Signaling Services through Price:

A Theory of Retailer Price-Ending Behavior

Debanjan Mitra
Scott Fay

September 7, 2006

Debanjan Mitra and Scott Fay are Assistant Professors of Marketing at the Warrington College of Business Administration, University of Florida. The authors thank Peter Golder, Chris Janiszewski, and Robert Shoemaker for their valuable comments on initial versions of the paper and Juliano Laran for his help in conducting the lab survey.
Signaling Services through Price:
A Theory of Retailer Price-Ending Behavior

Abstract

Although 9-ending prices are common, some retailers avoid them. We propose that such divergent price-ending behavior is an artifact of retailers using price to signal their services. For example, retailers signaling ‘no-frills’ service through lower prices are more likely to use ‘random’-endings (i.e., price-endings other than 9 or 0). We find compelling evidence consistent with the ‘service signaling’ theory and discuss implications.

(Signaling, pricing, price-ending, price threshold, retailing)
Prices of Desk Lamps: 6.92, 38.87 (Lowes); 9.99, 39.99 (Bed Bath and Beyond); 17.00, 60.00 (Macy’s).

INTRODUCTION

There has been considerable research in marketing and economics on retail price-endings. Past studies propose different psychological and economic theories to explain the “ubiquitous” practice of 9-ending prices (e.g., Basu 2006; Bergen et al. 2003; Kashyap 1995; Sims 2003; Schindler and Kirby 1997; Thomas and Morwitz 2005). Other studies empirically investigate the effects of such ‘odd’ price-endings using various methods such as laboratory experiments (Lambert 1975; Ruffle and Shtudiner 2003; Schindler and Wiman 1989), controlled field studies (Anderson and Simester 2003b; Schindler and Kibarian 1996), simulation of demand functions (Gedenk and Sattler 1999), and econometric analysis of panel data (Blattberg and Wiesniewski 1987; Stiving and Winer 1997). While past studies have adequately explored and explained the practice of 9-ending prices, many retailers avoid such prices. For example, Wal-Mart and Tesco prefer ‘random’-ending prices (i.e., digits other than 9 or 0). So do many e-retailers like Backcountry and Homeclick. Others like Nordstrom and Gap seem to prefer 0-ending prices.

Given all the psychological and economic processes that favor usage of 9-ending prices, why do some retailers use different price-endings? Do these divergent price-ending behaviors contain any information (Naipaul and Parsa 2001; Schindler 1991)? If so, it is not clear how such information conveyed through ‘costless’ price-endings can be credible, effective, and sustainable over time (Basu 1997; Schindler 2001; New York Times 2004). Stiving (2000) provides an interesting explanation of one such divergent price-ending behavior. Specifically, he shows that 0-ending prices are more likely to be used by firms that use high price to signal high product
quality.¹ This still leaves unanswered the question, when are retailers more likely to use price-endings other than 9 or 0? In this regard, note that past studies have found that at least 30% of the retail prices do not end in either 9 or 0 (Anderson and Simester 2003, Stiving 2001).

Thus, while much has been learnt about price-endings and how customers process and recall such information, this knowledge has not been fully integrated with the actual price-ending behavior of retailers. In this paper, we modify and extend the Stiving (2000) model and show that it not only helps understand 0-ending prices but also other divergent price-ending behavior of retailers. In particular, low service cost retailers signaling ‘no-frills’ service through lower price will be more likely than non-signaling retailers to use ‘random’-ending prices (i.e., endings other than 9 or 0). We empirically examine price-endings of 55 large retailers as well as price-endings of identical products available with multiple retailers. We also use a laboratory survey to examine the information content of price endings, if any. In all cases, we find strong evidence consistent with the predictions of our service signaling theory. Overall, we address several related questions, answers to which make a unique contribution to the pricing literature:

• What is the extent of different price-endings used by US retailers?
• Do individual retailers use different or similar price-endings on different products?
• When do retailers use different price-endings?
• Is there any information content in price-endings?

The paper is organized as follows. First, we briefly review the literature on the existence of price thresholds, propose modifications of the original Stiving (2000) model, and provide the intuition for signaling retail services. The second section presents the model and illustrates how

¹ Later, Shoemaker et al. (2004) show that this result is only relative, i.e., 9-ending is still more likely at the absolute level but the likelihood of 0-ending prices is significantly higher compared to the ‘no-signal’ case.
price can signal service levels in a separating equilibrium. In the third section, we use a simulation to examine different price-endings in equilibrium and draw specific testable propositions for retail price-endings. The fourth section describes the data, sampling methods, estimation procedures, and presents the empirical results. Finally, we conclude by summarizing the key findings, discussing the implications and providing directions for further research.

