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Segmented Switchers and Retailer Pricing Strategies

Empirical studies reveal a surprisingly wide variety of pricing strategies among retailers, even among Internet sellers of undifferentiated homogeneous goods, such as books and music CDs. Several empirical findings remain puzzling; for example, within the same market, some small retailers decide to discount deeply, whereas others forgo the price-sensitive switchers and price high. The authors present theoretical and empirical analyses that address these varied pricing strategies. A model of three asymmetric firms shows that under multiple switcher segments, in which different switchers compare prices at different retailers, firm-specific loyalty is not sufficient to explain the variety of pricing strategies. The authors demonstrate that a retailer's strategy to discount deeply or frequently is driven by the ratio of the size of switcher segments for which the retailer competes to its loyal segment size. The relative switcher-to-loyal ratios among retailers explain situations in which a small retailer finds it optimal to price high, despite having few loyals, or to discount and go for the switchers. The results of two empirical studies confirm the model's predictions for varied pricing strategies in the context of Internet booksellers. The analyses also present several implications. A small retailer can sometimes benefit from strategically limiting its access to switchers to soften price competition. A midsized retailer can benefit from targeting its switcher acquisition activities toward its larger rival, given the shallower discounts involved. When most switchers widely compare prices, a large retailer should offer few shallow discounts because other firms will more aggressively discount. The importance of switcher segmentation suggests that managers should carefully measure switching behavior in devising pricing strategies.

Keywords: Internet retailing, pricing strategy, game theory, retailer loyalty, switcher segments

Internet retailing offers consumers considerable choices in terms of where to shop and purchase. For example, a search of several products on mySimon, a popular price comparison engine, reveals more than three dozen retailers for online books, more than 70 retailers offering printers, and more than 100 digital camera retailers. Many of these retailers are small compared with the big players in the category. For example, the Internet book retailer a1Books has less than 1% of the reach (number of viewers who visit the site) of Barnesandnoble.com (B&N). There are dozens of similarly small Internet booksellers that compete with one another and the considerably larger firms of Amazon.com and B&N for a wide assortment of books. What characterizes the price promotion strategies among these many large and small retailers?

In general, frequent discounting by small firms is consistent with extant theory (e.g., Narasimhan 1988; Raju, Srinivasan, and Lal 1990). Customers are conceptualized to possess different information for comparison shopping.

Customers who know the price of only one retailer are uninformed or "loyal" customers, whereas customers who know the prices of all retailers are "switchers." Urbany, Dickson, and Kalapurakal (1996) report various reasons more than half of grocery customers compare prices across retailers, and "cherry-picking" customers tend to benefit from going store to store for specials (Fox and Hoch 2005). Because a small firm has relatively few loyal customers, it typically has more incentive than a large firm to discount and attract the switchers. However, some small retailers decide to price high and sell only to their loyal or niche segment of customers. Although this strategy may be appealing for specialized or highly differentiated goods, it is unclear why a small retailer would price higher than a larger rival for a homogeneous good, such as a book. Clay, Krishnan, and Wolff (2001) report these types of "puzzling" Internet retailers in their empirical analyses—namely, small and undifferentiated firms that, nevertheless, charge relatively high prices. In general, Internet retailers exhibit considerable price dispersion as firms discount or price high, often in ways that are inconsistent with theoretical predictions (Pan, Ratchford, and Shankar 2004).

Especially problematic for conventional price promotion theories is the observation of some small retailers with heavy discounting and others with a high-price strategy in the same homogeneous goods market. Previewing our empirical analyses of Internet booksellers, both Worthy and a1Books are small retailers with similar Internet reach and site popularity. They sell many of the same books (a1Books carries 90% of the books carried by Worthy in our sample) and also compete with the larger retailers, such as Amazon.

com, on a wide variety of books. Despite such similarities, a1Books discounts heavily whereas Worthy typically has high prices that exceed those of both a1Books and Amazon.com. What explains these fundamental pricing differences among small retailers? How frequently do large retailers offer shallow or deep discounts? We present theoretical and empirical analyses that examine various observed price promotion strategies, such as in Internet retailing.

We address two fundamental shortcomings of conventional price promotion models: (1) The duopoly structure can be limited in the various price promotion strategies that are considered, and (2) switchers are usually assumed to be homogeneous in that they know the prices of all retailers. Retailer price promotion strategies from the standard duopoly approach (small versus large retailers) are driven by different loyal segment sizes and homogeneous switchers who compare all prices.[1] We present a model of an asymmetric triopoly (three firms) that includes multiple "switcher segments," in which switchers compare prices at different retailers. Markets involving several asymmetric firms may prove more insightful and reflective of actual market conditions than the conventional duopoly. Furthermore, in the context of multiple retailers, there may be multiple segments of "partially informed" switchers in addition to the typical switchers who compare prices for all retailers. Even in an Internet setting, in which retailers proliferate and many shoppers use price comparison engines, not all switchers will be exhaustive price comparison machines. For example, many online book customers may compare prices between the two larger firms, Amazon.com and B&N, while ignoring smaller retailers such as a1Books. Recent studies indicate that, on average, online shoppers visit only 1.2–1.4 booksellers (Johnson et al. 2004; Montgomery et al. 2004). Even the use of price comparison "shopbots" remains relatively low, given the various cognitive costs of evaluating many alternatives (Montgomery et al. 2004). Consumers are more likely to visit Internet retailers they trust because of an assortment of factors (e.g., Bart et al. 2005). If some customers prefer to compare prices only among trusted stores whereas other customers compare prices from multiple listed retailers, switcher segments with different types of price comparison behavior will occur. Therefore, the realistic assumption is that switchers are segmented because they compare a subset of retailer prices. By including segmented switchers in an asymmetric triopoly, our model derives a more complete set of promotion strategies that are not predicted under asymmetric duopolies.

Prior theoretical models, based largely on the work of Varian (1980) and Narasimhan (1988), report varied results for promotional activity under different conditions. Raju, Srinivasan, and Lal (1990) conclude that the average discount offered by the stronger brand (greater loyalty) is larger than the average discount offered by the weaker brand (less loyalty), but Rajiv, Dutta, and Dhar (2002) reach a different conclusion. Findings also differ about price promotion frequency. Narasimhan (1988) and Raju, Srinivasan, and Lal (1990) conclude that the promotional frequency of the stronger brand is less than that of the weaker brand.[2] Rajiv, Dutta, and Dhar (2002) conclude that high-service stores (as an analogue to a strong brand) promote more frequently under promotional advertising. Small retailers seem to promote with less intensity, though discount prices may have a higher expected payout to smaller stores (Hoch, Drèze, and Purk 1994; Shankar and Bolton 2004). The high versus low pricing dichotomy does not often fit the rich promotional strategies observed empirically (e.g., Bolton and Shankar 2003). There is a need for research that addresses these price promotion variations, particularly for the pricing strategies of small retailers.

We consider a homogeneous goods market with three firms that are asymmetrical in loyals and switchers, and our results clarify the varied price promotion strategies in equilibrium. For example, we show that a firm can adopt a "partitioned" pricing strategy that combines frequent, shallow discounts to compete with a higher-priced firm and infrequent, deep discounts to compete with a lower-priced firm. Our results also explain a situation in which a small firm is better off pricing high with little discounting, despite possessing few loyals. In general, our model not only encompasses a three-firm extension of prior duopoly models but also explains previously ambiguous situations, such as when a retailer has both few loyals and few switchers.

Our specific research questions include the following: How do multiple, asymmetric firms compete for multiple switcher and loyal segments? How do firms differ in their price dispersion, including the frequency and depth of their promotions, in terms of their loyal and switcher customer bases? and Why do some small retailers price high and others offer deep discounts? Our results demonstrate that a retailer's pricing is driven by the ratio of switchers for which the retailer competes to its loyal segment size. The retailers' relative switcher-to-loyal ratios (SLRs) explain when a large or small firm is more or less inclined to discount deeply or frequently or when a small firm with few loyals is better off pricing high.

We test our model's predictions with two empirical studies, using pricing data for numerous Internet book retailers for more than 1600 books. The two studies differ in how an empirical measure is formed for a retailer's SLR (the key variable of the model). The first study is exploratory, using publicly available descriptive data for the retailers. The second study uses comScore data of Internet browsing and purchase data for 100,000 panelists. Compared with the exploratory study, the panel data study has the advantage of more directly measuring switching and loyal behaviors; the disadvantage is that fewer retailers are represented. The empirical results for both studies confirm the model's predictions for retailer pricing based on the SLR, adding a new perspective to previous studies of dis-

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[1]Prior models have been applied to both brand and retailer competition. We model retailers given our focus on homogeneous goods and to be consistent with the context of our empirical setting.

[2]Narasimhan (1988) considers several cases in which the frequency and depth of discount changes according to switchers' brand preferences. For homogeneous goods, we compare our results with Narasimhan's basic results.

persed prices (Baye and Morgan 2001; Burdett and Judd 1983; Raju, Srinivasan, and Lal 1990; Salop and Stiglitz 1977).

We organize the remainder of this article as follows: We present our model, highlighting the strategic intuition in detail and contrasting our results with prior models. We also formulate several hypotheses from the model's results. We then describe our empirical studies and the results. We conclude with managerial implications and suggestions for further research.

Model and Analysis

Our model builds on the work of Narasimhan (1988) and Varian (1980). Whereas Varian considers many symmetric firms and Narasimhan studies two asymmetric firms, we analyze a market with three asymmetric firms and multiple switcher segments. Switcher segments among multiple, asymmetric firms are not components of prior models, which makes our research unique. For conventional retailers, it is easy to imagine that not all customers will be informed of all prices because of the high cost associated with searching prices. In an Internet setting, however, search costs are relatively low. We can reasonably assume that at least some customers are highly informed about online prices, even for low-cost items (Carlton and Chevalier 2001; Koçaş 2002; Smith and Brynjolfsson 2001). However, this assumption does not preclude multiple segments of switchers who do not compare prices among every retailer. Even with price comparison engines, not all retailers are listed, and not all customers use price comparison sites (Iyer and Pazgal 2003; Montgomery et al. 2004). Asymmetric awareness of retailers by price-sensitive switchers may lead to different pricing strategies (Pan, Ratchford, and Shankar 2004).

The fundamental intuition behind our model is that multiple switcher segments can lessen price competition among firms (for a model of price competitiveness in the context of consumer search costs, see Lal and Sarvary 1999). Firms with greater motivation to discount, because of a smaller loyal segment size and/or a greater number of switchers to potentially serve, will more actively compete for the fully informed switchers. This leaves firms with fewer relevant switchers for a given loyalty size to focus on their loyals and the subset of switchers who consider them in their price comparison search. In such cases, prices will typically be higher than they would be if the firm were to compete for all switchers. Other firms discount less in reaction to these higher prices, and thus the severity of price competition becomes less overall. Under some conditions, the firm with the fewest loyals can be the highest-priced firm, a result that asymmetric loyalty by itself cannot implement. Our model predictions reflect a wide variance in retailers' price dispersions, consistent with empirical observations.

Consider a market for a homogeneous good, such as a specific book or music CD, sold by three retailers. On the demand side, each customer purchases a single unit of the good if it is offered at or below the reservation price r, which is assumed to be homogeneous for all customers and across all retailers.[3] We model different segments of both loyal customers who buy from their preferred retailer as long as the price does not exceed r and switchers who comparison shop. The loyal customers are faithful to only one firm; the number of customers who are loyal to Firm i is n_i. Without loss of generality, we assume that $n_1 > n_2 > n_3$. We also assume the existence of two switcher segment sizes, s_{123} and s_{12}, whose members are not loyal to any firm but rather buy from the lowest-priced retailer among those they compare. Switcher segment s_{123} is fully informed, meaning that its members compare prices quoted by all three firms. Switcher segment s_{12} compares prices quoted only by the larger Firms 1 and 2. Although these partially informed switchers do not compare all retailer prices, they still compare the prices from the best-recognized retailers, which may have the largest reach and the most active communication channels.[4] Firms 1 and 2 would be like B&N and Amazon.com (the biggest online booksellers), whereas Firm 3 would be like a1Books. Although some switchers will compare prices at all three retailers (s_{123}), a1Books has less than 1% of B&N's reach, so there are likely to be other switchers who are unfamiliar with a1Books and compare only Amazon.com and B&N (s_{12}).

We normalize the market size to one ($n_1 + n_2 + n_3 + s_{12} + s_{123} = 1$) without loss of generality. Although the segment sizes and the reservation price are common knowledge, because of imperfect addressability and targetability, retailers cannot price discriminately (Blattberg and Deighton 1991; Chen, Narasimhan, and Zhang 2001). All firms face constant fixed and marginal costs, which we assume to be zero without loss of generality (Iyer and Pazgal 2003; Narasimhan 1988; Raju, Srinivasan, and Lal 1990). Overall, the model and its assumptions are similar to Narasimhan's (1988) model and other related models, except for analyses of three firms and two switcher segments.

