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New Model Introductions, Cannibalization and Market Stealing: Evidence from Shopbot Data

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Abstract

Incremental innovation plays an important role in competitive conduct in high-tech industries. This paper explores the impact of new model introduction by employing a nested logit specification to investigate the determination of market shares across and within sub-markets for a panel of 336 digital cameras. Our results confirm the existence of pronounced life cycle effects and the existence of statistically significant market stealing and cannibalization effects, particularly associated with the introduction of a technologically superior entrant into the model's market segment. The paper reveals significant differences in market outcomes, in both elasticity and response to entry, across sub-markets.

JEL codes: L11, C23.
Keywords: Differentiated products; Panel data; Internet; Digital cameras

I. Introduction

In high-tech markets, such as those for personal computers and consumer electronics goods, competitive conduct involves continuing incremental innovation embodied in a succession of model changes. New models, some incorporating 'frontier' technology, displace ageing predecessors. However, models are not simply collections of additive characteristics in a pure Lancastrian world. As Chumpitaz *et al.* (2010) point out; only certain combinations are feasible and sensible such that models form clusters in characteristics space. Thus the competitive impact of improvements in performance and/or functionality should be felt in the first instance by neighbouring models and only secondarily by more distant versions of the product. For example, a reduction in keyboard size may be an attractive innovation in hand-held computers, but irrelevant for desktop machines. Similarly, consumer preference intensity will vary, even over characteristics which are broadly 'vertical', in the sense that they convey measurable improvements in performance or functionality. This variation is most apparent in relation to 'frontier models', that is versions of the product conveying the highest technical specifications of those in their cluster, for which some consumers ('gadget geeks') appear willing to pay a premium price, notwithstanding their likely rapid post-introduction price fall.[1]

It may appear counter-intuitive that innovation is so routine in industries such as computers and consumer electronics, where imitation appears both easy and rapid. Economists since Arrow (1962) have modelled the incentive to innovate as a function of expected monopoly rents. However, following Bresnahan *et al.* (1997) the process of rivalry via product development in high tech markets has been characterised as one in which innovation creates a new market segment in which competition is temporarily dampened until imitative entry by rivals erodes any advantage. Thus the successful launch of an innovative model will steal market share from existing and now inferior models and/or give the seller at least a temporary opportunity to enjoy higher prices. However, determining the frequency and timing of new model release involves difficult trade-offs for the manufacturer. There are obvious costs associated with frequent model changes: these include the costs of model development and those associated with manufacturing re-tooling and short production runs. Bresnahan *et al.* (1997) concede that the gains from innovation - including

[1] Gowrisankaran and Rysman (2007) explicitly address the issue of potential consumers who hold out for an improved price-performance combination from high-tech goods undergoing rapid innovation. In their model consumers compare the utility flow from holding out with no good (or with an older, inferior model) to that of purchase of a later model. (In essence they model the renewal of the consuming public's stock of a durable good, in this case camcorders.) This allows the authors to estimate the dynamic elasticity and to compute the welfare benefit of new model introductions. However, our purpose is rather different: namely to evaluate the market impact of a stream of innovative and imitative new models. Our nested logit design implicitly addresses the hold out issue, in that consumers are assumed to choose between entering the product market or remaining outside and purchasing the numeraire good.

any premium attaching to novelty and the dampening of price competition following innovative entry - may be sufficiently short-lived to deny a positive return to the innovator. Moreover consumer preferences extend to brand-names, which appear to proxy poorly observable attributes such as reliability and subjective characteristics including styling, such that at least some of the gains from new model introduction are likely to be cannibalized from the manufacturer's existing model range.

Work by Hausman and Leonard (2002) [entry by toilet tissue brand], Van Heerde *et al.* (2004) [rising crust pizza] Van Heerde *et al.* (2010) [SUV/saloon crossover vehicle] and Davis (2006) [cinema openings] report significant stealing, cannibalization and pricing effects associated with entry. However, this literature has been concerned with evaluating the consequences of a discrete - and generally a posteriori successful - innovation. None of these markets exhibits new model-embodied performance improvements with the frequency that occurs on a routine basis in high-tech goods. The present paper explores the demand-side effects of new model introductions in digital cameras, a typical consumer electronics product displaying rapid improvements in performance and functionality. We circumvent the usual data problems by the use of price and quantity information from a price comparison site or 'shopbot'.[2]

Research on the market stealing and cannibalization effects of product innovation is generally limited by an absence of quantity (and sometimes price) data. Our data and empirical approach allow us to explore the effect of incremental innovation by model introduction in the context of competition across a large sample of models of different vintages. We give explicit recognition to the clustering of models in characteristics space by a nested logit design in which consumers choosing to buy the product initially select one of four product formats. However, the nested design also allows the evaluation of cross format effects which, as Van Heerde *et al.* (2010) note, may be a consequence of new improved combinations of performance

[2]Shopbots are of two kinds: the first is a programme that searches the Web on the buyer's behalf and locates the best price for a product being sought. The second, which is used in our research, is a two-sided e-market at which sellers post details of their offerings which are hosted by the shopbot in exchange for a levy on clicks through to final sale.

attributes. The distinctive effects of imitative and innovative entry, by both rival brands and improved models from the manufacturer's own brand are then captured by augmenting the basic nested logit model.

Using data for a 16 month period, we observe prices and quantities relating to 336 digital camera models, covering the four main broad formats of cameras. We then employ a nested logit model to investigate the determination of market shares across and within these market segments. The richness of the data set allows us to explore price, time and innovation influences. Price effects are largely as conjectured for a high-tech product without apparent network effects. The within-subgroup price elasticities are higher than the across-subgroup elasticities, supporting our nested design. Moreover, as the model ages – and thus loses any distinctive characteristics advantages it initially enjoyed over its rivals – the price elasticity rises in reflection of the increase in substitutes. Having controlled for (and suitably instrumented) price, market share follows a quadratic time path reflecting model life cycle considerations. However, introducing product count variables to capture the release of newer models confirms the existence of statistically significant market stealing and cannibalization effects, particularly where a technologically superior entrant joins the model's market segment.

The paper is organised as follows: Section II discusses the role of routine innovation in market rivalry. The sample and data are described in Section III. Section IV outlines the use of the nested logit in this context, with the results following in Section V. A brief conclusion follows.

