd (1984).

[2] The deregulated airline industry, the preferred example of a low sunk cost market was found to exhibit a persistent positive relationship between fares and seller concentration by route: see Morrison and Winston (1987), Hurdle et al. (1989) and references therein.

[3] This literature is reviewed in Haynes and Thompson (2008)

[4] See Rochet and Tirole (2006)

[5] Farrell shows that providing a low-cost poor experience product may be an optimal strategy for low-reputation entrants leading risk averse consumers to select the high-price alternative.

[6] In a similar context Google acknowledges that its algorithm gives additional prominence to advertisers it considers more likely to generate clicks and reduces that of poor reputation advertisers.

[7] 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.

[8] 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.

[9] Indeed, 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 (2004)].

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

[11] *NexTag.com* does not undertake to list/delist in under 48 hours, reducing the flexibility of both incumbents and entrants to react.

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

[13] 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.

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

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

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

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

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

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

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

[21] If we look at sellers who enter at or below the previous period's minimum price then that hazard is even higher (1.565).

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

[23] This result is not unexpected if incumbents exit to accommodate entrants.

[24] 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.

[25] These results are available from the authors.

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Appendix

Figure A1. Nextag Screen Output

NexTag® Comparison Shopping

Products | Mortgage | Travel | Degrees | Real Estate | more

NexTag Search

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

Sign In | 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

Compare Prices | Write Product Review | Price History

Seller	Seller Ratings	Description	Price	+Tax & Shipping (Zip: 03104 change)	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
US1 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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Figure 1. Kaplan-Meier Survival Function Estimate