In an effort to capture switcher segments, firms have an incentive to undercut the price of other firms that are competing for those switchers, a tendency that results in a downward push in prices. Motivation also exists to price at the reservation price, in case the switchers cannot be served with a lower price. A retailer's "minimum price" makes the firm indifferent between selling only to its niche of loyal customers at the reservation price and selling to its switcher segments, given it is the lowest-priced firm at the minimum price. A firm will never discount below its minimum price, because it could then do better by focusing on its loyal customers. A firm's smaller loyal segment size and larger

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[3]A common reservation price is a typical assumption (Iyer and Pazgal 2003; Narasimhan 1988; Raju, Srinivasan, and Lal 1990; Varian 1980). Narasimhan (1988) considers a case in which consumers have different reservation prices for brands.

[4]Consumers may choose not to compare a specific retailer's prices for several reasons, such as a lack of awareness or a lack of trust in the retailer. Our definition of switcher segments is based fundamentally on the set of retailers among which the switcher price compares. A dynamic extension to our model with endogenous segment sizes may take different forms depending on whether price comparisons are dependent on awareness or trust. We thank a reviewer for raising these distinctions.

switcher segment size provide a greater incentive to forgo selling only to the loyals. We define a firm's ratio of switcher-to-loyal segment sizes, ϕ_i, as $\phi_3 = s_{123}/n_3$, $\phi_2 = (s_{123} + s_{12})/n_2$, and $\phi_1 = (s_{123} + s_{12})/n_1$. Under segments s_{123} and s_{12}, Firms 1 and 2 compete for the same switchers, so Firm 2 always has a higher SLR (or ϕ_i) than Firm 1, given Firm 2's smaller loyal segment. However, Firm 3 can only capture switcher segment s_{123}, so its SLR may be higher or lower than that of both firms. Thus, Firm 3 may discount deeply to capture the switchers or play only its niche loyal segment and charge higher prices. Without multiple switcher segments, the relative order of ϕ_i for these firms would strictly be a function of the loyal segment sizes, as in prior models. Thus, our recognition of segmented switchers changes the nature of a retailer's incentive to discount.

A more general consideration of segmented switchers (adding s_{23} and s_{13} switcher segments) does not change the model's intuition or conclusions. Additional switcher segments modify the degree of a retailer's relative incentive to discount, but the pricing equilibrium remains a function of retailers' SLRs and their rank order. Generalizing to more than three asymmetric retailers also gives results that are similar to a triopoly (details are available on request). Thus, our model focuses on three firms and two switcher segments for relative tractability.

Equilibrium Price Promotion Strategies

The tension of selling to switchers and loyals results in a lack of pure strategies typical of such models. Therefore, we solve for a mixed-strategy equilibrium that depends on the relative sizes of the loyal and switcher segments. A mixed strategy can be interpreted as arising from a retailer's uncertainty about the pricing decisions of competing retailers (Gibbons 1992). Equilibrium prices are defined by a probability density function (PDF) that indicates the range of prices a retailer may charge (the retailer's price support). We find that equilibrium price promotion strategies fundamentally depend on the retailers' relative SLRs. Thus, we present the mixed-strategy equilibrium for the case that is more typical of prior models, in which the large Firm 1 has the lowest ϕ_i, as follows:

P_1: When $\phi_3 > \phi_1$, Firms 1 and 3 have mutually exclusive price ranges that, when combined, form Firm 2's price range. Firm 2 competes with Firm 3 in the lower part of its price range and with Firm 1 in the upper part of its price range (for a proof, see the Appendix).

The PDF and the cumulative distribution function (CDF) for the equilibrium prices appear in Figure 1. Firm 2 has greater motivation to compete for s_{123} than Firm 1, and because Firm 3 can only capture s_{123}, the competition between Firms 2 and 3 is fairly intense. The low prices Firm 2 quotes while trying to capture s_{123} make it easier for Firm 2 to sell to s_{12}. Thus, there is no guarantee that Firm 1 will capture any switchers, even at its minimum price, because the other two firms already compete for s_{123} at lower prices. Therefore, Firm 1 is less inclined to discount. The more intense competition between Firms 2 and 3 makes the lower bound of Firm 1's price range move up to the point in equilibrium at which Firm 1 no longer directly competes for

FIGURE 1
Equilibrium Prices in P_1, Illustrated for $s_{123} = s_{12}$

A: PDFs

B: CDFs
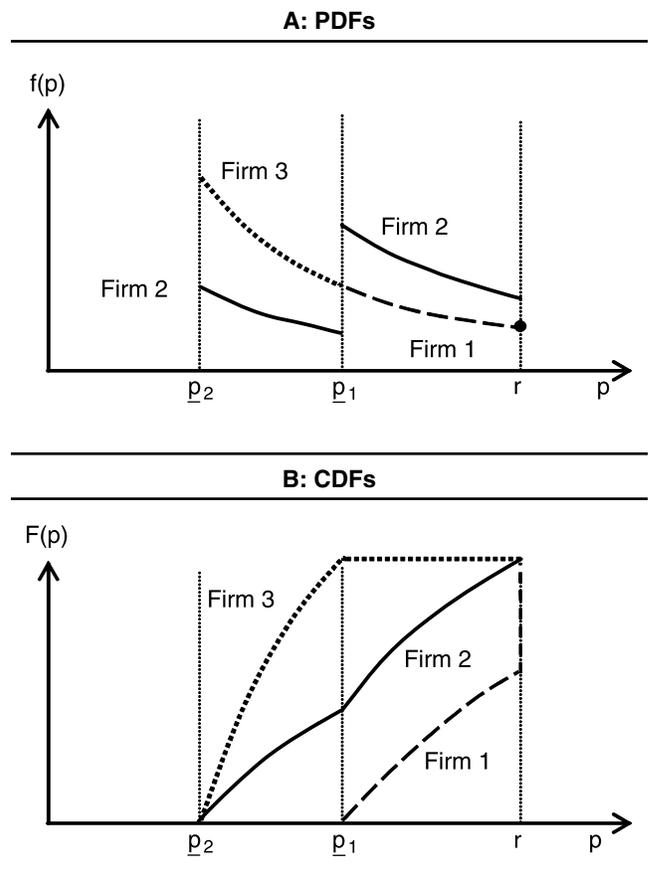
s_{123}. Thus, Firm 1's and Firm 3's equilibrium price ranges do not overlap. Moreover, when Firm 2 prices below Firm 1 to compete with Firm 3 for segment s_{123}, it also always serves segment s_{12}. That is, in the price region in which only Firms 2 and 3 compete, s_{12} effectively becomes a component of Firm 2's loyal segment. Because an effectively larger loyal segment means that Firm 2 now has more to lose from price cuts, the lowest price that Firm 2 can profitably quote increases, which lessens the severity of the price competition with Firm 3. Thus, the lowest price support for Firms 2 and 3 rises above the minimum prices (p_i^{min}) of both firms.

These results emerge mainly because of asymmetry in *both* the switcher and the loyal segment sizes. The lowest prices are higher in our model than in Varian's (1980), Narasimhan's (1988), and other models that lack multiple switcher segments. The existence of s_{12} as a switcher segment that omits Firm 3 leads to higher average prices for Firms 2 and 3, and their competition for segment s_{123} leads to higher average prices for Firm 1. At the extreme of $s_{12} = 0$ (where $\phi_3 > \phi_2$), the results represent a three-firm extension of Narasimhan's model, similar to other models of asymmetric oligopoly (Baye, Kovenock, and De Vries 1992; Koçaş and Kiyak 2006).

We find that the equilibrium of P_1 does not change, regardless of whether Firm 3's SLR exceeds that of Firm 2. The intuition is straightforward; the lower price support for

Firms 2 and 3 rises above their respective minimum prices. Therefore, the equilibrium is unaffected by whether the minimum prices of Firms 2 and 3 switch order, because neither is part of the equilibrium price ranges for those two firms. Furthermore, although Firm 2 may have the highest SLR, it still sets its lower price support partially in response to Firm 1's higher support, because Firm 1 forgoes competition for s_{123}. Firm 1's main issue is that both Firms 2 and 3 have higher SLRs, regardless of whose is greater.
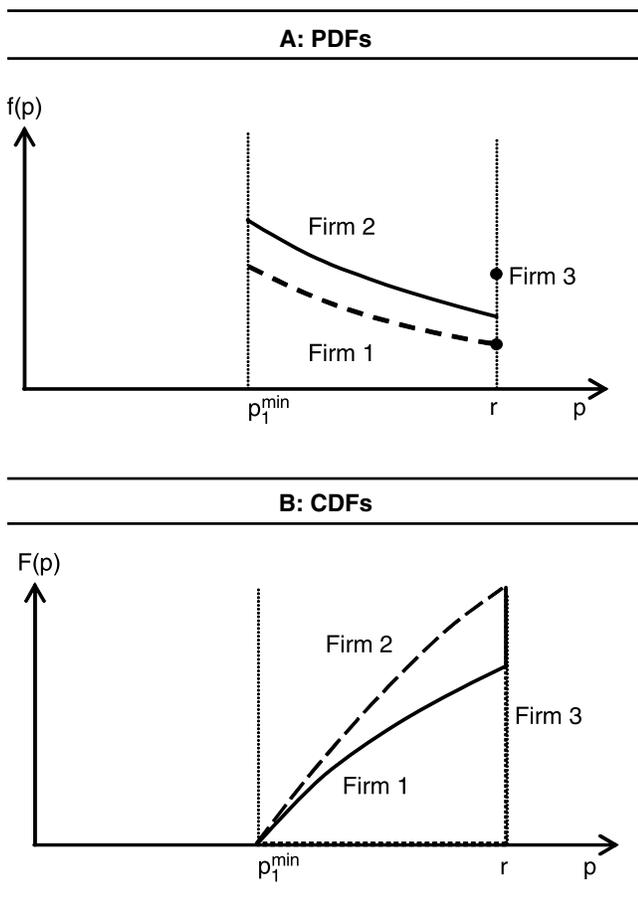
P_1 contrasts remarkably with the case in which Firm 3 has the (weakly) lowest SLR, or $\phi_3 \leq \phi_1$ (recall that $\phi_2 > \phi_1$). In this situation, Firm 3 lacks sufficient discount motivation to capture its switcher segment and thus becomes a high-priced niche retailer focusing on its loyal segment. Because Firm 1's SLR is not the lowest, it finds that it is worthwhile to play for s_{123}. Segments s_{12} and s_{123} implicitly combine into a single switcher segment that only Firms 1 and 2 serve. The resultant equilibrium is defined as follows:

P_2: When $\phi_3 \leq \phi_1$, only Firms 1 and 2 discount, whereas Firm 3's price is set at the reservation price r (for a proof, see the Appendix).

The PDFs and CDFs for the equilibrium prices appear in Figure 2. The lower price support is defined by Firm 1's minimum price because Firm 2 never needs to discount below this to compete for the switchers. Firm 3 is content to be a niche player, pricing high to serve only its relatively small loyal segment. Given that $n_1 > n_3$, the P_2 condition that $\phi_3 \leq \phi_1$ essentially represents the case in which s_{123} is small compared with s_{12} ($s_{123} = 0$ will always meet the condition of P_2). Firm 3 recognizes that most of the switchers compare prices only between Firms 1 and 2, so Firm 3 becomes a high-priced retailer.

Model Discussion

Before turning to the empirical validation of our model, we describe in more detail the firms' profits and prices in the presence of segmented switchers (for a summary, see Table 1). With a partially informed switcher segment s_{12} included, average prices and profits are generally higher because the price supports increase as Firm 1 "abandons" s_{123} under P_1. Thus, multiple switcher segments tend to reduce competition because not all firms are able to capture all switchers.

The relative sizes of the switcher segments shape the nature of competition between the firms. Under P_1, as Figure 3, Panel A, depicts, Firm 1's discount deepens as s_{12} exceeds s_{123} (when the total number of switchers is held constant). However, when the size of the fully informed segment increases, so does the severity of competition between Firms 2 and 3. This increased competition for segment s_{123} pushes Firm 2's and Firm 3's discounts deeper (Figure 3, Panel B). At the same time, it forces Firm 1 to offer shallower discounts because Firm 2 already serves more of segment s_{12} (in expectation) with its deeper discounts. Thus, the composition of switchers fundamentally affects when retailers should offer frequent or infrequent deep or shallow discounts.