II. Innovation and New Model Introductions

Producers of differentiated products typically seek to establish an advantage over rivals, or alternatively negate any advantage established by such rivals, by incorporating new or improved features over existing models. During periods of rapid technological advance, as experienced in computers and consumer electronics, successive models may display considerable improvements in performance and functionality over their predecessors. As Bresnahan *et al.* (1997) point out; such innovation effectively creates a new product market segment within which the innovator enjoys some shelter from competitive rivalry: First, because of the existence of some consumers ('gadget geeks' (Geroski, 2003)) with a strong preference for novelty who are prepared to pay a premium for the early acquisition of a frontier model. Second, because market segmentation via vertical differentiation is itself a means of dampening price competition.

Since key components in computing and electronic products, especially but not exclusively those based on semiconductors, have continued to display performance improvements.[3] Model changes continue to deliver vertical differentiation rather than the mere styling changes – or horizontal differentiation – typical of some more mature technologies. However, any competitive advantage secured by innovation is generally eroded as rivals imitate novel features and incorporate them into their own new models. This is particularly rapid in industries such as electronics and computers, where product improvements tend to be embodied in components that are available to many manufacturers. Research on high-tech markets, including computers (Stavins, 1995) and disk drives (Lerner, 1995), confirms that quality-adjusted prices do indeed fall as the density of sellers in proximate product space increases.

While new model launches are aimed at capturing sales from existing rivals, multi-product firms also risk the cannibalization of sales from their existing stock of models. Brands function as subjective quality indicators and may embody more intangible attributes such as styling and image. Therefore new model releases involve intra-brand as well as inter-brand competition. Theory suggests that producers will therefore space out their model launches according to the proximity of competitors in the market segment that each serves (e.g. Moorthy and Png, 1992; Desai, 2001).

[3]Semiconductors have broadly continued to double in capacity every 18 months, in accordance with the predictions of Moore's Law.

Ohashi (2005) provides a test of this hypothesis for the US video game market and demonstrates that the gap between release dates for pairs of games for the same platform is significantly greater for directly competing games and those with a common developer, especially if the latter also owns the platform. Corts (2001) demonstrates similar behaviour in the US motion picture industry, where joint ownership in production and/or distribution assists in timing release dates.

This research explores competition in the digital camera market. Unlike most high-tech goods that have been the subject of recent research in the area (including PCs, DVDs, spreadsheets and video games), the digital camera has no obvious direct or indirect network effects (Shapiro and Varian, 1999). In other respects however, it appears typical of other high-tech products. Models possess a very short product life cycle, such that it is not uncommon for some manufacturers to replace them within nine months. Table 1 summarises the announcements of leading manufacturers' new models, excluding minor variants and re-bundling of existing models, as recorded by a prominent industry web site over the years 2004-2007. The digital camera also shares with other electronics products the experience of very rapid aggregate sales growth after the product's initial launch: for example, sales in the US market increased from a few thousand units in 1996 to over 30 million by 2003. This was accompanied by very substantial improvements in performance and functionality and a substantial sustained fall in the quality-adjusted camera price, consequent upon a continued fall in the cost of semi-conductor-based sensor which digitalizes light images.

It might appear counter-intuitive that the market for a new product embodying proprietary technology, such as the digital camera market, should experience many entrants in its emergent stage. It is, however, consistent with the contention of Geroski (2003) that effective barriers to entry are generally low in new markets before economies of scale considerations dominate. Entrants to the digital camera market came from traditional photography, photocopying and consumer electronics industries. They were able to utilize common components - especially the key semiconductor-based sensor - across standardized interfaces as elsewhere in consumer electronics.[4] Ironically, Kodak, the firm whose lavish R and D expenditures did most to develop digital camera technology, was unable to prosper in the new market and has since failed.[5]

TABLE 1
New Digital Camera Model Announcements by Leading Manufacturers 2004-7

	2004	*2005*	*2006*	*2007*
Kodak	13	15	11	12
Nikon	11	16	15	18
Sony	12	14	12	18
Pentax	12	14	14	11
HP	5	8	5	7
Casio	11	9	8	8
Olympus	13	19	20	20
Canon	19	17	17	19
Fuji	15	9	13	13
Samsung	13	7	7	18
Panasonic	8	9	12	14

Source: *dpreview.com*

In high-tech product markets it might be expected that the short model life, curtailed as imitative rivals erode any distinctive advantage and innovative rivals establish superiority, leads manufacturers to seek to recoup development costs early in the life cycle. This is reinforced by the observation (e.g. by Ohashi, 2005) that such products frequently demonstrate 'L-shaped' sales profiles, with very rapid declines after a limited period. However, where network effects predominate, manufacturers tend to adopt penetration pricing strategies to boost the installed base. Thus, Clements and Ohashi (2005) find that the absolute price elasticity for games consoles *falls* consistently over a product's life as manufacturers *increase* the price-cost

[4] Sturgeon (2002) has described the global re-organisation of the electronics industry on the basis of outsourcing manufacturing to contractors who, in turn, source components from major subcontractors who maximize economies of scale by consolidating demands and supplying similar components for inclusion in competing brands.

[5] Many patent disputes notwithstanding, the technology developed by Kodak (with Apple) was widely adopted by rivals such that the company's patent portfolio became its principal asset. See: http://www.appleinsider.com/articles/12/01/20/apple_claims_ownership_of_digital_photography_patents_asserted_by_kodak_.html Accessed on 25/2/2012.

margin in response to the increasing number of game applications available. By contrast, the digital camera, with no apparent network effects, might be expected to display *increasing* price elasticity as each model loses any distinctive advantage and undergoes commoditisation. This implies higher price-cost margins in the early part of the life cycle.

When investigating the model life cycle using e-retailer data it should be noted that there is an asymmetry between model entry and exit. New entry is a discrete event occurring when supplies reach at least one seller; although there may be some lag before non-authorized dealers, who make up a significant part of e-markets, receive shipment. By contrast, exit is an extended process since some sellers typically retain inventory long after production has ceased. Furthermore, freed from the costs and constraints of shelf space provision some e-sellers may offer apparently obsolete models for the benefit of enthusiasts.[6]

It was noted above that aggregate sales of many high-tech product models tend to follow an 'L-shaped' pattern, with a rapid decline setting in after some relatively short interval. Since our data extend back to a maximum of 16 monthly observations prior to end-March 2005, we do not necessarily observe each model's launch and its initial aftermath. Furthermore, as shopbot markets contain many sellers who are not manufacturers' authorised agents and who therefore obtain supplies with some lag, it might be expected that observed aggregate shopbot sales (i.e. leads) increase more gradually than those of authorised retailers alone. These observations suggested the need for a quadratic time trend to capture sluggish behaviour at either end of the life cycle.