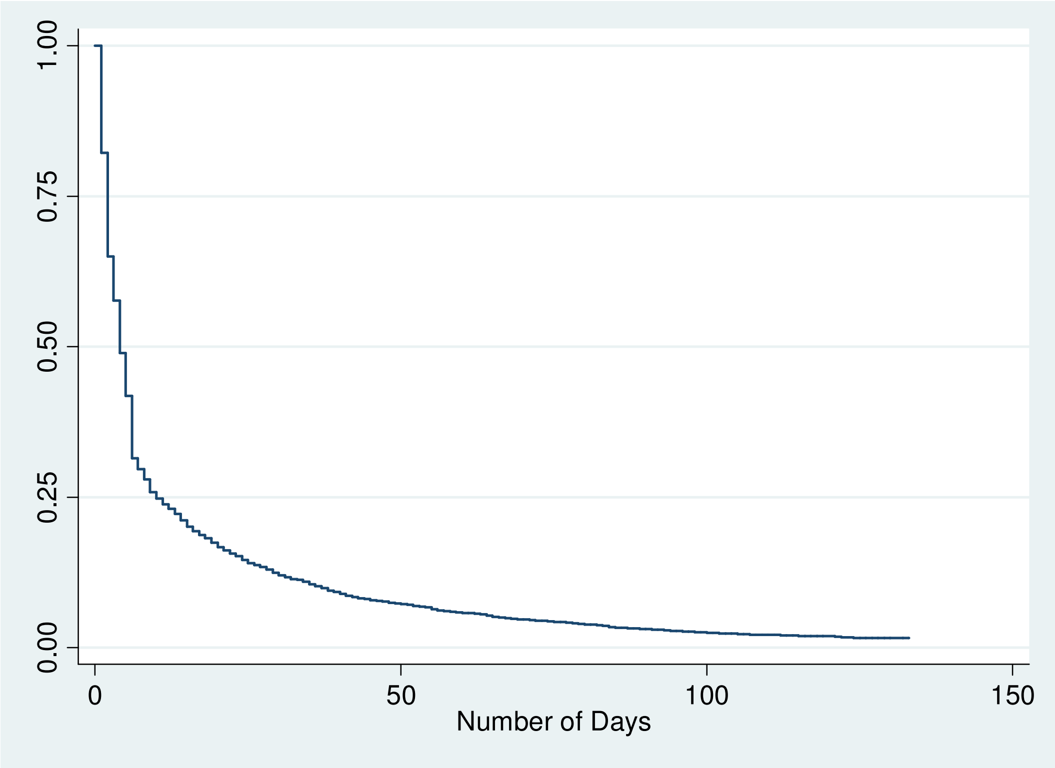

Figure 2. Kaplan-Meier Survival Function Estimate by Seller Reputation

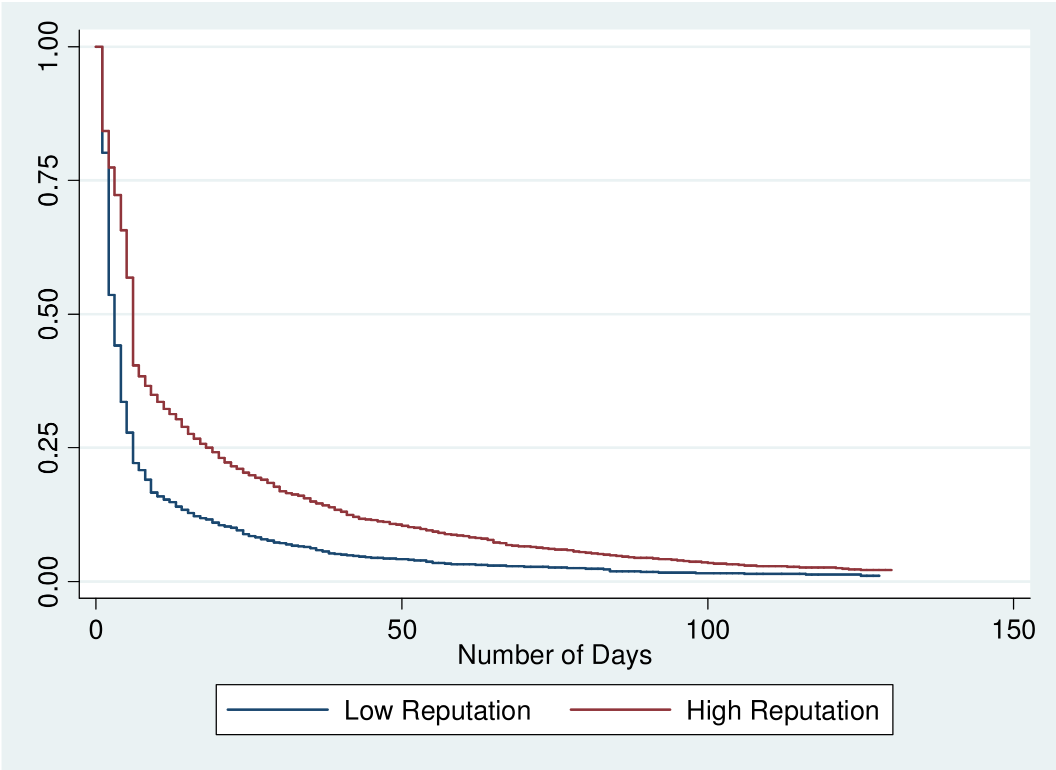

Figure 3. Kaplan-Meier Survival Function Estimate by Entry Price Strategy

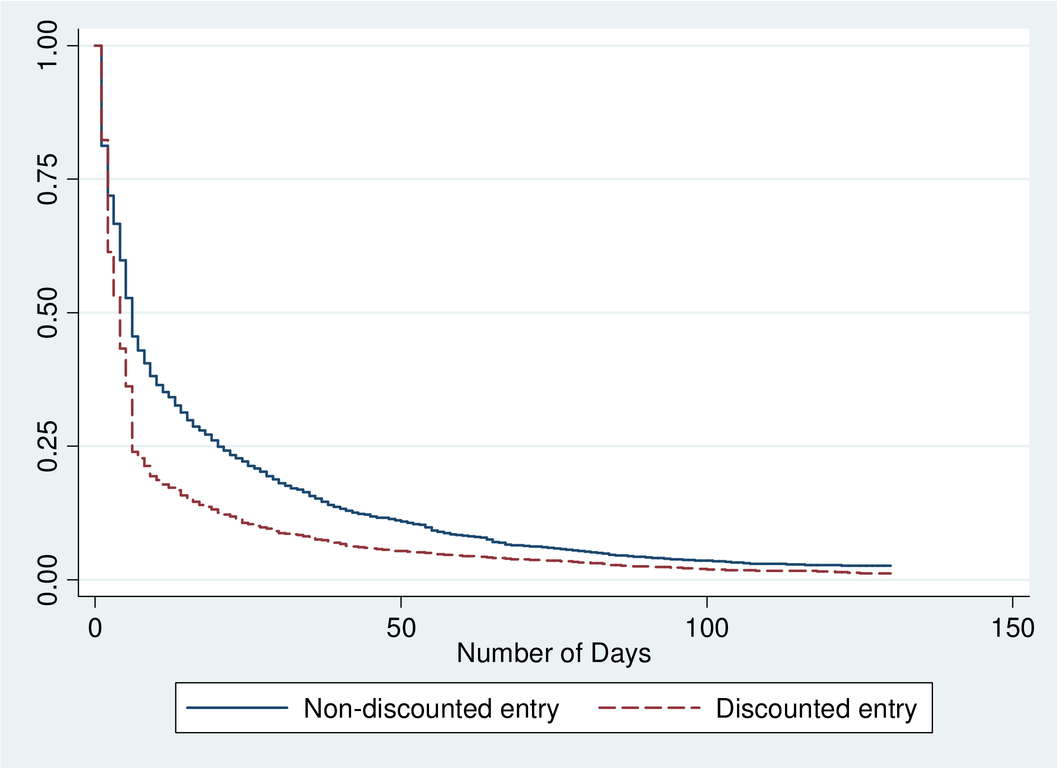

Table 1. Summary Statistics

	Mean	Median	S.D.	No. of Obs.
Sellers	16.26	16	7.28	187,727
Leads	473.18	208	731.41	187,727
Market Size	0.135	0.062	0.320	187,727
Co-entrants	1.054	1	1.491	187,727
Age (days)	267	220	180.25	187,727
Entrant's position	8.681	7	6.85	187,727
Entrant's relative price at exit	4.069	90.12	5.248	187,727

Table 2. Duration of Entrants' Participation: Cox Proportional Hazard Model Including Time Varying Regressors

Discounted Entry	1.3286
	(0.0205)***
Seller Position	1.0024
	(0 .0012)**
Number of co-entrants	0 .9452
	(0 .0022)***
Top 100	0.8519
	(0 .0128)***
Seller Stars	0.8998
	(0 .0044)***
Authorised Dealer	0.8407
	(0 .0315)***
Number of Sellers	0.9898
	(0 .0011)***
Log of Market Size	1.0038
	(0 .0060)
Discounted exit	1.0005
	(0 .0001)***
Age	0 .9999
	(0.0001)
Age-squared	0.9999
	(0.0000)
SLR	0.9136
	(0 .0229)***
Compact	0.9818
	(0 .0211)
Ultra-compact	0.9858
	(0 .0215)