When we compare firms' profits as the composition of switcher segments varies, we first observe that Firm 1 is indifferent because it always receives the guaranteed profit ($n_i r$). Firm 2's profits increase when s_{12} increases at the expense of s_{123}, given that segment s_{12} acts as a second-degree loyal segment to Firm 2. A more notable result pertains to the profits of Firm 3 under P_1. Firm 3 can benefit

Figure 2
Equilibrium Prices in P_2

A: PDFs

B: CDFs

TABLE 1
Summary of Equilibrium Results in P_1 and P_2

	P_1 ($\phi_3 > \phi_1$)		P_2 ($\phi_3 \leq \phi_1$)	
	Profits	Lowest Price	Profits	Lowest Price
Firm 1	$n_1 r$	$\underline{p}_1 > p_1^{min}$	$n_1 r$	p_1^{min}
Firm 2	$(n_2 + s_{12})\underline{p}_1 > n_2 r$	$\underline{p}_2 \geq p_2^{min}$	$(n_2 + s_{12} + s_{123})p_1^{min} > n_2 r$	p_1^{min}
Firm 3	$(n_3 + s_{12} + s_{123})\underline{p}_2 > n_3 r$	$\underline{p}_2 \geq p_3^{min}$	$n_3 r$	r

FIGURE 3
Depth and Frequency of Promotions

A: Size of the Fully Informed Switcher Segment Is Smaller Than the Size of the Partially Informed Switcher Segment ($s_{123} < s_{12}$; P_1)

f(p)

Firm 3

Firm 2

Firm 2

Firm 1

$\underline{p}_2$ $\underline{p}_1$ r   p
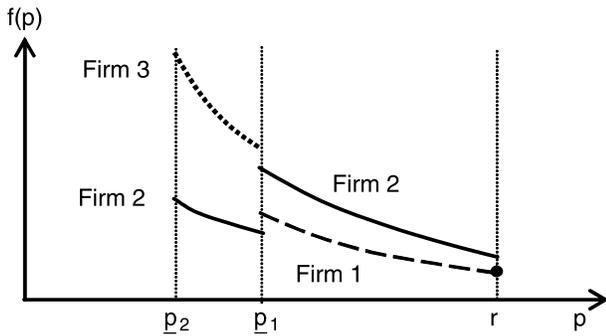
B: Size of the Fully Informed Switcher Segment Is Larger Than the Size of the Partially Informed Switcher Segment ($s_{123} > s_{12}$; P_1)

f(p)

Firm 2

Firm 3

Firm 1

Firm 2

$\underline{p}_2$ $\underline{p}_1$ r   p
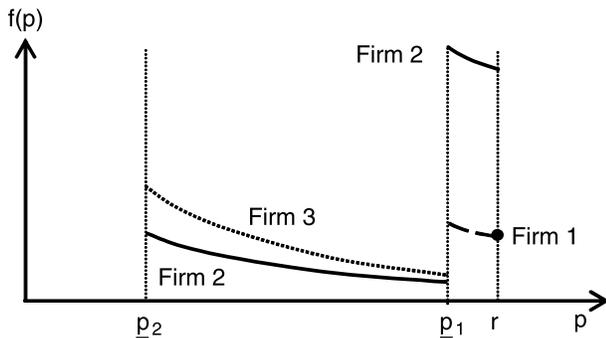
from a positive s_{12} customer base as long as the higher price support more than compensates for the loss of some s_{123} customers as s_{12} increases. In general, Firm 3's profits do not reach a maximum when all switchers belong to s_{123}.[5] Thus, Firm 3 may strategically choose to limit its exposure to switchers (lowering s_{123} and increasing s_{12}) to make Firm 2 focus more on its competition with Firm 1. That is, Firm 3 benefits from a more balanced distribution of switchers, a condition that places Firm 2 in a more balanced consideration for both switcher segments. Thus, our model complements Iyer and Pazgal's (2003) and Baye and Morgan's (2001) results, which pertain to retailers belonging (or not) to Internet agents that facilitate price comparisons. By considering various-sized switcher segments, our model points to a small retailer potentially benefiting from some degree of price comparison strictly between the larger or better-known firms. This result further highlights the competitive

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[5]Firm 3's profits for at least some positive region of s_{12} are higher than its profits at $s_{12} = 0$. More specifically, as long as the total number of switchers remains above a modest threshold, Firm 3's profit has a positive slope at $s_{12} = 0^+$, such that there is at least some positive s_{12} in which Firm 3 is better off.

nature of the asymmetric triopoly. Firm 3's prices and profits depend critically on how Firms 1 and 2 compete with each other for its switcher segment.

When the relative size of the fully informed switcher segment is small, Firm 3 may prefer to ignore the switchers completely and offer no discounts at all (P_2). This result represents an important distinction between our segmented-switcher model and other models of asymmetric loyalty. When multiple switcher segments exist, loyal segment sizes are not sufficient to describe the nature of competition among the various firms. The relative sizes of the switcher segments must also be considered because they affect the SLRs (ϕ_i) among the firms. Thus, a small firm may discount or price high to play its niche, depending on its relative SLR.

Comparison with Prior Models

Our model complements various prior findings for promotion frequency and depth. In terms of promotion frequency, in general, P_1 results follow the work of Narasimhan (1988) and Raju, Srinivasan, and Lal (1990) in that they predict that a strong retailer (one with greater loyalty) promotes less frequently. However, our model also predicts that a strong retailer can promote more frequently if it has relatively more interest in the switchers than the weaker retailers have (e.g., Firm 1 promotes more often than Firm 3 under P_2). Narasimhan notes that a strong brand may be promoted more frequently (with shallower discounts) if switchers prefer that brand, whereas our results pertain to the switcher segment sizes rather than brand or retailer preference. Rajiv, Dutta, and Dhar (2002) conclude that a high-service (i.e., strong) store offers advertised sales more frequently, albeit to build traffic. The results of P_2 concur with the predictions of Rajiv, Dutta, and Dhar, even in the absence of traffic considerations, suggesting that a relatively larger size of switchers targeted by high-service stores can explain a higher frequency of advertised sales.

In the case of promotion depth, recall that Narasimhan (1988), Raju, Srinivasan, and Lal (1990), and Rajiv, Dutta, and Dhar (2002) all examine asymmetric duopolies. Under their respective models, Narasimhan suggests that the two stores offer the same depth of discounts (for indifferent switchers); Raju, Srinivasan, and Lal predict that the stronger (or larger) store should offer deeper discounts; and Rajiv, Dutta, and Dhar predict that the stronger store should offer shallower discounts. Our model of segmented switchers predicts the conditions under which a store may offer deeper or shallower discounts. More specifically, a strong store may indeed offer shallower discounts if it has the least motivation to promote, as characterized by its smaller SLR (P_1). A strong store may also offer the same discount depth as a smaller store if no other weak firms compete for switchers (P_2; Firms 1 and 2). A strong store may even offer deeper discounts than a weak store if its share of switchers is relatively larger than that of the weak store (P_2; Firms 1 and 2 compared with Firm 3). Thus, our three-firm model with segmented switchers encompasses various cases of prior duopoly models.

Iyer and Pazgal (2003) present a model of many firms (as in Varian 1980) with switchers and asymmetric loyalty,

but they include, at most, two types of firms. Iyer and Pazgal also consider "partial loyals," who behave as loyals with a lower reservation price. In contrast, we model three asymmetric firms with multiple switcher segments. Therefore, some of our results differ from those of Iyer and Pazgal and other models that lack segmented switchers. In particular, we predict the existence of a high-priced niche strategy for a small retailer, which we empirically observe. Other models do not make such predictions for homogeneous goods.

Our model also offers some unique insights into price strategies when a retailer competes on multiple fronts. The novel discounting behavior of Firm 2 in P_1 completely draws from the three-firm asymmetry with segmented switchers. Firm 2 offers two types of discounts: deep discounts to compete with Firm 3 and shallow discounts to compete with Firm 1. Furthermore, as Figure 3 depicts, depending on the relative sizes of the switcher segments, the frequency of deep and shallow discounts varies. Competing with different firms for different switcher segments enables a retailer to develop a partitioned pricing strategy, in which the depth and frequency of discounts vary on each competitive front.

Model Predictions

To demonstrate that our model can explain pricing behavior in a rich empirical context, we present testable model predictions and examine them with pricing data from Internet book retailers. Our model yields price distributions as equilibrium strategies that depend on the relative SLRs of the firms.[6] Although summary statistics that describe the promotion strategies can be used to test the fit of pricing data in general, a more robust method is to compare the empirical and theoretical price distributions themselves. We offer predictions based on summary statistics in H_1 and predictions based on the price distributions in H_2 and H_3.

> H_1: On average, retailers with a higher SLR have (a) lower average prices, (b) higher standard deviations in prices, (c) more frequent discounts, (d) a higher maximum discount frequency, (e) greater discount depth, and (f) a greater maximum discount depth.

Under the model's propositions, firms with a higher SLR will have lower average prices (H_{1a}) and a higher standard deviation in prices (H_{1b}) in relation to price deviation from the reservation (regular) price. The frequency of price discounts is related to the likelihood that a retailer will price below the maximum retail price. Under P_1, Firms 2 and 3 will discount more frequently than Firm 1, and under P_2, a firm with a higher SLR will promote more frequently than a firm with a lower SLR. Overall, a firm with a higher SLR will discount at least as often as a firm with a lower SLR and therefore will discount more frequently (H_{1c}) and have a higher maximum discount frequency (H_{1d}), on average.

From our model, a firm with a lower price support will tend to have a greater depth of discount. Under P_1, for example, Firm 2 has a greater probability of discounting at a lower price than Firm 1, as evidenced in the CDF plot of Figure 1, Panel B. Across all possible conditions of the model's propositions, we expect to observe that, on average, retailers with higher SLRs will have greater discount depth (H_{1e}) and a greater maximum discount depth (H_{1f}).

Although summary statistics of retailers' prices can indicate whether the SLR explains price promotions, a more rigorous test would consider the entire price dispersion curve. Theoretically, we have clear predictions about how equilibrium price distributions should appear (Figures 1 and 2). We test whether the empirical price distributions vary as predicted by analyzing stochastic dominance. For any two CDFs, $F_j(x)$ first-order stochastically dominates $F_i(x)$ iff $F_j(x) \leq F_i(x)$, $\forall x$. In other words, if Firm j's price CDF lies nowhere above and somewhere below Firm i's distribution, Firm j first-order dominates. In Figure 1, Panel B, for example, Firm 1 first-order stochastically dominates Firms 2 and 3, and Firm 2 dominates Firm 3. First-order dominance is a fairly strict standard when considering empirical price distributions that may include shocks or random error. Second-order stochastic dominance is similar except that it considers the deficit functions, or the integral of the CDF. Second-order stochastic dominance holds under first-order dominance, but not vice versa. Our model predicts that, on average, a firm with a lower SLR will stochastically dominate a firm with a higher SLR.

> H_2: The price distributions of retailers with a lower SLR first- and second-order stochastically dominate firms with a higher SLR.

H_2 addresses the relationship between SLR and price distributions among all retailers, and H_3 more narrowly focuses on retailers with the smallest loyal segment size (Firm 3). Small retailers with a high SLR should discount heavily (P_1), whereas small firms with a low SLR should price high (P_2). Therefore, we can distinguish the pricing strategies of small retailers according to their SLR values.

> H_3: The price distributions of small retailers with a high SLR are first- and second-order stochastically dominated by small firms with a lower SLR.

Empirical Methodology Overview

We test the predictions of our modeling effort by using pricing data collected for online book retailers. A book is a homogeneous product that is uniquely identified by an ISBN (International Standard Book Number), a classification that is widely used and recognized by both customers and sellers. To ensure that the online retailers in our data set

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[6]Mixed strategies in pricing are usually assumed to be observable through temporal price dispersion (Narasimhan 1988; Varian 1980) that is pooled across multiple products and retailers (e.g., Iyer and Pazgal 2003; Raju, Srinivasan, and Lal 1990). Data for multiple products (in our case, books) represent repeated observations of a mixed pricing strategy over time. Our analysis is consistent with this view in that we define "discount" in terms of temporal price changes, and we consider a retailer's average discounting behavior across books. Therefore, the hypotheses state the overall average effects we should observe given both propositions taken in tandem. On a case-by-case comparison of retailer pairs, all the hypotheses strictly hold, with a single technical exception to H_{1b}, H_{1e}, and H_2 (Firms 2 and 3 when Firm 2 has the higher SLR under P_1). In its most general form, a mixed strategy is a probability distribution over pure strategies, such that price dispersion may be reflected across books as well as time (for a discussion of mixed-strategy interpretations, see Gibbons 1992).

share at least a common switcher segment, we collected daily data on book prices from all the retailers listed on the price comparison site mySimon. In the period during which our data were collected, mySimon was the leading price comparison engine, with 80% of the price comparison site visit market share (Media Metrix and Nielsen//NetRatings; see also Allen and Wu 2002; Koçaş 2002). Our consideration of booksellers listed on mySimon establishes the existence of a "fully informed" switcher segment (s_{123} in our model), without precluding the existence of other switcher segments. Prices reported on mySimon are taken directly from each retailer's Web site, reflecting the book's offered price to all shoppers at that time, net of shipping and handling costs.