While manufacturers clearly influence retail prices, not least via their own recommended prices, transaction prices reflect micro market structure: e.g. recent price comparison site research suggests that model price is negatively related to the number of sellers (Baye *et al.*, 2004; Haynes and Thompson, 2008). Since digital cameras

[6]This is the so-called 'long tail' phenomenon observed in e-tail markets: see Anderson (2006).

vary hugely in price and sophistication, we followed the industry's classification used over this period by, for example, *dpreview.com*, and distinguish four product formats: namely compact, subcompact, SLR and SLR-type, with the expectation that rivalry would be keener within each group than between them and that measured cross price elasticities would reflect this. The compact and subcompact are each 'point-and-shoot' cameras for the general user, distinguished by the latter's diminutive size. SLR models, offering high quality performance, allow the user to observe the optical image directly through the shutter; while SLR-type look similar but use a digital viewfinder and generally exhibit somewhat lower quality components. In each case, however, the quality of resolution depends critically on sensor size.

Our data allow us to model the effects of increased competition on models in each segment as more and better rival models are introduced. To achieve this, we augment the basic estimating equation with a series of count-based variables reflecting cumulative entry to the segment from all comers, superior rival offerings and superior own offerings, respectively. This allows the separate evaluation of the market stealing and market cannibalization effects of new model introductions.

III. Sample and Data

The data used in this paper relate to monthly price listings for digital cameras sold on the price comparison site *NexTag.com*, from December 2003 to March 2005, a period during which manufacturers continued to introduce new models which demonstrated vertical superiority over their predecessors. *NexTag.com* is one of the largest shopbots, or price (and product) comparison engines, on the internet, with claimed visits running at 11 million a month over the period in question and coverage extending to a wide range of electronic, household and other goods and services. Potential consumers select a product type and can then sort by various characteristics, including specifications, price range, or brand. They next select a model and then receive a list of participating suppliers' offers, including item prices and terms. Listing is free to suppliers, who merely pay for 'leads' or 'clicks' through to the seller's web site. The price paid for these varies according to a supplier's position on the page, with a higher payment necessary to secure a top-of-the-page position.[7] Some sellers also pay for positional adverts.

The *NexTag.com* site provides historical data on price and number of sellers, typically dating back to a model's introduction, and a histogram of leads dating back 16 months for cameras listed.[8] *NexTag.com* also provides current data on price/suppliers and limited information on model characteristics, which we supplemented with material from other on-line camera listings. An advantage of this site for our research is that the *NexTag.com*'s listing of digital camera models over the period appeared exhaustive of those on general sale in the USA, even including many discontinued models which were largely untraded. Missing or incomplete price and lead data[9] reduced the sample size from approximately 465 to 336.

We follow previous research (e.g. Baye *et al.*, 2004, 2009) on price comparison sites in using clicks through - or 'leads'- as a proxy for quantity. Of course, a lead is not a final sale and some transactions will not be completed. Baye *et al.* (2009) point out that using leads as a proxy for quantity in demand estimation hinges on the conversion rate (i.e. sales/leads) being independent of own price. In support of this assumption they note that the whole logic of the price comparison site is that the prospective buyer uses it to search out price (x_i) and all other relevant information, including delivery terms, (X_1) prior to clicking on the seller's site. Provided that (x_i,X_1) is sufficiently attractive to merit purchase, the consumer will proceed to the seller's site. Therefore the conversion rate should be independent of x_i. Support for this reasoning comes from both theory and empirical evidence. Clearing house models

[7] *NexTag.com* warns that the minimum payment may be insufficient to secure any listing if the number of sellers is particularly high.

[8] This data was extracted from the screen display using xyExtract^{TM}, a proprietary digitization programme.

[9] In a small minority of cases suppliers had purchased exclusive positions and clicking on the model took the searcher directly to the supplier's site with no historical data available. Some models also displayed gaps in their histories. Normally these appeared to be very thinly traded models.

deployed in PCS research - discussed in Baye *et al.* (2004), Haynes and Thompson (2008) - suggest price-sensitive consumers use a PCS to locate and click on the cheapest seller, supporting the separation of search and purchase. Baye *et al.* (2009) provide evidence of a substantial clicks discontinuity between the cheapest and next-cheapest seller, again indicating that relevant search is completed *before* generating the lead such that the conversion rate should be independent of price.

There are two further advantages of clicks data in the present context: First, since leads payments are the principal revenue source for *NexTag.com* and a non-trivial outgoing for sellers, both sides of the platform have an incentive to maintain the integrity of the data.[10] Second, our work computes model-level elasticities with leads totals that are aggregated across all sellers in the period. This avoids the problem with seller-level data where differences in the attractiveness or usability of sellers sites could generate inter-seller variation in the conversion rate.

Monthly data were collected on prices and number of leads. Cameras were then classified into the four formats using industry sources.[11] This allowed us to confirm that our sample was entirely representative of the population of new camera models entering the US market over our period.[12]

Data on camera resolution (measured in megapixels) was collected to proxy camera quality. We also obtained information on the month and year in which the camera was introduced to the market. Summary statistics by camera format are provided in

[10]Since sellers must pay for all leads, including those not resulting in a sale, the PCS format should reduce the incentive for sellers to engage in 'bait-and-switch' tactics (Ellison and Ellison, 2009) in which prospective buyers find attractive offers are unattainable and are encouraged to upgrade.

[11]Principally, the digital camera archive site *dpreview.com* which assigns every new model to one of the formats.

[12]Table 2 gives the composition of the sample by camera type. We compared this with the types of the 150 new models announced on *dpreview.com* for the calendar year 2004. (Almost all the new models announced will have entered the US market, although a small number of cheaper compact models are specific to Europe or Asia.) The proportions of sample (and 2004 announcements) were as follows: compact 53.3% (60.3%), ultra-compact 25.9% (22.0%), SLR 9.8% (9.7%) and SLR-type 11.0% (8.0%). Innovation in digital camera performance has led *dpreview.com* to introduce a new classification since our data were initially collected, but the timeline of new model introductions is accessible at: `http://www.dpreview.com/products/timeline?year=2004&brand=&category=cameras`

Table 2. This shows that SLR cameras are the most expensive, have the longest life-cycle and have the highest average sales and resolution; compacts have the highest number of brands, total sales and market share.