Wald test	2524.27
[p-value]	[0.000]
Number of Cameras	295
Number of Observations	187,727

Notes: Robust standard errors are given in parentheses below the estimated coefficients: *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Effect of Entry on Change in Incumbents' Price

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
$Entry_{t-1}$	-0.003546	-0.0053422	-0.0009022
	(6.42)***	(6.02)***	(1.63)
Multiple $Entry_{t-1}$	-0.004562	-0.0066296	-0.000722
	(6.22)***	(5.65)***	(0.98)
$Exit_{t-1}$	0.0034191	0.0060304	0.000517
	(7.02)***	(7.66)***	(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 4. Effect of Entry on Change in Incumbents' Price, Split by Entrants' Reputation

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
$Low\_Rep\_Entry_{t-1}$	-0.0038175	-0.0076373	0 .0003051
	(5.00)***	(6.25)***	(0.40)
$High\_Rep\_Entry_{t-1}$	-0.0032949	-0.0032702	-0.0020002
	(4.61)***	(2.86)**	(2.80)***
Multiple $Entry_{t-1}$	-0.0045831	-0.0068564	-0.0006125
	(6.24)***	(5.82)***	(0.83)
$Exit_{t-1}$	0.0034136	0.0060142	0.0005206
	(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 5. Effect of Discounted and Non-discounted Entry on Change in Incumbents' Price