Internet Retailer Pricing Data

We compiled a sample of 2207 books from various sources.[7] From June 2001 to August 2002, we collected daily price data on these books from all the bookstores returned by a search on mySimon. Eliminating duplicates and books not carried by any of the mySimon bookstores left 1640 books. We prefer that price changes in the data reflect the mixed-strategy discounting of retailers rather than systematic changes from price shocks (e.g., net price changes due to a switch over to free shipping) or reservation price changes. Price data collected over longer periods have a greater risk of being contaminated by systematic price adjustments. To alleviate this problem, our empirical analyses use daily pricing data on the 1640 books for a period of 26 days in June 2002. This month represents the most recent period for which we have complete data from all the retailers and no systematic price adjustments. This 26-day window also spans a relatively short period to minimize reservation price adjustments.[8]

In our June 2002 sample period, 28 unique mySimon retailers carried at least 1 of the 1,640 books. All books in the sample were offered by multiple retailers. To compare retailers that carry a similar assortment of books, we ranked the booksellers with respect to the percentage of books they carried from the total list of 1640. We observed a gap between the top 14 retailers, which carried at least 40% of the books, and the bottom 14 retailers, which carried, at most, only 9% of the books. On the basis of this observation, we limit our analyses to the 14 retailers that carried at least 40% of the books. The final sample of retailer prices has 392,245 total observations, or an average of approximately 28,000 per retailer.

Price Promotion Measures and Dispersion

For each retailer, we calculate various measures of price-discounting activity. We do so with the view toward price discounts reflecting price changes over time. During June 2002, each book had a sequence of daily retailer prices. Average price for any retailer is the average of all normalized prices for that retailer; we calculate normalized prices by dividing any given book price by the highest price quoted for that book by any one of the 14 retailers in the sample period. The standard deviation of the normalized prices in each sequence, averaged over all the books carried by the retailer, gives the average standard deviation. For each retailer, we also count the number of price changes in our daily data. We then average that figure across all the books the retailer sold to calculate the average number of price changes (discount frequency). We find the maximum by taking the highest number of price changes for the retailer across books. We calculate the retailer's absolute changes in normalized prices, averaged across all books, to obtain the average and maximum depth of discounts across books for that retailer.

The summary retailer price statistics appear in Table 2. Figure 4 presents the empirical CDF of normalized prices for the 14 retailers. The numbers in parentheses next to each retailer in the figure refer to the same ordering as in Table 2.[9]

Study Procedure

Our objective is to observe how the relative SLRs of the retailers affect their pricing strategies. To form an empirical proxy of the SLR, we need indicators of retailer-specific loyal and switcher segment sizes. We conduct two studies. The first is an exploratory study using readily available descriptive statistics for the retailers. The advantage of this approach is that data for all 14 retailers can be obtained, and the disadvantage is that aggregate retailer descriptives may inadequately proxy the SLR. The second study uses a large Internet panel database that tracks all Internet site visits and purchases for 100,000 panel members. This study's advantage is the rich set of microlevel data to form switcher and loyalty measures. However, the database contains information on a more limited set of Internet booksellers. Given the advantages and disadvantages of each study, we present both as independent tests of our model predictions.

To test H_1, we compare the pricing statistics with retailer SLR values. H_2 and H_3 relate our model predictions

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[7]These sources consisted of four book lists that were publicly available on the Internet: (1) 140 books from the *Publisher's Weekly* bestsellers list on June 4, 2001; (2) 730 books from "One Book List: Collaborative Books to Read," a list compiled by the Usenet newsgroup (see rec.arts.books); (3) 60 books from the Latest Acquisitions by Government Environmental Library 2001; and (4) 1277 books bought by Sidney Sussex University Library in 2001.

[8]Empirical studies strive to use a "large enough" number of periods to capture temporal realizations of the mixed strategy. Our number of periods is similar to that used by others (e.g., Clay, Krishnan, and Wolff 2001; Raju, Srinivasan, and Lal 1990), though we use daily rather than weekly data to minimize systematic price adjustments. We examined three- and six-month versions of the data set (87 and 184 days, respectively), and the overall results and conclusions were the same. We then repeated our analyses after eliminating bestseller books from the sample. Bestsellers typically have more price dispersion and are more likely to be traffic generators than nonbestsellers (Clay, Krishnan, and Wolff 2001). Our hypotheses remain significantly supported if bestsellers are eliminated.

[9]Figure 4 shows normalized prices for all books across all days. From our model, a retailer that stochastically dominates another retailer for one book should do so for all books (only the reservation price varies across books). Thus, we examine price distributions across both books and time to test for stochastic dominance.

TABLE 2
Summary Statistics for the Retailer Prices

Retailer	Average	SD	Average Frequency	Maximum Frequency	Average Depth	Maximum Depth
Double Discount	.669	.0097	2.150	5	.094	.530
TextatCost	.749	.0017	.048	3	.003	.223
eCampus	.744	.0115	.643	17	.034	.718
a1Books	.749	.0008	.124	1	.009	.363
Books-A-Million	.834	.0017	.060	5	.003	.251
1Bookstreet.com	.935	.0027	.048	2	.002	.100
Amazon.com	.829	.0045	.073	5	.004	.260
B&N	.870	.0137	.206	4	.012	.351
Page One	.742	.0000	.120	2	.000	.045
BookVariety.com	.869	.0000	.000	0	.000	.000
Words Worth Books	.876	.0046	.140	2	.006	.109
Varsity	.919	.0014	.034	1	.002	.091
Worthy	.898	.0000	.000	0	.000	.000
Sam Goody	.773	.0007	.020	1	.001	.066
Retailer average	.818	.0038	.262	3	.012	.222

to measures of stochastic dominance. Figure 4 shows that at the lower price levels, most firms have a small percentage of observed prices. This observation makes a strict test of stochastic dominance problematic because a retailer that may have highly discounted a few books on a few days (of 28,000 prices quoted by the average retailer) distorts the notion that the same retailer may have relatively high prices for all other books across all days. Furthermore, the retailers' CDFs may cross in closely spaced price regions, meaning that neither firm stochastically dominates the other. Therefore, to test H_2 and H_3, we eliminate the 5% lowest prices quoted by each retailer and consider retailer pairs in which stochastic dominance is evident.[10]

Exploratory Study with Retailer Descriptive Data

The model's findings relate retailer pricing to the SLRs (H_1 and H_2) and reveal different strategies for small retailers depending on their SLR values (H_3). To identify the relatively small retailers, we examine reach and link popularity, which capture a retailer's number of visitors and Internet connectivity. Reach measures the number of users who visit a given Internet site and can be obtained from Alexa. Link popularity refers to the total number of links that a site has across the Internet. We measure link popularity as the sum of all retailer links found by the search engines AlltheWeb, AltaVista, Google/AOL, HotBot/Inktomi, and MSN. More specific to booksellers, we measure book-link popularity as the number of sites that link to a book retailer and contain the word "book" on the same page in which the link appears, which we determined using AltaVista. Table 3 pre-

sents the reach and popularity measures for the retailers. As we expected, Amazon.com and B&N are the largest retailers by these measures. Books-A-Million has the third-largest reach and popularity, with a book-link popularity comparable to B&N. The other 11 retailers are all relatively small in comparison.

SLR Proxy

A proxy for the SLR should capture a retailer's relative proportion of switchers and loyal customers. Recent studies have pointed to page views per user as a measure of online loyalty (Demers and Lev 2001; Goldfarb 2002). Page views per user, which we obtained from Alexa, are the average number of unique pages viewed per user by site visitors each day. Research has examined the drivers of trust and loyalty in online shopping, and Web site navigation issues arise as important factors (e.g., Bart et al. 2005; Shankar, Smith, and Rangaswamy 2003; Srinivasan, Anderson, and Ponnavolu 2002). Navigating Web site information for in-depth content increases satisfaction and loyalty (Shankar, Smith, and Rangaswamy 2003). Demers and Lev (2001) and Danaher, Mullarkey, and Essegaier (2006) find that page views per user are positively correlated with the frequency of visits, and frequent visitors tend to be more likely to purchase (Moe and Fader 2004a). More page views can also be associated with "lock-in," or an unwillingness to switch sites (Bucklin and Sismeiro 2003).[11] Thus, the page-views-per-user metric represents a reasonable proxy for loyalty, given its association with in-depth navigation and

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[10]The lowest 5% of a retailer's prices represent prices that are at least eight standard deviations (in intertemporal terms) below the average price for each retailer. This procedure reflects the concept of "almost" stochastic dominance (see Leshno and Levy 2002).

[11]Several studies (e.g., Bucklin and Sismeiro 2003; Danaher, Mullarkey, and Essegaier 2006; Johnson, Bellman, and Lohse 2003; Johnson et al. 2004) note a learning effect whereby frequent visitors become more efficient in browsing over time. However, this does not mean that frequent (i.e., more loyal) visitors browse less than infrequent visitors. Danaher, Mullarkey, and Essegaier (2006) show that more frequent visitors view more pages.

FIGURE 4
Retailer CDFs for All Books

Cumulative
Probability

— — (6) 1Bookstreet.com
——◆—— (4) a1Books
——□—— (7) Amazon.com
——○—— (8) B&N
——◁—— (5) Books-A-Million
——❙—— (10) BookVariety.com
——■—— (1) Double Discount
——●—— (3) eCampus
——◀—— (9) PageOne
——❙—— (14) Sam Goody
——◇—— (2) TextatCost
——✳—— (12) Varsity
——+—— (11) Words Worth Books
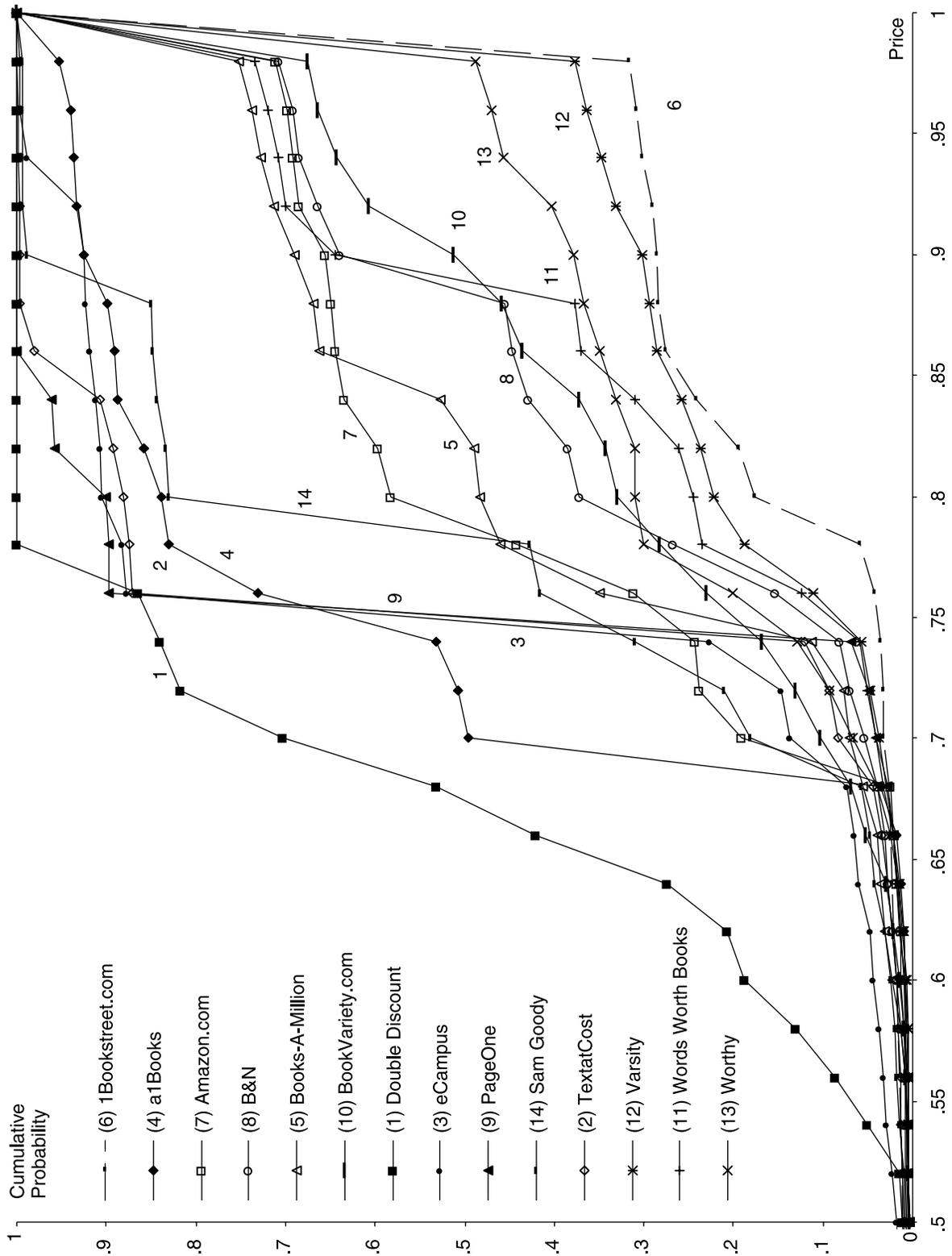——✕—— (13) Worthy