PRICE THRESHOLDS AND RETAIL PRICE-ENDINGS

Price thresholds refer to abrupt changes in customer demand at certain price points (Gabor and Granger 1964; Kalyanam and Shively 1998; Wedel and Leeflang 1998). Several theories have been proposed as to why thresholds might exist at 9-ending price points. Stiving and Winer (1997) classify these under “level” and “image” effects. Level effects summarize the behavior of customers in neglecting the price-ending while comparing prices because of several economic and psychological reasons. These include rounding down, left-to-right comparison, limited memory, inattention, and rational expectations (Basu 1997; Brenner and Brenner 1982; Schindler and Kirby 1997; Schindler and Wiman 1989; Sims 2003). Image effects summarize the informational content of specific price-endings (Anderson and Simester 2003; Lambert 1975; Schindler and Kibarian 2001). While the level effects imply flat demand between different price-endings and a downward threshold at 9-ending price-points, the image effects can result in a positive or negative spike at specific price-endings. As in Stiving (2000), we assume that the net of these level and image effects is a kinked demand function with discontinuities between consecutive 9-ending and 0-ending price points (see Figure 1). To preserve analytical simplicity and also since the evidence for demand spikes is mixed, we do not formally include any “spikes” in demand.\(^2\)

\(^2\) However, as shown by Stiving (2000), augmenting the model to include spikes at 9-endings would not qualitatively change our conclusions. Thus, the relationships described in Propositions 1 and 2 would be preserved.
While the demand function is identical to the original Stiving model, we propose two modifications so as to extend it to a retail setting. First, the prices are set by retailers and not manufacturers. This modification may seem obvious but it raises a conceptual issue with the original finding. Why should a retailer (as opposed to a manufacturer) incur a cost to signal the quality of a product that is also available with a competing retailer? For example, why should Macy’s signal the quality of a Polo shirt made by Ralph Lauren that is also available at T.J.Maxx?

To address this question, we propose a second modification to the original model – retailers signal the services provided at the store (as opposed to the quality of products). Traditionally, in a retail context, the word ‘service’ is used to mean ‘customer service’ (Homburg et al. 2002; Kumar 2005). We expand this to include “all activities carried out for the purpose of encouraging the conclusion of a transaction” (European Court of Justice 2005). This means that activities like selection, procurement, assortment, location, access, display, aesthetics, layout, sales help, empathy, trust, assurance, credit, delivery, and returns are all included under retail services. Assuming efficient markets, the level of these retail services will correlate to the cost of providing these services. Retail price of a product, in turn, is determined both by its purchase price (commonly referred to as cost of goods sold or COGS) as well as the service cost. As a result, the price of an identical product available from multiple retailers varies depending on the differences in service costs of the retailers. For example, many national brands are available at different retail stores who price it differently (Brynjolfsson and Smith 2000, Zhao 2006). Furthermore, many different brands are often de facto identical and even manufactured by the same firm (Sullivan 1998, Customers Union 2005).

The broad definition of retail service also allows us to conceptualize customers as to
preferring low or high levels of service rather than assume that a high level of service is universally preferred. Of course, it is easy to conceive situations when customers have a higher utility for higher retail service. For example, when customers are less knowledgeable about a product or their own preferences, they depend more on the retailer to provide the ‘selection’ service. But when will customers have a higher utility for lower levels of service? Though at first glance, it seems unlikely and even perverse, on closer scrutiny one can conceive many situations fitting this description. For example, consider frequently purchased product categories in which customers often purchase multiple products in one shopping trip. These customers are knowledgeable about the products to be purchased, yet sometimes uncertain about their purchase decisions during the shopping process. In other words, many of these customers are unsure of their precise shopping basket prior to the trip. These customers will prefer shopping at a low service ‘no-frills’ retailer who is likely to have a lower price for an ‘average’ basket of products.\(^3\)

When customers prefer a low level of service, if a retailer can credibly inform customers that it provides bare minimum or ‘no-frills’ service, then it is likely to be a more attractive option. Note that this is not possible in the original Stiving model, in which customers always prefer high product quality and, therefore, it would not be rational for any manufacturer to signal low product quality. However, similar (though not identical) to the original model, if customers prefer a high level of service, a high service cost retailer can gain if it can provide credible information regarding its higher level of service. Next, we formally present the service signaling model.