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
Discounted_Entry$_{t-1}$	-0.0086056	-0.0110433	-0.0036694
	(12.87)***	(10.33)***	(5.45)***
Non-discounted_Entry$_{t-1}$	0.0043899	0.0042407	0.0033419
	(5.42)***	(3.25)***	(4.11)***
Multiple Entry$_{t-1}$	-0.004932	-0.0070479	-0.0009365
	(6.74)***	(6.01)***	(1.27)
Exit$_{t-1}$	0.0034056	0.0059908	0.0005154
	(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 6. Effect of Entry into Top 3 and Outside Top 3 Position

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
$Top3\_Entry_{t-1}$	-0.0056184	-0.0079575	-0.0016505
	(6.26)***	(5.40)***	(1.82)*
$Outside\_Top3\_Entry_{t-1}$	-0.0027073	-0.0043812	-0.0006086
	(4.35)***	(4.44)***	(0.98)
Multiple $Entry_{t-1}$	-0.0045682	-0.0066382	-0.0007245
	(6.23) ***	(5.65)***	(0.98)
$Exit_{t-1}$	0 .0033647	0.0059676	0.0004992
	(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 7. Effect of Entry on Change in Incumbents' Price, Split by Entrants' Reputation & Pricing Strategy

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
$Low\_Rep\_Disc\_Entry_{t-1}$	-0.00828 (7.71)***	-0.019293 (11.27)***	0.0014857 (1.37)
$Low\_Rep\_Non\text{-}Disc\_ Entry_{t-1}$	0.0085324 (6.23)***	0.0155987 (7.06)***	0 .000972 (0.71)
$High\_Rep\_Disc\_Entry_{t-1}$	-0.0071845 (7.31)***	-0.0018555 (1.19)	-0.0075223 (7.64)***
$High\_Rep\_Non\text{-}Disc\_Entry_{t-1}$	0.0038541 (3.27)***	-0.0034132 (1.28)	0.0065778 (5.56)***
Multiple $Entry_{t-1}$	-0.0041649 (5.75)***	-0.0064992 (5.62)***	-0.0004098 (0.56)
$Exit_{t-1}$	0.0031497 (6.52)***	0.0057117 (7.31)***	0.0004136 (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 8. 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$_{t-1}$	-0.0157488 (10.43)***	-0.0294304 (12.05)***	0.0021914 (1.42)
Low_Non-Disc_Top3_ Entry$_{t-1}$	0.0132243 (6.15)***	0.0235189 (6.52)***	0.0000213 (0.10)
Low_Disc_Out_Top3_ Entry$_{t-1}$	-0.0071587 (6.85)***	-0.016646 (10.13)***	-0.0002613 (0.25)
Low_Non-Disc_Out_Top3_ Entry$_{t-1}$	0.0033238 (2.43)**	0.010974 (5.10)***	-0.0000544 (0.40)
High_Disc_Top3_Entry$_{t-1}$	-0.0110108 (7.06) ***	-0.0021891 (0.86)	-0.0122054 (7.75)***
High_Non-Disc_Top3_ Entry$_{t-1}$	0.0030875 (1.62)	-0.0080821 (2.54)**	0.0067326 (3.50)***
High_Disc_Out_Top3_ Entry$_{t-1}$	-0.0062842 (6.06) ***	-0.0031553 (1.24)	-0.0055866 (5.39)***
High_Non-Disc_Out_Top3_ Entry$_{t-1}$	0.0033644 (2.71)***	-0.0020736 (1.05)	0.0059264 (4.78)***
Multiple Entry$_{t-1}$	-0.0049801 (6.79)***	-0.0078384 (6.68)***	-0.0006135 (0.83)
Exit$_{t-1}$	0.0033273 (6.86)***	0.0060272 (7.69)***	0.0004423 (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 9. Effect of Temporary and Long-term Entry on Change in Incumbents' Price

	All Incumbents (a)	Low Reputation (b)	High Reputation (c)
Temporary_Entry$_{t-1}$	-0.0050153	-0.0080643	-0.0003356
	(7.24)***	(7.21)***	(0.48)
Long-term_Entry$_{t-1}$	-0.0009532	-0.0018803	0 .0002326
	(1.24)	(1.52)	(0.30)
Multiple Entry$_{t-1}$	-0.0033831	-0.0044871	-0.0003341
	(4.74)***	(3.93)***	(0.47)
Exit$_{t-1}$	0.0031563	0.0058187	0.0005171
	(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