Price

TABLE 3
Exploratory Study Measures for the Retailers

Retailer	Reach/ Millions per Day	Link Popularity	Book-Link Popularity	Page Views per User	Search Share	Normalized Page Views	SLR	SLR Tier
Double Discount	16.5	16,371	100	2.6	1.0	.377	2.65	
TextatCost	24.5	61,585	2897	3.3	1.0	.478	2.09	High
eCampus	75.5	37,418	1998	3.4	1.0	.493	2.03	
a1Books	6.3	25,693	4173	3.5	.7	.507	1.38	
Books-A-Million	81.0	164,506	56,890	5.3	.9	.768	1.17	
1Bookstreet.com	6.65	34,239	6722	2.7	.4	.391	1.02	
Amazon.com	23,600.0	57,347,588	3,676,495	6.8	1.0	.986	1.01	Medium
B&N	1775.0	839,878	46,155	6.2	.9	.899	1.00	
Page One	1.5	9925	274	2.4	.3	.348	.86	
BookVariety.com	1.0	184	24	1.0	.1	.145	.69	
Words Worth Books	2.85	20,409	1309	2.6	.2	.377	.53	
Varsity	8.85	31,589	1923	3.9	.3	.565	.53	Low
Worthy	4.4	19,999	206	1.8	.1	.261	.38	
Sam Goody	63.0	38,012	271	6.9	.1	1.000	.10	
Retailer average	n.m.	n.m.	n.m.	3.7	.57	.54	1.10	

Notes: n.m. = not meaningful, given extraordinary values for Amazon.com and B&N.

loyalty behaviors typically absent from price-sensitive switchers.

To form an indicator of the relative switcher generation potential of the retailers, we observe that a bookstore that wants to attract more switchers may be listed more often in a price comparison query. For a particular set of price comparison sites, we formulate a retailer's search share as the proportion of price comparison sites that return prices for that retailer. Greater search share means that the retailer is listed on more book price comparison sites and thus may attract more switchers from various segments. Although search share does not differentiate switcher segment sizes, it gives a firm-specific indication of switcher intensity (SLR incorporates the sum of a retailer's switcher segment sizes). We use the nine top-ranked book price comparison sites and mySimon to formulate a list of price comparison sites for books.[12] There are several reasons a firm might be listed in a price comparison engine. Sometimes, a price comparison site uses a retailer's prices without specific action on the part of the retailer. In addition, relatively high-cost retailers are not necessarily absent from price comparison sites. A firm with comparably higher prices may want greater access to all potential buyers, and therefore it may share its pricing data with the search engine (Iyer and Pazgal 2003). Whether retailers are high priced or low priced, those listed in price comparison sites have access to a greater number of switchers. Therefore, the degree of participation in price comparison engines serves as an indicator of the retailer's access to switchers who become informed of its prices.

Given these measures, we form a proxy measure of SLR (ϕ_i) as the ratio of search share (a switcher metric) to the normalized page views per user (a loyalty metric). Values appear in Table 3, which orders the retailers by decreasing SLR. Note that the three largest retailers—Amazon.com, B&N, and Books-A-Million—have SLRs in the middle range. For the smaller firms, the SLR separates those with a high SLR (e.g., eCampus) from those with a low SLR (e.g., Varsity), enabling a test of H_3. For example, although eCampus and Varsity have nearly the same popularity and page views per user, the SLR is higher for eCampus than for Varsity. We now show empirically that the relative SLRs explain the discounting behavior of the retailers, consistent with our model predictions.

Analysis of Pricing Strategies

To test the expected price relationships under H_1, we use the firms' SLRs along with the pricing data from Table 2. In regression analyses for the 14 retailers studied, we use a price statistic as the dependent variable and SLR as the independent variable. By definition, the resultant standardized coefficient of the SLR and its significance are identical to the Pearson correlation coefficient and its significance. We report these correlations in Table 4.[13] We observe that

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[12]These book price comparison sites are the top nine sites that identify the booksellers from which they quote prices, as ranked by Google, BookFinder.com, AddAll.com, BestBookDeal.com, AllBookstores.com, TextbookLand.com, AAABookSearch.com, CampusBooks, Compare Shop Books, and ANYBOOKSFOR-LESS.com. We did not include other general price comparison sites beyond mySimon, because mySimon represents more than 80% of all price comparison activity conducted on the Internet.

[13]The inverse of page views has no significant pricing correlations, but search share (the numerator of SLR) has significant correlations with some pricing variables. We also analyzed the correlations of the pricing statistics with reach and link popularity after omitting Amazon.com and B&N because of their high values. The correlations remain nonsignificant, except for a positive correlation of .64 ($p < .05$) between reach and maximum discount frequency. The page view measures for Amazon.com and Sam Goody may reflect more than book searches by consumers. Delet-

TABLE 4
Correlations of Exploratory Study Variables and Retailer Prices

Predictor Variables	Observed Price Promotion Statistics					
	Average	SD	Average Frequency	Maximum Frequency	Average Depth	Maximum Depth
Reach/millions per day	.051	.093	−.098	.111	−.093	.067
Link popularity	.041	.054	−.097	.107	−.094	.055
Book-link popularity	.042	.051	−.098	.108	−.095	.055
Page views per user	−.040	.258	−.161	.155	−.134	.185
Search share	−.483*	.610**	.435	.628**	.477*	.810***
SLR	−.673***	.503*	.720***	.568**	.744***	.791***
Hypothesis	H_{1a}	H_{1b}	H_{1c}	H_{1d}	H_{1e}	H_{1f}
Predicted relationship to SLR	−	+	+	+	+	+

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: N = 14.

the SLR is significantly correlated with the firms' price discounting. The results support H_1, demonstrating that, on average, retailers with a higher SLR have lower prices (H_{1a}) and a higher standard deviation (H_{1b}). They also discount more often (H_{1c} and H_{1d}) and with greater depth (H_{1e} and H_{1f}). We conclude that a firm's SLR is a significant predictor of its promotional activity.

Tests of Retailer Price Distributions

For a given pair of retailers, our model predicts that the retailer with a lower SLR should stochastically dominate the other. The test is based on a distinct rank ordering of the 14 retailers (see Table 3 and Figure 4). However, the SLR proxy based on aggregate retailer data may lack a high degree of precision in distinguishing retailers with comparable SLR values. Therefore, we categorize retailers into three groups with high, medium, or low SLR values and compare retailers in different SLR tiers.[14] The three largest retailers have similar SLR values, ranging from 1.00 to 1.17. Using the spread of .17 as a guideline, 1Bookstreet.com and Page One appear to have SLRs that are relatively close to those of the three large firms, such that it is empirically difficult to classify either firm as having a clearly higher or lower SLR. This observation reveals that four Internet booksellers—Double Discount, Textat-Cost, eCampus, and a1Books—are small retailers with high SLRs; here, we expect P_1 to hold. There are also five small retailers—BookVariety.com, Words Worth Books, Varsity, Worthy, and Sam Goody—with lower SLRs; here, we expect P_2 to hold.

Table 3 indicates the tiers of high, medium, and low SLRs. To test H_2, a retailer in a lower tier of SLR should stochastically dominate retailers in a higher SLR tier. We can examine 65 total pairs of retailers in different tiers for stochastic dominance. Of the 40 retailer pairs whose CDFs

do not intersect, the SLR values correctly predict first-order stochastic dominance for 32 pairs (80%), in support of H_2 ($\chi^2 = 14.40$, $p < .01$). We use the deficit functions (integral of the CDFs) to test second-order dominance. Of the 49 retailer pairs whose deficit functions do not intersect, the SLR values correctly predict second-order dominance for 41 pairs (84%), in support of H_2 ($\chi^2 = 22.22$, $p < .01$).[15] For retailers exhibiting stochastic dominance over retailers in the other SLR tiers, the SLR values predict the relative price dispersions.

To test H_3, we examine the price dispersion of small retailers with high or low SLRs in more detail. Table 3 shows four high-SLR small retailers, which H_3 predicts will be stochastically dominated by the five low-SLR small retailers. Of the 20 small retailer pairs, 14 (15) have CDFs (deficit functions) that do not intersect, and the SLR values correctly predict first-order (second-order) stochastic dominance for all retailer pairs ($p < .01$).[16] Thus, H_3 is supported; the SLR can explain significantly whether small firms are high-priced niche players or low-priced discounters.

Exploratory Study Summary

The exploratory study presents evidence that supports the hypotheses, indicating that a retailer's SLR explains its pricing behavior consistent with the model's predictions. The SLR is also adept at explaining whether small firms take a high-priced or low-priced approach. For example, we can explain why Worthy prices high and a1Books prices

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ing these two retailers does not change the nonsignificance of the page view correlations in Table 4, and the SLR correlations remain significant, except for the standard deviation in prices ($p = .12$).

[14]We thank a reviewer for this suggestion.

[15]As a robustness check, we repeat the analysis putting Books-A-Million in the highest SLR tier and Page One in the low-SLR tier, and again, we find support for H_2 ($p < .01$). We also examine all 91 pairs of the 14 retailers (a nontiered analysis) and again find support for H_2 ($p \leq .01$).

[16]As a robustness check, we repeat the analysis, treating Page One as a low-SLR small retailer, and find support for H_3 ($p < .01$). The results also hold if we place Books-A-Million in the high-SLR tier, though it is not clear whether it is a small retailer. We further examine all 36 pairs of the 9 small retailers (a nontiered analysis) and again find support for H_3 ($p \leq .01$).

low, though both firms are small in the same homogeneous goods market. We also test pricing strategies according to the entire price dispersion curve by using tests of stochastic dominance. The empirical literature has no clear consensus on suitable price dispersion constructs (Pan, Ratchford, and Shankar 2004). The stochastic dominance tests correspond to the predicted theoretical relationships and represent a more complete perspective on retailer price dispersion.

As a summary, consider the microcosm of the three retailers, all dealing in college textbooks: TextatCost, eCampus, and Varsity. From the retailer information given in Table 3, Varsity is the smallest retailer of the three in terms of reach and popularity. Although it experiences similar page views, it receives a lower search share and reach than the other two firms. Standard models and predictions would likely suggest that Varsity take the high-discount approach as the small firm, but the opposite is true. Varsity is the premium-priced retailer among the three. This scenario is possible in our model if Varsity has the lowest SLR, which it does. Furthermore, Varsity carries 89% of the books from our sample that Amazon.com carries (compared with only 57% for eCampus and 48% for TextatCost) and charges higher prices than Amazon.com (see Figure 4). Varsity apparently leverages its low SLR into greater assortment while charging high prices.

Despite the supportive results, the exploratory study's SLR proxy is not ideal, given that it is based on aggregate data. Although page views have been associated with loyalty traits in prior studies, the correlation may be weak for purchasing behavior. The search share measure may not correspond well to retailer-specific switcher sizes, because it is based on price comparison sites that offer a limited perspective on actual switching behavior. Therefore, we conduct a second study using a large panel database of Internet browsing and purchase. This allows for a more microlevel behavioral construction of loyalty and switcher measures, albeit for a more limited number of retailers.

Internet Panel Study

The second study uses the comScore 2002 panel data set to develop switcher and loyal measures. Households in the Internet panel have their Web-browsing and purchase activity recorded. Several recent studies have used comScore data (Danaher 2007; Johnson, Bellman, and Lohse 2003;

Moe and Fader 2004a, b; Park and Fader 2004). The data set we use contains 100,000 panelists in the United States from June 2002 to December 2002. Data include site domains visited, number of page views, duration visiting the site, and transaction data if a purchase is made. The data set allows us to formulate switcher and loyalty proxies based on microlevel browsing and purchasing behaviors.