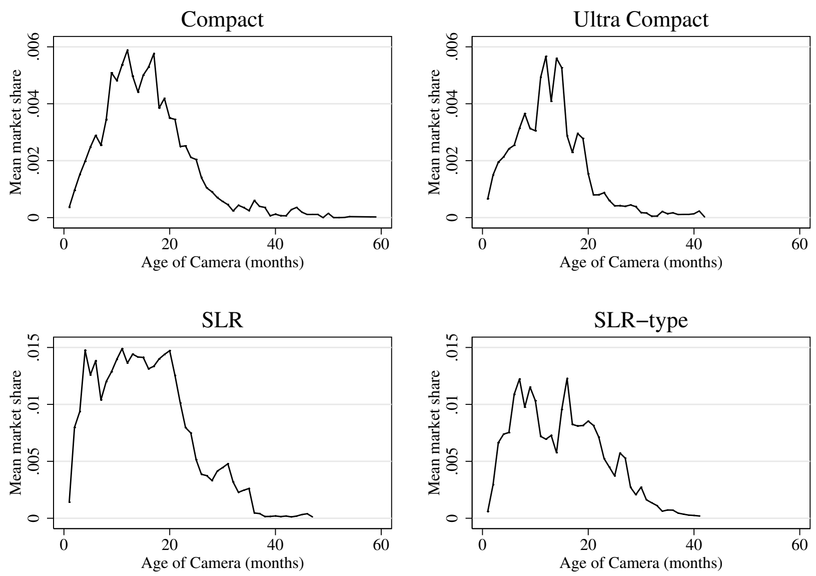
TABLE 2
Summary Statistics by Camera Format

	Compact	*Ultra-Compact*	*SLR*	*SLR-type*
Number of Brands	179	87	37	33
Average Number of Sellers	18	16	20	28
Average age of camera (months)	14	13	16	13
Average Resolution (megapixels)	3.7	3.6	7.8	5.2
Average Minimum Price ($)	242	261	1558	398
Average Median Price ($)	286	300	2013	504
Average Total Sales per year	56,777	21,523	34,421	21,229
Average Sales per model	574	493	1,794	1,196
Market Share (%)	42	16	26	16

Note: Averages taken over brands and time periods.

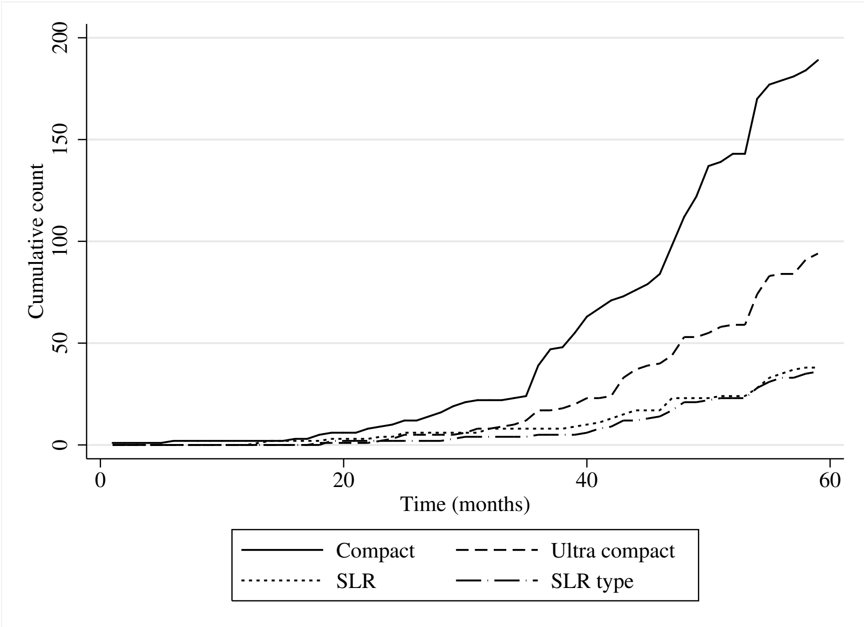
Figure 1 shows the evolution of mean market share, by camera format, over the lifetime of a camera. The figure shows that, for all camera formats, a camera's market share initially increases following its launch and then declines over time, despite the fact that the minimum price of a camera declines sharply over its lifetime.

Figure 1. The evolution of market share by camera format



As posited above, one factor which might explain the evolution of market share is the introduction of new cameras into the market. Figure 2 shows that just under 400 new cameras were introduced in a 60 month period, with the highest number of model launches occurring in the compact and ultra-compact camera segments.

Figure 2. The cumulative number of new models introduced by format



IV. Methodology

In order to examine market share determination, we estimate a nested logit model of demand using panel data on the monthly quantity of digital cameras sold through *Nextag.com* over a 16 month period. The nested logit model (McFadden, 1978) is based on an underlying random utility model in which there are n brands of a differentiated product $q = (q_1, ..., q_n)$ and an 'outside good' q_0. In the model, consumers are assumed to be utility maximisers and will consume one unit of the product from which they derive the highest utility[13]. The n brands can be divided in to G subgroups, indexed by $g = 1, ..., G$ and the outside good is group 0. The divisions are chosen so that similar products are in the same group.

[13] This assumption seems reasonable in the case of digital cameras where multiple purchases are likely to be negligible.

In the context of modelling digital cameras, the first stage is a choice over the camera format (compact, ultra-compact, SLR and SLR-type). The second stage is a specific choice of brand within their chosen subgroup. This implies that, for given market shares, consumers substitute more towards other cameras in the same than in other formats. That consumers will typically buy merely a single unit of the good (rather than, say, a selection as with books or CDs) is supportive of our choice of the nested logit model.

Expressed in market shares, the nested logit framework gives us the following estimating equation:

$$\ln(s_{it}) - \ln(s_{0t}) = \beta x_{it} - \alpha_i p_{it} + \sigma_g \ln(\bar{s}_{it|g}) + \xi_{it} \tag{1}$$

Where, s_{it} is product i's share of the market at time t, $s_{0t} = 1 - \sum s_{it}$ is the share of the outside good, x_{it} is a vector of observable characteristics of that product, p_{it} is the product price, $\bar{s}_{it|g}$ is the product's share of the format group g to which it belongs and ξ_{it} is an unobserved random component. Expressions for own-price (η_{ii}) and cross-price (η_{ij}) elasticities within and between groups can be derived from equation (1):

$$\eta_{ii} = \alpha_i p_i \left[s_i - \frac{1}{1-\sigma_g} + \frac{\sigma_g}{1-\sigma_g} \bar{s}_{i|g} \right] \tag{2}$$

$$\eta_{ij} = \begin{cases} \alpha_j p_j \left[s_j + \frac{\sigma_g}{1-\sigma_g} \bar{s}_{j|g} \right] & \text{if } j \neq i \text{ and } j \in g \\ \alpha_j p_j s_j & \text{if } j \neq i \text{ and } j \notin g \end{cases} \tag{3}$$

To the basic regression we add time since model i's initial launch, T_{it}, included as a quadratic, to capture life cycle effects.[14] By taking time since the launch we allow for any sluggish behaviour in the post-entry and pre-exit period which, as indicated above, may be particularly pronounced in shopbot-generated data.