SLR Proxy

We use behavior-based measures to form the SLR proxies. We focus on Internet booksellers in the data set that received purchases; a retailer with only browsing activity would correspond to an undefined SLR. Six retailers for which we have pricing data had purchases in the panel data: 1Bookstreet.com, Amazon.com, B&N, Books-A-Million, eCampus, and Varsity. Book purchases were made by 5304 unique panelists at these retailers over the six-month period.

We take a share-of-purchase perspective (e.g., Tellis 1988) that recognizes Internet retailer loyalty as a lack of search across retailers when making a purchase (Srinivasan, Anderson, and Ponnavolu 2002), consistent with our model's premise.[17] A given purchase occasion corresponds to loyal behavior if no other book retailers or price comparison shopbots are searched before purchase or to switcher behavior if at least one other book retailer or shopbot is searched before purchase.[18] This results in a retailer's SLR measure being the ratio of switcher purchase occasions to loyal purchase occasions. Consistent with prior studies (e.g., Danaher 2007; Moe and Fader 2004a; Park and Fader 2004), we take a daily perspective on panelists' purchase activity in forming the measures.

The retailer data with SLR measures appear in Table 5. In general, there is a high level of loyal purchases. Johnson and colleagues (2004) report that Internet book shoppers in their data set visit approximately 1.2 retailers (compared with 1.25 in our data) and that 70% are loyal to a single site (compared with 79% in our study). The SLR values correlate well with those of the exploratory study for the six retailers ($r = .85$, $p = .03$). Note that four of the six retailers correspond to the closely spaced medium level of the

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[17]A repeat-purchase measure for loyalty is not feasible given the few observations for two of the six retailers.

[18]The price comparison sites checked are those of the search share measure in the exploratory study.

TABLE 5
Retailer Panel Data

Retailer	Total Purchase Visits	Average Number of Retailers Visited	Switcher Purchases	Loyal Purchases	Panel Data SLR
eCampus	72	1.72	37	35	1.06
Books-A-Million	142	1.70	60	82	.73
B&N	1794	1.40	583	1211	.48
Varsity	26	1.23	6	20	.30
1Bookstreet.com	10	1.50	2	8	.25
Amazon.com	5519	1.19	891	4628	.19

Source: comScore (2002; see http://wrds.wharton.upenn.edu).

exploratory SLR (Table 3), and the panel data measure creates a more distinctive spread in the SLR values (Table 5).

Analysis

Table 6 presents correlations of the comScore-based SLR proxies with pricing statistics for the six retailers. The comScore proxy correlates well with the pricing statistics in the expected direction. Even with the small number of retailers, all the correlations are significant, except for the standard deviation in prices. The results support H_1.

Examining the price dispersions among the six retailers, we find that the comScore SLR values correctly predict first- and second-order stochastic dominance for 10 of 13 pairs of nonintersecting price distributions (the distribution of Amazon.com intersects with eCampus and Books-A-Million). Second-order dominance is correctly predicted for 11 of 15 retailer pairs (no intersecting deficit functions). These results support H_2 (first-order $\chi^2 = 3.77$, $p = .05$; second-order $\chi^2 = 3.27$, $p = .07$). Only Amazon.com is out of place in assessing stochastic dominance according to the comScore SLR values. Thus, for the small retailers, the SLR values correctly predict whether they are relatively high or low priced in all cases, consistent with H_3.

Summary of Panel Data Study

The comScore data set allows for a microlevel formulation for a retailer's SLR. Six retailers represent a small sample for analysis, but the results support the model's predictions. An analysis using a retailer's loyal segment size instead of SLR reveals that loyalty alone is incapable of capturing the retailer's pricing strategies. The number of loyals does not correlate significantly with any pricing variable (this result does not change if Amazon.com and B&N are eliminated as large outliers). Loyalty alone also poorly explains the price dispersions, with only 3 of 13 (4 of 15) pairs of retailer distributions correctly predicted for first-order (second-order) stochastic dominance. The results reiterate the important distinction between our segmented-switcher model and those based on loyalty sizes. We also note that analyses using only the first two months of the comScore data set to generate SLR values yield similar results, but 1Bookstreet.com is eliminated because of few switchers or loyals.

The reasonable correlation between the SLR proxies of both studies and the supportive results suggest that a larger retailer sample would generate similar results. Six retailers

do not allow for definitive conclusions, but we note that page views from the exploratory study correlate well with the number of loyals from the comScore data (r = .76, $p <$ .10), and the search share measure positively correlates with the number of switchers but not significantly (r = .54, n.s.). In total, the studies provide evidence that the SLR can explain pricing strategies, consistent with our model.

Discussion

Price competition among retailers, large and small, involves fundamental decisions about whether and how often to discount prices. Most theoretical models based on asymmetric duopolies suggest that small retailers discount to capture the lucrative switcher market. However, observed price promotion strategies reflect a wide variety of approaches, with some small retailers pricing high and others discounting deeply. Our model examines competitive promotional strategies in an asymmetric oligopoly with segmented switchers. Reflecting the realistic assumption that price-sensitive switchers do not necessarily compare prices at all retailers, switcher segments add an important strategic dimension beyond asymmetric retailer loyalty. Although firms may be classified as large, medium, or small with respect to their loyal segment sizes, this ranking may have little to do with the price-discounting behavior of the firm. We find that the firm's ratio of the relative size of switchers (consumers who consider the retailer's prices) to the relative size of its loyal customers is a better indicator of the firm's price-discounting strategy than loyalty alone. Our model is the first to consider multiple switcher segments, enabling us to categorize a small or large firm as a heavy or light promoter under different loyal and switcher segment compositions. We provide empirical support for our model's key predictions in two studies of Internet booksellers. The segmented-switcher perspective identifies whether a small firm will discount, as is usually predicted, or price high and play the niche. Overall, our model captures a wide variety of price promotion activity, consistent with empirically observed price dispersions. We can summarize our key findings as follows:

•Asymmetry, in terms of different loyal segment sizes and the existence of switcher segments, leads to a multiplicity of discounting strategies. It is possible to categorize when firms will be frequent or deep discounters using the retailers' relative SLRs.

TABLE 6
Correlations of Panel Data SLR Values and Retailer Prices

	Observed Price Promotion Statistics					
	Average	SD	Average Frequency	Maximum Frequency	Average Depth	Maximum Depth
SLR	−.779*	.460	.810*	.839**	.805*	.833**
Hypothesis	H_{1a}	H_{1b}	H_{1c}	H_{1d}	H_{1e}	H_{1f}
Predicted relationship to SLR	−	+	+	+	+	+

*$p < .10$.
**$p < .05$.
Source: comScore (2002; see http://wrds.wharton.upenn.edu).

- A large firm may find it more profitable to offer deeper (shallower) discounts than a smaller firm if the relative share of switchers for which it competes is large (small).
- For midsize firms, a partitioned discounting strategy—one that combines frequent shallow and infrequent deep (or infrequent shallow and frequent deep) discounts—is possible as a result of competition on multiple fronts.
- A small firm may find it profitable to price high and play the niche if the other firms are already intensely competing for the switcher segments the small firm could serve. A small firm may also benefit from strategically choosing to limit its exposure to switchers in the market to reduce the market's overall competitive price intensity.

Using data from the online book market, we empirically validate our model's key implications. Empirical SLR measures from two studies significantly explain price dispersion among retailers, consistent with our model's predictions. The first study uses descriptive retailer statistics to proxy SLR values, and the second study uses a rich set of panel data to determine the number of retailer customers exhibiting loyal or switching behavior. Both studies support the pricing hypotheses that result from our model. Our tests of stochastic dominance are related to the entire price dispersion curve, which is more comprehensive than testing summary price statistics alone.

Managerial Implications

Our results have numerous implications for retailer pricing strategies. Larger firms often face a dilemma due to having both a large loyal following and access to a large number of switchers. The frequency and depth of discounts depend critically on the mix of switcher segments in the overall competitive context. When a vast majority of switchers widely compare prices, the large firm should offer few shallow discounts because other firms will more aggressively discount. In the case in which many small retailers are ignored by the bulk of the switchers, a large firm may find itself more deeply discounting to compete with it nearest rival (e.g., Amazon.com and B&N exhibit moderate levels of discounting). A midsized firm has considerable flexibility in its discounting strategy, such as offering frequent and shallow discounts to compete with the larger retailer but infrequent and deep discounts to compete with smaller firms. The midsized retailer should discount often enough to convince its larger rival to concede some of the switchers, who then behave like loyals to the midsize firm.

Small retailers (even of homogeneous goods) with relatively few loyal customers should not take a deep discount strategy without carefully assessing its access to price-sensitive switchers. If awareness is low or switchers are difficult to reach, a high-priced niche strategy is likely to be more optimal. However, if a wide switcher market is accessible, the depth of discounts depends critically on the specific switcher segments. If most switchers widely compare retailers' prices, in general, the small retailer should offer deep discounts. However, if most switchers concentrate on the larger firms, the small retailer's discounts should be shallower or largely nonexistent if its SLR is small.

The results based on segmented switchers imply certain strategies in how aggressively retailers should reach out to switchers. A small firm that discounts may choose to limit its reach among switchers to some degree to reduce overall price competition. Pursuing fewer switchers can be advantageous for retailers if shallower discounts can be used to capture the switchers that remain. Notably, mySimon considerably reduced the number of firms from which it quoted prices after late June 2002, simultaneously increasing its strength of strategic alliances with its participant stores. By reducing the number of firms returned as the comparison set, mySimon helps these participant stores enjoy higher profits, as our model predicts, while generating higher commissions and referral fees for itself.

The existence of multiple, partially informed switcher segments tends to reduce price competition among the retailers. Retailers must consider carefully not just their loyal customers but also the specific composition of the switcher segments. Acquiring more switchers can be more or less valuable, depending on the segment to which they belong. For example, a midsized retailer would often benefit from targeting its switcher acquisition activities toward its larger rival, given the shallower discounts involved. Overall, the strategies are more than a simple dichotomy of acquisition versus retention because a switcher's value to the retailer depends on its specific switcher segment.

The importance of switcher segmentation suggests that managers should carefully measure switching behaviors. The retailer's value to the switcher and the likelihood of acquiring a switcher customer are both important, but so is the switcher's segment membership. More complete measurement of prior switching behaviors and switcher segment sizes relative to loyals is needed (see Rust, Lemon, and Zeithaml 2004).

Limitations and Further Research

Our model distinguishes between different pricing strategies, such as high-promoter and low-promoter firms, without relying on traffic-building or product differentiation considerations. A segmented-switcher perspective enables us to resolve some varied results found in previous models. We consider this article a unifying extension to stylized game-theoretic models of price comparison and related empirical research. However, we also recognize several limitations. By omitting traffic building from our model, we are unable to observe how segmented switchers alter retailers' traffic-related strategies. Empirically, our proxies for the SLR have several difficulties. Although the exploratory study is supportive, it relies on aggregate descriptive statistics that may not capture microlevel shopping behaviors (see Bucklin and Sismeiro 2003). The study using comScore panel data more directly reflects loyal and switching behaviors based on a retailer's individual customers, but the number of retailers is limited. Future studies could address a variety of product categories to validate our results more robustly. Recent research in trust and loyalty for Internet retailers (e.g., Bart et al. 2005; Shankar, Smith, and Rangaswamy 2003) may suggest other approaches to the loyalty component of SLR.

Endogeneity questions also deserve future study. Retailer pricing strategies may influence the sizes of various switcher and loyal segments as opposed to the exoge-

nous segment sizes in our model. Although our pricing data represent a limited period with no systematic price adjustments, endogenous customer behavior is a potential limitation. Dynamic analyses that capture changes in a person's switcher and loyalty behaviors over time would be fruitful research (for examples on search behavior, see Bucklin and Sismeiro 2003; Johnson, Bellman, and Lohse 2003; Johnson et al. 2004; Moe and Fader 2004a, b).

Further research could also extend recent analyses of Internet shopping agents and firms' strategies regarding the degree of price comparison. The work of Iyer and Pazgal (2003) is an excellent starting point, and our results complement some of their key findings. The existence of segmented switchers and the varied strategies that result give a richer context in which firms can contemplate not only whether to participate in shopping agents but also when to participate in different sites that reach different switcher segments. Our results show that segmented switchers can relax price competition. The implication is that retailers should think not only about how best to invest in loyalty building but also about how they can invest in limiting or expanding switcher segments in relation to other firms in their market. We hope that our theoretical and empirical results motivate further research that more precisely captures not only the retailers' multiple switcher segments but also the pricing strategies that result.

Appendix

Under the model assumptions, the profit functions of the firms are given by the following equation:

$$\pi_i(p_i, p_{-i}) = p_i(n_i + \delta_{12}s_{12} + \delta_{123}s_{123}),$$

where p_i represents the price quoted by Firm i, p_{-i} represents the vector of prices quoted by other firms, and δ_{ij} takes values from the set [0, 1] based on the lowest quoted price. The term δ_{12} applies to Firms 1 and 2 and equals 1 for the lower-priced firm, ½ in the event of a tie in prices, and 0 for the higher-priced firm. The term δ_{123} applies similarly to all three firms, but if two firms quote the lowest price, δ_{123} equals ½ for those firms and 0 for the other firm. For a three-way tie in prices, δ_{123} equals ⅓ for all three firms. We begin with three lemmas that establish properties of the equilibrium solution (proofs are available on request):

Lemma 1: There is no Nash equilibrium in pure strategies.
Lemma 2: Let S_i^*, i = {1, 2, 3}, be the best-response strategy sets (i.e., the set of prices) in the mixed-strategy equilibrium. There is no gap (p_1, p_2) within the joint support $S_1^* \cup S_2^* \cup S_3^*$, where $f_i(p) \equiv 0$ for two or more firms. That is, at least two firms possess positive support at any point within the joint support of prices.
Lemma 3: The CDFs of firms' prices F_i, i = {1, 2, 3}, are continuous, except possibly at r. That is, there are no mass points in the interior or at the lower boundary of the joint support $S_1^* \cup S_2^* \cup S_3^*$.

Proposition 1

P_1 states that when $\phi_3 > \phi_1$, Firms 1 and 3 have mutually exclusive price ranges that, when combined, form Firm 2's price range. Firm 2 competes with Firm 3 in the lower part of its price range and with Firm 1 in the upper part of its price range. The equilibrium CDFs, $F_i(p)$, of the firms' prices are given by the following:

$$F_1(p) = \begin{cases} 0 & p < \underline{p}_l \\ (p - \underline{p}_l)(n_2 + s_{12})/(ps_{12}) & \underline{p}_l \le p < r \\ m & p = r \\ 1 & p > r \end{cases},$$

$$F_2(p) = \begin{cases} 0 & p < \underline{p}_2 \\ (p - \underline{p}_2)(n_3 + s_{123})/(ps_{123}) & \underline{p}_2 \le p \le \underline{p}_l \\ 1 - n_1(r - p)/(ps_{12}) & \underline{p}_l \le p \le r \\ 1 & p \ge r \end{cases}, \text{ and}$$

$$F_3(p) = \begin{cases} 0 & p < \underline{p}_2 \\ 1 - (\underline{p}_l - p)(n_2 + s_{12})/(ps_{123}) & \underline{p}_2 \le p \le \underline{p}_l \\ 1 & p \ge \underline{p}_l \end{cases},$$

where m is Firm 1's mass point at the reservation price, $\underline{p}_l$ is the lower bound of Firm 1's support, and $\underline{p}_2$ is the common lower bound of Firm 2's and Firm 3's supports given by the following:

$$\underline{p}_l = \frac{n_1 r(n_2 + s_{12} + s_{123})}{s_{12}(n_2 - n_3 + s_{12}) + n_1(n_2 + s_{12} + s_{123})} > p_1^{min}, \text{ and}$$

$$\underline{p}_2 = \frac{n_1 r(n_2 + s_{12})}{s_{12}(n_2 - n_3 + s_{12}) + n_1(n_2 + s_{12} + s_{123})} \ge p_2^{min}, p_3^{min}.$$

Proof of Proposition 1

From Lemma 1, there is no pure strategy. A detailed exposition of mixed-strategy solution mechanics for models similar to ours is found in the work of Narasimhan (1988). We first define the upper and lower boundaries of the firms' supports. The upper bound of the feasible price set is r. Prices higher than the reservation price will result in no sales, whereas positive profits are possible when the reservation price is quoted. Therefore, the highest price that any firm can charge is the common reservation price r. To determine the lower boundaries, there will likely be two price regions. The lower price region is where only Firms 3 and 2 compete, with an upper bound determined by the lowest price that Firm 1 will quote. The higher price region is determined from this price upward. The minimum price for any firm is when it is indifferent between selling only to its loyals and offering a deep discount to capture the switchers. The minimum prices are $p_i^{min} = n_i r/(n_i + s_{12} + s_{123})$ for Firms 1 and 2 and $p_3^{min} = n_3 r/(n_3 + s_{123})$ for Firm 3. Because $n_1 > n_2 > n_3$, it is always true that $p_2^{min} < p_1^{min}$. Under P_1's assumption that $p_3^{min} < p_1^{min}$, we must consider two cases of whether Firm 3's minimum price is less than or greater than that of Firm 2.

Under the condition that $p_3^{min} < p_2^{min} < p_1^{min}$, Firm 2 can compete with Firm 3 at prices below p_1^{min}, such that both Firms 2 and 3 have positive support below p_1^{min}. Therefore, Firm 1 cannot capture the switcher segments with certainty, even if it prices at p_1^{min}. This conclusion means that the low-

est price to which Firm 1 is willing to discount, $\underline{p}_1$, must be higher than p_1^{min} to balance the prospect of receiving fewer switchers in expectation. Denoting $F_i(p)$ as the cumulative distribution probability of Firm i's prices, we equate Firm 1's profit selling only to its loyals and its profit when also selling to the switchers at $\underline{p}_1$, given the probability that Firms 2 and 3 quote higher prices:

$$n_1r = n_1\underline{p}_1 + [1 - F_2(\underline{p}_1)]\underline{p}_1 s_{12} + [1 - F_2(\underline{p}_1)][1 - F_3(\underline{p}_1)]\underline{p}_1 s_{123}$$

$$\Rightarrow \underline{p}_1 = \frac{n_1r}{n_1 + [1 - F_2(\underline{p}_1)]s_{12} + [1 - F_2(\underline{p}_1)][1 - F_3(\underline{p}_1)]s_{123}}.$$

At prices lower than $\underline{p}_1$, Firms 2 and 3 compete for segment s_{123}, and Firm 2 receives all of segment s_{12} with certainty. Firm 3 has the lowest minimum price, so it will find it profitable to include as a lower support bound only the lowest price Firm 2 will quote. However, because Firm 2 also competes with Firm 1 for s_{12} and Firm 1 has a lower support above p_1^{min}, Firm 2 may find it profitable to adapt a lower support that is higher than p_2^{min}. Thus, Firms 2 and 3 will compete with prices at least up to $\underline{p}_1$. In doing so, they share a common lower bound $\underline{p}_2$, which may be higher than p_2^{min}.

To establish the equilibrium profits, all firms can guarantee the profit n_ir by choosing to price at r. However, in terms of undercutting other firms and serving the switcher segment, Firms 2 and 3 are at an advantage. Firm 3 can improve its profit above n_3r by pricing at the lowest price any other firm ever discounts, $\underline{p}_2$, and serving s_{123}, which results in a profit of $(n_3 + s_{123})\underline{p}_2$ for Firm 3. Pricing below $\underline{p}_2$ is never optimal for Firm 3, because it could then raise its price and still capture s_{123} for sure. Similarly, Firm 2 can improve its profit above n_2r by pricing at the minimum price Firm 1 will ever feasibly reduce its price to, $\underline{p}_1$, and serving s_{12}, which results in a profit of $(n_2 + s_{12})\underline{p}_1$ for Firm 2. The equilibrium solution reveals that Firm 2 would never deviate and price below the lower bound $\underline{p}_2$, because it would lose more profit from selling at a lower price to s_{12} and n_2 than it could gain by capturing s_{123} with higher probability.

When Firms 2 and 3 compete with prices between $\underline{p}_2$ and $\underline{p}_1$, both have lower prices than Firm 1 with a probability of 1. Thus, either one can capture the switcher segment s_{123} if it can price lower than the other. The competition in this interval is similar to Narasimhan's (1988) base model, with two exceptions. First, the upper limit of the interval is not r, but rather $\underline{p}_1$, which is less than r. Second, Firm 2 also considers that whenever it prices in $[\underline{p}_2, \underline{p}_1]$, it will serve the switcher segment s_{12} with a probability of 1. Firms 2 and 3 will randomize their prices in this interval so that the expected profit will be equal to their equilibrium profits. We can write the equilibrium conditions for the interval $[\underline{p}_2, \underline{p}_1]$, with the exception of $\underline{p}_1$, as follows:

(A1) $\quad E\pi_2 = (n_2 + s_{12})\underline{p}_1 = n_2p + s_{12}p + [1 - F_3(p)]ps_{123}$, and

(A2) $\quad E\pi_3 = (n_3 + s_{123})\underline{p}_2 = n_3p + [1 - F_2(p)]ps_{123}$.

Note that in Equation A1, Firm 2 serves its loyal segment and switcher segment s_{12} with any price it quotes. It serves switcher segment s_{123} only if its price is lower than Firm 3's price. In Equation A2, Firm 3 serves its loyal segment with any price it quotes, but it serves switcher segment s_{123} only if its price is lower than Firm 2's price. Although attempts to price low in this interval increase Firm 2's chances of serving s_{123}, they also decrease Firm 2's guaranteed profit from s_{12}. Thus, because $p_3^{min} < p_2^{min} < \underline{p}_2$, both firms will share $\underline{p}_2$ as the lower bounds of their supports, as in the work of Narasimhan (1988). This also means that neither firm will have a mass point at $\underline{p}_2$, because in that case, the other firm would have a motivation to undercut $\underline{p}_2$. Therefore, $F_2(\underline{p}_2)$ and $F_3(\underline{p}_2)$ both equal zero.

To solve Equations A1 and A2, we also need to specify values for $\underline{p}_2$ and $\underline{p}_1$. Note that $\underline{p}_1$ is the lowest price Firm 1 will quote. Thus, the profit Firm 1 makes with the price $\underline{p}_1$ must be equal to its expected profit:

(A3) $\quad E\pi_1 = n_1r = n_1\underline{p}_1 + [1 - F_2(\underline{p}_1)]\underline{p}_1 s_{12}$

$\qquad\qquad + [1 - F_2(\underline{p}_1)][1 - F_3(\underline{p}_1)]\underline{p}_1 s_{123}$.

By solving Equations A1, A2, and A3 simultaneously, in combination with the cumulative distribution conditions at $\underline{p}_2$, we find the solutions to this set of equilibrium conditions in the interval $[\underline{p}_2, \underline{p}_1]$, with the exception of $\underline{p}_1$, as follows:

(A4) $\quad F_2(p) = \dfrac{(p - \underline{p}_2)(n_3 + s_{123})}{ps_{123}}$,

(A5) $\quad F_3(p) = 1 - \dfrac{(\underline{p}_1 - p)(n_2 + s_{12})}{ps_{123}}$,

(A6) $\quad \underline{p}_1 = \dfrac{n_1r(n_2 + s_{12} + s_{123})}{s_{12}(n_2 - n_3 + s_{12}) + n_1(n_2 + s_{12} + s_{123})}$, and

(A7) $\quad \underline{p}_2 = \dfrac{n_1r(n_2 + s_{12})}{s_{12}(n_2 - n_3 + s_{12}) + n_1(n_2 + s_{12} + s_{123})}$.

On the basis of this solution set, we also observe that $F_3(\underline{p}_1)$ equals 1, thus showing that in the next interval, upward of $\underline{p}_1$, only Firms 1 and 2 will compete. Furthermore, the solution holds as long as $\underline{p}_2 < p_1^{min}$, because otherwise, Firm 1 would have an incentive to discount below $\underline{p}_1$. For $n_1 \geq n_2 + s_{12} + n_3(s_{12}/s_{123})$, $\underline{p}_2$ will never exceed p_1^{min}. In general, Lemma 2 proves that there are no gaps in the support. Lemma 3 proves continuity in the distribution functions.

To solve for the pricing behavior in the next support interval $[\underline{p}_1, r]$, we write the equilibrium conditions, with the exception of r, as follows:

(A8) $\quad E\pi_1 = n_1r = n_1p + [1 - F_2(\underline{p}_1)][1 - \bar{F}_2(p)]ps_{12}$, and

(A9) $\quad E\pi_2 = (n_2 + s_{12})\underline{p}_1 = n_2p + [1 - F_1(p)]ps_{12}$,

where $\bar{F}_2(p)$ is the conditional CDF given that $p > \underline{p}_1$ for Firm 2. Firm 2's unconditional CDF in the interval $[\underline{p}_1, r]$ is given by $F_2(\underline{p}_1) + [1 - F_2(\underline{p}_1)]\bar{F}_2(p)$. The solution to this set of equations gives the final results, where the mass point for Firm 1 at r is a straightforward calculation, given $F_1(p)$:

$$m = \frac{n_1(n_2 + s_{12} + s_{123}) - n_2(n_2 - n_3 + s_{12})}{s_{12}(n_2 - n_3 + s_{12}) + n_1(n_2 + s_{12} + s_{123})}.$$

This concludes the solution for $p_3^{min} < p_2^{min} < p_1^{min}$.