[14]This time trend possibly conflates a number of effects such as saturation (consumers buy and leave the market for a while, instead of making a sequence of repeat purchases) and learning effects spreading through the pool of potential consumers.

We make the assumption that the numeraire good is the same for all cameras, but varies by time period. Since the logarithm of the share of the outside good is subtracted from product i's share of the market in each time period, we can control for the share of the outside good by the inclusion of monthly time dummies.[15]

In order to examine the impact of the introduction of new cameras into the market, we ranked all cameras in terms of their resolution. This is then used as an approximate measure of product quality[16]. A number of different cumulative count measures were then constructed: Firstly, the cumulative number of newer cameras introduced into the same camera format as the model itself. This is a measure of crowding (and therefore a likely proxy for rivalry) within each format clustering in characteristics space. Secondly, the cumulative number of newer cameras introduced into the same format group that have an equal or higher ranking, in terms of resolution, than the model itself. This is a measure of the extent of competition from superior rivals within each segment. A final measure that we experiment with is the cumulative number of newer cameras introduced into the same format group as the model itself, that are better than or equal to the median camera quality. Each measure is introduced separately into equation (1) and also as an interaction with price. In addition, each of these measures is split into rival-brand (to examine market stealing effects) and own-brand cameras (to examine cannibalization effects).

Unlike most products whose demand has been investigated using the nested logit model, high tech goods such as digital cameras offer consumers a continuously changing quality ranking. Moreover new entrants vary in their competitive position with respect to each incumbent such that a uniform market share response to segment entry would be highly unlikely. Augmenting the nested logit with the cumulative

[15]This is the identical procedure followed by Slade (2004, p.147), and yields the same coefficient estimates as would be obtained by using fundamental demographics to define the outside good. For instance, previous studies such as Kaiser (2006) use the target population. Note also that such variables are also typically only available on an annual basis.

[16]In hedonic price regressions (e.g. Manninen, 2005) resolution dominated other quality indicators. Moreover, over this period it was a principal determinant of picture quality and one on which manufacturers actively competed to outdo their rivals.

introduction variables to control for the changes in each model's competitive environment is used here as a tractable alternative to further nesting based on successively finer levels of product definition. Our approach parallels that of Kaiser (2006) who augments his nested logit model of magazine circulation with a variable which reflects the internet presence of rival magazines.

A feature of the nested logit model estimated in shares is that both the price and group share variables are likely to be endogenous. Equation (2) is therefore estimated using instrumental variable techniques, where we use as instruments: the count of brands produced by the same company; the count of brands in the same segment; the count of brands in the same segment produced by the same firm; the mean characteristics of all other brands by the same producer, the mean characteristics of other brands in the same segment; lagged values of price and group shares. The validity of the instrument set is examined using the Hansen statistic.

V. Results

The nested logit results examining the impact of any newer camera introduced into the same camera format are given in Table 3. All equations are estimated in first differences to remove camera fixed effects, and all estimations include monthly time dummies. Since the lack of second order serial correlation in the error is essential for the consistency of the estimates, a robust N(0,1) test for its presence is presented in each case, and reveals no evidence of statistically significant second-order serial correlation. Similarly, the Hansen test of instrument validity does not reject exogeneity of the instrument set at the 5% significance level.[17] Columns (1) to (3) in Table 3 show the results using the three different cumulative count measures.

Examining the parameter estimates, the coefficient on price is negative and highly significant. The coefficients on the group share variables are always positive and

[17] In nine of the twelve cases where the Hansen test is reported we do not reject the exogeneity of the instrument set at 10% or greater.

less than one. Again, they are highly significant apart from the coefficient on SLR-type. The life cycle effect on market share is as expected, reflecting a significantly determined quadratic time path. This suggests the *ceteris paribus* maximum for market share is reached about 17 months from model release, a result consistent with the raw data displayed in Figure 1.

The nested logit results can be used to calculate the own- and cross-price elasticities of demand. At the mean of the data, the own-price elasticity estimates for compact, ultra-compact, SLR and SLR-type cameras are −1.22, −0.77, −5.89 and −0.97 respectively.[18] The very much higher price of SLRs, shown in Table 2, might be expected to encourage search and resulting price sensitivity, following the classic Stigler (1961) argument, consistent with the higher elasticity estimate for this segment. Also, the buyers of such cameras, as 'serious hobbyists', may be more sophisticated consumers than the buyers of 'point and shoot' models. It may also be that e-retailing is proportionately more important to these specialist models that are less likely to figure on the shelves of general retailers.

The within-group elasticities (0.0073, 0.0076, 0.1642 and 0.0214) are higher than the across-group elasticities (0.0050, 0.0032, 0.0014 and 0.0024), as expected, and an indication that most substitution occurs within format groups. This supports the nesting design employed. Again the higher within-group elasticity for the SLR format is consistent with greater price sensitivity among buyers of the specialist models. Similarly, the very low across-group elasticity for SLRs is indicative of very little substitutability between these very high quality models and the rest.

The variables of particular interest to this paper are those intended to capture the impact of the introduction of new cameras into the market. As shown, all the cumulative count measures are negative and statistically significant. Thus, as anticipated, each model suffers a *ceteris paribus* decline in its market as new entry occurs. The largest marginal impact comes from the cumulative number of newer

[18] The relatively low own price elasticity for ultra-compact cameras is not unexpected, given that horizontal differentiation (i.e. styling) is more important in this segment.