For the second case of $p_2^{min} \leq p_3^{min} < p_1^{min}$ (i.e., $\phi_2 \geq \phi_3 > \phi_1$), the mixed-strategy equilibrium is identical to that described previously for $p_3^{min} < p_2^{min} < p_1^{min}$ (the proof is available on request). Q.E.D.

Proposition 2

P_2 states that when $\phi_3 \leq \phi_1$, only Firms 1 and 2 discount, whereas Firm 3's price is set at r. The resultant CDFs are as follows:

$$F_1(p) = \begin{cases} 0 & p < p_1^{min} \\ 1 - \dfrac{p_1^{min}(n_2 + s_{12} + s_{123}) - n_2 p}{p(s_{12} + s_{123})} & p_1^{min} \leq p < r \\ \dfrac{n_1 - n_2}{n_1 + s_{12} + s_{123}} & p = r \\ 1 & p > r \end{cases},$$

$$F_2(p) = \begin{cases} 0 & p < p_1^{min} \\ 1 - \dfrac{n_1(r - p)}{p(s_{12} + s_{123})} & p_1^{min} \leq p \leq r \\ 1 & p \geq r \end{cases}, \text{ and}$$

$$F_3(p) = \begin{cases} 0 & p < r \\ 1 & p \geq r \end{cases}.$$

Proof of Proposition 2

Under $p_2^{min} < p_1^{min} \leq p_3^{min}$, Firm 3 has the highest minimum price and thus has no advantage in offering deep enough discounts to serve the switcher segment s_{123}. However, Firms 2 and 3 will be competing for the business of s_{12} and s_{123}. Compared with Firm 1's position in P_1, Firm 3 is essentially a high-priced niche player that serves only its loyals. Firm 3 will not serve segment s_{123}, because both Firm 1 and Firm 2 quote lower prices with positive probability as they compete for s_{12}. Thus, the candidate equilibrium profits for Firms 1, 2, and 3 are $n_1 r$, $(n_2 + s_{12} + s_{123})p_1^{min}$, and $n_3 r$, respectively. Although Firm 2 can offer the lowest price, it will never discount below p_1^{min}, the price at which it can successfully capture both switcher segments. In this case, Firms 1 and 3 have equilibrium profits they would make from sales to their loyal segments only. For Firms 1 and 2, we solve as follows:

(A10) $\quad E\pi_1 = n_1 r = n_1 p + [1 - F_2(p)]p(s_{12} + s_{123})$, and

(A11) $\quad E\pi_2 = (n_2 + s_{12} + s_{123})p_1^{min}$

$\qquad\qquad = n_2 p + [1 - F_1(p)]p(s_{12} + s_{123})$.

The solution to this set is as follows:

(A12) $\quad F_1(p) = 1 - \dfrac{p_1^{min}(n_2 + s_{12} + s_{123}) - n_2 p}{p(s_{12} + s_{123})}$, and

(A13) $\quad F_2(p) = 1 - \dfrac{n_1(r - p)}{p(s_{12} + s_{123})}$.

To show that Firm 3 will indeed never discount in equilibrium, the lowest price Firm 3 will ever quote is p_3^{min}. At this price, its expected profit is represented by the following:

(A14) $\quad \pi_3(p_3^{min}) = n_3 p_3^{min}$

$\qquad\qquad + [1 - F_2(p_3^{min})][1 - F_1(p_3^{min})]p_3^{min} s_{123}$.

Inserting values from Equations A12 and A13 into Equation A14, we indeed find that $\pi_3(p_3^{min}) < n_3 r$, which means that Firm 3 will never price at p_3^{min}, given that Firms 1 and 2 are already competing for the switcher segments below this price. In addition, because it is only Firms 1 and 2 that can compete at p_3^{min}—and possibly above, as we have just shown—the CDFs presented by Equations A12 and A13 will also remain valid above p_3^{min}. We can solve for the lowest price point above p_3^{min} to which Firm 3 will ever reduce its price by solving the following:

(A15) $\quad n_3 r = n_3 p + [1 - F_1(p)][1 - F_2(p)]ps_{123}$.

The only solution to this equation that rises above p_3^{min} is r. Thus, given that Firms 1 and 2 are already competing for the switcher segment below p_3^{min}, Firm 3 will never price in the interval $[p_3^{min}, r]$. Rather, it will only price at r. Thus, the solutions to Equations A12 and A13 remain valid until r. With this solution, Firm 1 also has a mass point at r that equals $(n_1 - n_2)/(n_1 + s_{12} + s_{123})$. Although both Firms 1 and 3 have positive masses at r, because Firm 2 has a lower price than r with a probability of 1, Firms 1 and 3 will receive their guaranteed profits $n_i r$, whereas Firm 2's profit will be higher than $n_2 r$. Q.E.D.

REFERENCES

Allen, Gove and Jianan Wu (2002), "Data Collection from Intelligent Agents: When Is Enough, Enough?" working paper, Freeman School of Business, Tulane University.

Bart, Yakov, Venkatesh Shankar, Fareena Sultan, and Glen Urban (2005), "Are the Drivers and Role of Online Trust the Same for All Web Sites and Consumers? A Large-Scale Exploratory Empirical Study," *Journal of Marketing*, 69 (October), 133–52.

Baye, Michael R., Dan Kovenock, and Casper G. de Vries (1992), "It Takes Two to Tango: Equilibria in a Model of Sales," *Games and Economic Behavior*, 4 (4), 493–510.

——— and John Morgan (2001), "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," *American Economic Review*, 91 (3), 454–74.

Blattberg, Robert and John Deighton (1991), "Interactive Marketing: Exploiting the Age of Addressability," *Sloan Management Review*, 33 (1), 5–14.

Bolton, Ruth N. and Venkatesh Shankar (2003), "An Empirically Derived Taxonomy of Retailer Pricing and Promotion Strategies," *Journal of Retailing*, 79 (4), 213–24.

Bucklin, Randolph E. and Catarina Sismeiro (2003), "A Model of Web Site Browsing Behavior Estimated on Clickstream Data," *Journal of Marketing Research*, 40 (August), 249–67.

Burdett, Kenneth and Kenneth L. Judd (1983), "Equilibrium Price Dispersion," *Econometrica*, 51 (4), 955–69.

Carlton, Dennis W. and Judith A. Chevalier (2001), "Free Riding and Sales Strategies for the Internet," *Journal of Industrial Economics*, 49 (4), 441–61.

Chen, Yuxin, Chakravarthi Narasimhan, and Z. John Zhang (2001), "Individual Marketing with Imperfect Targetability," *Marketing Science*, 20 (1), 23–41.

Clay, Karen, Ramayya Krishnan, and Eric Wolff (2001), "Prices and Price Dispersion on the Web: Evidence from the Online Book Industry," *Journal of Industrial Economics*, 49 (4), 521–39.

Danaher, Peter J. (2007), "Modeling Page Views Across Multiple Websites with an Application to Internet Reach and Frequency Prediction," *Marketing Science*, 26 (3), 422–37.

———, Guy W. Mullarkey, and Skander Essegaier (2006), "Factors Affecting Web Site Visit Duration: A Cross-Domain Analysis," *Journal of Marketing Research*, 43 (May), 182–94.

Demers, Elizabeth and Baruch Lev (2001), "A Rude Awakening: Internet Shakeout in 2000," *Review of Accounting Studies*, 6 (2–3), 331–69.

Fox, Edward J. and Stephen J. Hoch (2005), "Cherry-Picking," *Journal of Marketing*, 69 (January), 46–62.

Gibbons, Robert (1992), *Game Theory for Applied Economists*. Princeton, NJ: Princeton University Press.

Goldfarb, Avi (2002), "Online Marketing Metrics and Financial Performance," working paper, Department of Economics, Northwestern University.

Hoch, Stephen J., Xavier Drèze, and Mary E. Purk (1994), "EDLP, Hi-Lo, and Margin Arithmetic," *Journal of Marketing*, 58 (October), 16–27.

Iyer, Ganesh and Amit Pazgal (2003), "Internet Shopping Agents: Virtual Co-Location and Competition," *Marketing Science*, 22 (1), 85–106.

Johnson, Eric J., Steven Bellman, and Gerald L. Lohse (2003), "Cognitive Lock-In and the Power Law of Practice," *Journal of Marketing*, 67 (April), 62–75.

——— Wendy W. Moe, Peter S. Fader, Steven Bellman, and Gerald L. Lohse (2004), "On the Depth and Dynamics of Online Search Behavior," *Management Science*, 50 (3), 299–308.

Koçaş, Cenk (2002), "Evolution of Prices in Electronic Markets Under Diffusion of Price-Comparison Shopping," *Journal of Management Information Systems*, 19 (3), 99–119.

——— and Tunga Kiyak (2006), "Theory and Evidence on Pricing by Asymmetric Oligopolies," *International Journal of Industrial Organization*, 24 (1), 83–105.

Lal, Rajiv and Miklos Sarvary (1999), "When and How Is the Internet Likely to Decrease Price Competition?" *Marketing Science*, 18 (4), 485–503.

Leshno, Moshe and Haim Levy (2002), "Preferred by 'All' and Preferred by 'Most' Decision Makers: Almost Stochastic Dominance," *Management Science*, 48 (8), 1074–1085.

Moe, Wendy W. and Peter S. Fader (2004a), "Capturing Evolving Visit Behavior in Clickstream Data," *Journal of Interactive Marketing*, 18 (1), 5–19.

——— and ——— (2004b), "Dynamic Conversion Behavior at E-Commerce Sites," *Management Science*, 50 (3), 326–35.

Montgomery, Alan L., Karthik Hosanagar, Ramayya Krishnan, and Karen D. Clay (2004), "Designing a Better Shopbot," *Management Science*, 50 (2), 189–202.

Narasimhan, Chakravarthi (1988), "Competitive Promotional Strategies," *Journal of Business*, 61 (4), 427–49.

Pan, Xing, Brian T. Ratchford, and Venkatesh Shankar (2004), "Price Dispersion on the Internet: A Review and Directions for Future Research," *Journal of Interactive Marketing*, 18 (4), 116–35.

Park, Young-Hoon and Peter S. Fader (2004), "Modeling Browsing Behavior at Multiple Websites," *Marketing Science*, 23 (3), 280–303.

Rajiv, Surendra, Shantanu Dutta, and Sanjay K. Dhar (2002), "Asymmetric Store Positioning and Promotional Advertising Strategies: Theory and Evidence," *Marketing Science*, 21 (1), 74–96.

Raju, Jagmohan, V. Srinivasan, and Rajiv Lal (1990), "The Effects of Brand Loyalty on Competitive Price Promotional Strategies," *Management Science*, 36 (3), 276–304.

Rust, Roland T., Katherine N. Lemon, and Valarie A. Zeithaml (2004), "Return on Marketing: Using Customer Equity to Focus Marketing Strategy," *Journal of Marketing*, 68 (January), 109–127.

Salop, Steven and Joseph Stiglitz (1977), "Bargains and Rip-Offs: A Model of Monopolistically Competitive Price Dispersion," *Review of Economic Studies*, 44 (3), 493–510.

Shankar, Venkatesh and Ruth N. Bolton (2004), "An Empirical Analysis of Determinants of Retailer Pricing Strategy," *Marketing Science*, 23 (1), 28–49.

———, Amy K. Smith, and Arvind Rangaswamy (2003), "Customer Satisfaction and Loyalty in Online and Offline Environments," *International Journal of Research in Marketing*, 20 (2), 153–75.

Smith, Michael and Erik Brynjolfsson (2001), "Consumer Decision-Making at an Internet Shopbot: Brand Still Matters," *Journal of Industrial Economics*, 49 (4), 541–58.

Srinivasan, Srini S., Rolph Anderson, and Kishore Ponnavolu (2002), "Customer Loyalty in E-Commerce: An Exploration of Its Antecedents and Consequences," *Journal of Retailing*, 78 (1), 41–50.

Tellis, Gerard J. (1988), "Advertising Exposure, Loyalty, and Brand Purchase: A Two-State Model of Choice," *Journal of Marketing Research*, 25 (May), 134–44.

Urbany, Joel E., Peter R. Dickson, and Rosemary Kalapurakal (1996), "Price Search in the Retail Grocery Market," *Journal of Marketing*, 60 (April), 91–104.

Varian, Hal R. (1980), "A Model of Sales," *American Economic Review*, 70 (4), 651–59.