TABLE 3

Nested Logit Demand Equations

	Cumulative no. of newer cameras in same camera format (1) Any quality	(2) Higher quality	(3) Higher than median quality
p_{it}	-0.00105^{***}	-0.000901^{*}	-0.00110^{**}
	(0.00047)	(0.00047)	(0.00047)
$\ln(\bar{s}_{it\|1})$	0.726^{***}	0.730^{***}	0.735^{***}
	(0.13)	(0.13)	(0.13)
$\ln(\bar{s}_{it\|2})$	0.418^{*}	0.447^{**}	0.411^{*}
	(0.24)	(0.23)	(0.24)
$\ln(\bar{s}_{it\|3})$	0.916^{***}	0.945^{***}	0.878^{***}
	(0.28)	(0.26)	(0.29)
$\ln(\bar{s}_{it\|4})$	0.306	0.322	0.340
	(0.22)	(0.22)	(0.22)
T_{it}	0.0750^{**}	0.0720^{**}	0.0759^{**}
	(0.033)	(0.031)	(0.033)
T_{it}^2	-0.00192^{***}	-0.00171^{***}	-0.00188^{***}
	(0.00060)	(0.00059)	(0.00060)
Cumulative measure	-0.00510^{***}	-0.00725^{***}	-0.00751^{**}
	(0.0019)	(0.0025)	(0.0030)
Serial Correlation p-value	0.148	0.176	0.134
Hansen p-value	0.141	0.079	0.122
Wald-test p-value	0.000	0.000	0.000
BIC	1.168	1.055	1.155
No. of cameras	336	336	336
No. of observations	2872	2872	2872

Notes
The dependent variable is camera i's share of the market at time t.
All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
Format groups 1 to 4 correspond to compact, ultra-compact, SLR and SLR type respectively.
Hansen is a chi-square test of the overidentifying restrictions. The serial correlation test is an N(0,1) test for second-order serial correlation.
Robust standard errors are given in parentheses below the estimated coefficients
f *** p<0.01, ** p<0.05, * p<0.10

cameras in the same camera format that are better than the camera itself, or better than the median camera in that format. The best fit, as measured by the Bayesian Information Criteria (BIC), is where the cumulative number of cameras is better than the camera itself. These results are consistent with the existence of market stealing effects associated with the introduction of technologically superior cameras into a format group.

In order to examine the cannibalization and market stealing effects further, the cumulative count measures are split in to the cumulative number of newer rival brand cameras introduced into the same format group as the camera itself and the cumulative number of newer own-brand cameras introduced into the same format group as the camera itself. These results are presented in Table 4. As can be seen, all of the cumulative measures relating to rival producers are negative and significant. These results are consistent with the existence of market stealing effects associated with the introduction of new rival cameras into a format group. The largest marginal impact is for those newer rival brand cameras introduced into a format group that are better than or equal to the median camera quality. The coefficients on the cumulative measures relating to own brand introductions are negative and larger than the market stealing effects (although statistically insignificant for better than the median measure). These results are consistent with the importance of cannibalization effects on a camera's market share when a new own-brand camera is introduced into the same format group.

It was noted above that manufacturers in high-tech product markets, including consumer electronics, compete via the introduction of new models with greater performance and/or functionality. While some care needs to be exercised in generalising from the *average* consequence of new model introduction, not least because the sales distribution across the set of new models is highly skewed, the innovating manufacturer faces a number of crucial trade-offs. Our results confirm that introducing a new model would be expected to capture market share, particularly where the newcomer

Table 4

Market Stealing versus Cannibalization Effects

	Cumulative no. of newer cameras in same camera format		
	(1) Any quality	*(2) Higher quality*	*(3) Higher than median quality*
p_{it}	-0.00123^{**}	-0.00110^{**}	-0.00114^{**}
	(0.00052)	(0.00052)	(0.00052)
$\ln(\bar{s}_{it\|1})$	0.729^{***}	0.740^{***}	0.709^{***}
	(0.14)	(0.13)	(0.14)
$\ln(\bar{s}_{it\|2})$	0.386	0.400	0.406
	(0.26)	(0.25)	(0.26)
$\ln(\bar{s}_{it\|3})$	0.897^{***}	0.932^{***}	0.950^{***}
	(0.32)	(0.30)	(0.30)
$\ln(\bar{s}_{it\|4})$	0.302	0.309	0.249
	(0.23)	(0.22)	(0.24)
T_{it}	0.0741^{**}	0.0714^{**}	0.0725^{**}
	(0.034)	(0.032)	(0.034)
T_{it}^2	-0.00193^{***}	-0.00170^{***}	-0.00201^{***}
	(0.00063)	(0.00062)	(0.00064)
Cumulative measure:			
-rival brand	-0.00437^{**}	-0.00617^{**}	-0.0132^{***}
	(0.0020)	(0.0026)	(0.0051)
-own brand	-0.0153^{*}	-0.0275^{**}	-0.0117
	(0.0090)	(0.013)	(0.013)
Serial Correlation p-value	0.149	0.161	0.167
Hansen p-value	0.228	0.199	0.261
Wald test p-value	0.000	0.000	0.000
BIC	1.298	1.254	1.278
No. of cameras	336	336	336
No. of observations	2872	2872	2872

Notes
a The dependent variable is camera i's share of the market at time t.
b All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
c Format groups 1 to 4 correspond to compact, ultra-compact, SLR and SLR type respectively.
d Hansen is a chi-square test of the overidentifying restrictions. The serial correlation test is an N(0,1) test for second-order serial correlation.
e Robust standard errors are given in parentheses below the estimated coefficients
f *** p<0.01, ** p<0.05, * p<0.10

offers some tangible qualitative advantage over its immediate competitors. However, it will also tend to cannibalize sales from the manufacturer's other models, especially any in the same segment. In timing any launch these effects need to be compared with any additional costs associated with a new model introduction. It should also be remembered that the manufacturer has at least one other alternative strategy: namely she can initiate a significant cut in the retail price by announcing a reduction in the manufacturer's recommended selling price, with corresponding price cuts to distributors. This appears to be a commonplace act by electronics manufacturers, often in direct response to the introduction of a rival model.[19]

Further Experiments with the Data

To investigate these effects further, Table 5 shows the market stealing and cannibalization results split by camera format. The cannibalization effect appears to be most pronounced for ultra-compacts. There is a negative and significant coefficient for an own camera introduction, particularly if the newcomer exhibits vertical superiority over the existing camera. The greater sensitivity of ultra-compact model sales to new entry is consistent with the greater importance of horizontal differentiation – e.g. brand preferences, including design appearance – for this format. With regards to market stealing, once again the largest impact is from the introduction of newer rival brands which are better than the existing camera. The market stealing effects are negative and significant in both compact and ultra-compact formats, with weaker effects for SLRs and SLR-type cameras.

Not merely are there inter-format differences, in support of the nested logit model specification, but it is clear that in both elasticity magnitude and relative invulnerability to market stealing the SLR format is something of an outlier. This is not unexpected for three reasons: First, the SLR will tend to be purchased by enthusi-

[19] For example, *dpnow.com* announced (1st May 2004) that 'Olympus E-1 digital SLR marketing effort has stepped up a couple of gears today with the announcement that the E-1 body on its own has been reduced by 400 to 999, while the body plus . . . (augmented) zoom has been reduced similarly from 1799 to 1399'. `http://dpnow.com/740.html`

asts who might be expected to make better informed price comparisons than buyers of cheaper, point-and-shoot models[20]; Second, our quality measure is probably less reliable for SLR cameras[21]; Third, SLR cameras are used with a stock of transferable ancillary equipment, including lenses, which is usually forwardly compatible within–and sometimes across–brands, but whose existence will influence replacement/upgrade decisions.

Table 6 presents the results for equation (1) when the cumulative measures are interacted with price. For all three cumulative count measures the interaction term is statistically significant at the 1% level. The negative coefficient indicates that the impact of new camera introduction is to increase the price elasticity of camera demand. This supports the argument of Bresnahan *et al.* (1997) that innovation-generated market segmentation functions to dampen competition in high-tech industries, allowing innovators to enjoy rents which are subsequently eroded by entry elsewhere. Innovative entry again delivers the greatest blow as consumers are attracted to a new frontier model. However, that entry in general should also raise the elasticity is consistent with Stavins (1995) and Lerner (1995) who find that price competition intensifies as imitative entry populates market segments. Our results make an interesting comparison with those of Clements and Ohashi (2005) on video games consoles. The latter product is associated with strong network effects as its attraction increases with the availability of games to run on it. Accordingly, a penetration pricing strategy is optimal such that the price-cost margin *increases* over the console's economic life, implying a *falling* price elasticity. By contrast, here there are no network effects and the consequences of the inevitable rival entry are unambiguously harmful. Therefore it is unsurprising that our results are suggestive of a

[20] Unsurprisingly, given their lower sales volumes, SLR models have a longer economic life than their inferior quality alternatives. Since most enthusiasts' purchases will be upgrades or replacements some might be expected, in the spirit of Gowrisankaran and Rysman (2007), to hold out against purchase, except at times of very low prices. This would increase the measured elasticity. If greater search activity, consequent upon higher absolute prices, produces more clicks through to the sites of potential sellers it will raise measured quantity and so reinforce this effect.

[21] The resolution of the SLR sensor, a component typically based around a CMOS semi-conductor, is more sensitive to configuration than that of the point-and-shoot model, which is generally based around a CCD chip.

Table 5
Market Stealing versus Cannibalization Effects: By Camera Format

	Cumulative no. of newer cameras in same camera format		
	(1) Any quality	*(2) Higher quality*	*(3) Higher than median quality*
p_{it}	-0.00141	-0.000479	-0.00168
	(0.00116)	(0.000754)	(0.00145)
$\ln(\bar{s}_{it\|1})$	0.656***	0.715***	0.583**
	(0.229)	(0.151)	(0.266)
$\ln(\bar{s}_{it\|2})$	0.575***	0.761***	0.642***
	(0.149)	(0.199)	(0.176)
$\ln(\bar{s}_{it\|3})$	0.998***	1.026***	1.070***
	(0.26)	(0.308)	(0.278)
$\ln(\bar{s}_{it\|4})$	0.368*	0.246	0.245
	(0.222)	(0.241)	(0.263)
T_{it}	0.0813	0.109***	0.0685
	(0.0522)	(0.0361)	(0.0619)
T_{it}^2	-0.00184**	-0.00131*	-0.00201*
	(0.000923)	(0.000737)	(0.00109)
Cumulative measure:			
-rival brand, compact	-0.00694***	-0.0215**	-0.0131**
	(0.00229)	(0.00859)	(0.00616)
-rival brand, ultra-compact	-0.0131***	-0.0307**	-0.0254**
	(0.00463)	(0.0146)	(0.0104)
-rival brand, SLR	-0.0139	0.0135	-0.0852
	(0.0195)	(0.0526)	(0.0554)
-rival brand, SLR-type	-0.0268*	-0.0366	-0.00806
	(0.0138)	(0.0804)	(0.0323)
-own brand, compact	-0.0046	-0.0412**	-0.00197
	(0.00638)	(0.019)	(0.0103)
-own brand, ultra-compact	-0.0317**	-0.0674***	-0.02
	(0.013)	(0.0257)	(0.0188)
-own brand, SLR	-0.0934*	-0.134	-0.0704
	(0.055)	(0.138)	(0.0967)
-own brand, SLR-type	0.0473	0.108	-0.0737
	(0.055)	(0.111)	(0.068)
Serial Correlation p-value	0.116	0.161	0.200
Hansen p-value	0.14	0.06	0.07
Wald test p-value	0.000	0.000	0.000
BIC	1.033	0.583	1.427
No. of cameras	336	336	336
No. of observations	2872	2872	2872

Notes
a The dependent variable is camera i's share of the market at time t.
b All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
c Format groups 1 to 4 correspond to compact, ultra-compact, SLR and SLR type respectively.
d Hansen is a chi-square test of the overidentifying restrictions. The serial correlation test is an N(0,1) test for second-order serial correlation.
e Robust standard errors are given in parentheses below the estimated coefficients
f *** p<0.01, ** p<0.05, * p<0.10

Table 6

Nested Logit Demand Equations: Interaction of Price with the Cumulative Count Measures

	Cumulative no. of newer cameras in same camera format		
	(1) Any quality	*(2) Higher quality*	*(3) Higher than median quality*
pit	-0.000749^{***}	-0.000680^{***}	-0.000771^{***}
	(0.00025)	(0.00025)	(0.00027)
$\ln(\bar{s}_{it\|1})$	0.781^{***}	0.837^{***}	0.789^{***}
	(0.1)	(0.084)	(0.12)
$\ln(\bar{s}_{it\|2})$	0.508^{**}	0.512^{**}	0.516^{**}
	(0.23)	(0.23)	(0.23)
$\ln(\bar{s}_{it\|3})$	1.206^{***}	1.229^{***}	1.110^{***}
	(0.31)	(0.26)	(0.28)
$\ln(\bar{s}_{it\|4})$	0.138	0.169	0.157
	(0.17)	(0.17)	(0.17)
T_{it}	0.0335	0.0196	0.0154
	(0.052)	(0.057)	(0.053)
T_{it}^2	-0.000843^{*}	-0.000454	-0.000879^{**}
	(0.00044)	(0.00052)	(0.00040)
$T_{it} * p_{it}$	0.0000715^{***}	0.0000611^{***}	0.0000683^{***}
	(0.000018)	(0.000013)	(0.000019)
*Cumulative measure*price*	-0.0000143	-0.0000242^{**}	-0.0000135
	(0.0000091)	(0.000012)	(0.000014)
Serial Correlation	0.412	0.227	0.225
Hansen p-value	0.481	0.481	0.515
Wald test p-value	0.000	0.000	0.000
BIC	1.087	1.172	0.96
Number of cameras	326	326	326
No. of Observations	2696	2696	2696

Notes

a The dependent variable is camera i's share of the market at time t.
b All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
c Format groups 1 to 4 correspond to compact, ultra-compact, SLR and SLR type respectively.
d Hansen is a chi-square test of the overidentifying restrictions. The serial correlation test is an N(0,1) test for second-order serial correlation.
e Robust standard errors are given in parentheses below the estimated coefficients
f *** p<0.01, ** p<0.05, * p<0.10

‘cream skimming’ strategy, in which innovative products enter with higher price-cost margins that are subsequently eroded.

In common with most applications of the nested logit model, the sample of products included - although very substantial at 336 cases - fall short of the entire population of the camera market due to the unavailability of data for certain less widely available camera models. As a check on the robustness of our approach we separately estimated a series of ad hoc regressions in which the dependent variable is the log of camera i's sales at time t. These results are available in Appendix A and are qualitatively similar to those obtained using the nested logit framework.

VI. Conclusions

This paper has explored a curious property of high tech markets: namely that routine innovation is a central component of competitive rivalry despite rapid imitation and short product model lives, features that might appear to reduce the incentive to innovate by lowering expected monopoly rents. The paper has explored the relationship between market share and incremental product innovation using a specially constructed unbalanced panel of 336 digital cameras belonging to four distinct product formats. It employs a nested logit design, in which consumers choosing to buy a camera are assumed to first select a format and then one model from within that format's competing model set. Working at the model-level, with price and (proxy) quantity data available, has allowed a much more detailed evaluation of the consequences of new model introduction than would ordinarily be possible. The results confirm the importance of product life cycle effects in markets for technologically evolving consumer electronics products, such as digital cameras. They also confirm and quantify the existence of market stealing and, in some segments, cannibalization effects associated with new entry. They further suggest, as would be expected in a strongly vertically differentiated product, that one of the key drivers of market share over the life cycle of a product is the introduction of more technologically advanced models. They also confirm the existence of significant and plausible inter-format differences, in support of our nested design.

The market stealing effects uncovered, taken together with the implied elasticity estimates, are strongly supportive of the Bresnahan *et al.* (1997) view of innovative entry as a strategy of market segmentation. The introduction of a vertically superior model secures a temporary advantage which is subsequently undermined by imitation and innovation elsewhere. As the model ages its increasing price elasticity indicates a falling price-cost margin in reflection of its declining competitiveness.

While the results reflect retail market competition, they illustrate the trade-off manufacturers face when considering new model introductions. The clear market stealing benefits must be considered net of any losses via cannibalization when set against the costs of creating and launching a new model. Inevitably, given data limitations, we are estimating a reduced form for market share. A fully specified supply side would necessitate access to production and product development costs for alternative new products. Of course, the outside researcher cannot get access to such cost data, particularly at a sufficiently disaggregated level.

Furthermore, our results necessarily relate to effects evaluated at the mean. The outcome for any particular new model introduction is difficult to predict and a strongly skewed sales distribution suggests that many models probably fail to recoup their development costs.

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Appendix

Table A.1
Demand Equations

	Cumulative no. of newer cameras in same camera format		
	(1) Any quality	*(2) Higher quality*	*(3) Higher than median quality*
log(pit)	−1.658***	−1.637***	−1.657***
	(0.121)	(0.121)	(0.121)
log(price other, same format)	1.755***	1.755***	1.749***
	(0.355)	(0.350)	(0.356)
log(price other, different format)	−0.848	−0.838	−0.864
	(0.702)	(0.696)	(0.704)
Cumulative measure	−0.00330**	−0.00454***	−0.00504**
	(0.00134)	(0.00141)	(0.00223)
Hansen p-value	0.211	0.236	0.183
Wald test p-value	0.000	0.000	0.000
BIC	3.30	3.297	3.301
No. of cameras	336	336	336
No. of observations	2872	2872	2872

Notes
a The dependent variable is log of camera i's sales at time *t*.
b All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
c Hansen is a chi-square test of the overidentifying restrictions.
d Robust standard errors are given in parentheses below the estimated coefficients
e *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table A.2

Market Stealing versus Cannibalization Effects

	Cumulative no. of newer cameras in same camera format		
	(1) Any quality	*(2) Higher quality*	*(3) Higher than median quality*
log(pit)	−1.545∗∗∗	−1.545∗∗∗	−1.573∗∗∗
	(0.118)	(0.118)	(0.120)
log(price other, same format)	1.756∗∗∗	1.733∗∗∗	1.756∗∗∗
	(0.336)	(0.335)	(0.340)
log(price other, different format)	−0.626	−0.693	−0.669
	(0.669)	(0.670)	(0.678)
Cumulative measure:			
-rival brand	−0.00285∗∗	−0.00552∗∗∗	−0.00946∗∗∗
	(0.00140)	(0.00154)	(0.00346)
-own brand	−0.0172	0.00186	0.0000356
	(0.0105)	(0.0127)	(0.0145)
Hansen p-value	0.267	0.291	0.315
Wald test p-value	0.000	0.000	0.000
BIC	3.298	3.294	3.297
No. of cameras	336	336	336
No. of observations	2872	2872	2872

Notes
a The dependent variable is log of camera i's sales at time *t*.
b All equations are estimated using instrumental variable techniques. Columns 1 to 3 show the results using the three different cumulative count measures. All equations include time dummies.
c Hansen is a chi-square test of the overidentifying restrictions.
d Robust standard errors are given in parentheses below the estimated coefficients
e *** p<0.01, ** p<0.05, * p<0.10