\(^3\) For example, this is consistent with an environment in which only a portion of a retailer’s products are advertised (and known to the customers) but customers care about the total price of a shopping basket (Simester 1995).
A MODEL OF RETAIL PRICE SIGNALING RETAILER SERVICES

Mathematically, our model is equivalent to Stiving (2000). In particular, a market consists of \( M \) heterogeneous customers, each of whom will purchase at most one unit of a product. Customers have utility functions of the form \( U = V \theta - \phi \), where \( V \) is distributed uniformly between 0 and \( M \), and the value of the outside option is normalized to zero. The term \( \phi \) represents the customer’s perception of price. We assume prices are restricted to integer values, where \( \rho \) is the last digit and \( \delta \) is the retailer’s price truncating this last digit. For example, a price of 137 would be associated with \( \delta = 130 \) and \( \rho = 7 \). In accordance with this notation, a 9-ending price would be any price such that \( \rho = 9 \). A proportion \( \gamma \) of the population perceives the entire price: \( \phi = \delta + \rho \). But \((1-\gamma)\) cognitively constrained customers only consider the truncated price: \( \phi = \delta \).

In contrast to Stiving (2000), we assume that retailers sell equivalent products but offer heterogeneous levels of services. Thus, in our paper, \( \theta \) represents the customer’s belief about the retailer’s service type rather than its product quality. \( \theta = 1 \) corresponds to the belief that the retailer provides ‘luxury’ service; \( \theta = s \) corresponds to the belief that the retailer offers ‘no-frills’ service. We assume the retailer’s service type is given exogenously (e.g. determined by historical investments in people, sales, distribution, marketing and location). We normalize the cost of providing ‘no-frills’ service to zero and assume ‘luxury’ service is provided at a cost \( c_H > 0 \). We allow customers to prefer to purchase from either a ‘no-frills’ \((s > 1)\) or ‘luxury’ service environment \((s < 1)\).

The existence of a segment of customers that neglects the last price digit leads to a demand function that is kinked at all 9-ending points since a one unit increase in price from a 9-ending to a 0-ending price results in a larger decrease in demand than does a one unit increase in
any other region. Figure 1 illustrates such a demand curve, assuming customers prefer ‘no-frills’ service environment, i.e. \( s > 1 \). If customers preferred ‘luxury’ service environment \( (s < 1) \), then the low service cost retailer would face a lower demand curve, i.e. \( Q_L^D < Q_H^D \).

**Complete Information**

Suppose all customers can perfectly observe the retailer’s service type. Following Stiving (2000) and taking into account the correction identified in Shoemaker et al. (2004), the demand faced by the retailer with low \((L)\) or high \((H)\) service cost is:

\[
Q_L^D = \gamma \text{Max} \left[ M - \frac{\delta + \rho}{s}, 0 \right] + (1 - \gamma) \text{Max} \left[ M - \frac{\delta}{s}, 0 \right] \\
Q_H^D = \gamma \text{Max} \left[ M - (\delta + \rho), 0 \right] + (1 - \gamma) \text{Max} \left[ M - \delta, 0 \right]
\]

Profit to the retailer is:

\[
\Pi_L = (\delta + \rho)Q_L^D \\
\Pi_H = (\delta + \rho - c_H)Q_H^D
\]

Figure 1 illustrates the demand and profit functions using \( M = 150, c_H = 40, \gamma = .8, \) and \( s = 1.2 \). Note the kinks in the profit functions at each price where \( \rho = 9 \). Thus, when there is complete information, profits are almost always maximized at a 9-ending price. For example, for the chosen parameters in Figure 1 a low service cost retailer maximizes profit at a price of 89 and a high service cost retailer maximizes profit at 99. The intuition behind this result is fairly simple. For a standard linear demand curve, at its apex, there is no first order effect from a change in price. However, with a kinked demand curve, there is a first order (negative) effect from increasing a price from a 9-ending to a 0-ending. Thus, as long as the segment of customers truncating prices is sufficiently large, deviating to the next lowest 9-ending price is profitable for the retailer.
For the analysis that follows, it is important to notice the shape of the profit function in Figure 1. In particular, there is a discontinuity between each 9-ending and each 0-ending. Also, the slope of the profit function before each of these downward jumps is decreasing as price increases. Notice that this implies that on the RHS of the profit function, at a substantial distance from the apex of the curve, profit is monotonically decreasing in price.

**Incomplete Information**

We now consider the case where at least some customers cannot completely observe all the retailer’s services. This is quite possible since many elements of a retailer’s service like procurement policy (e.g. fashion leader or follower), buyer quality (e.g. specialized knowledge of merchandise buyers), ease of returns (e.g. time or hassle involved in returning), etc., may be either completely unobservable or prohibitively costly to observe, at least in the short term. For example, an apparel retailer may employ a merchandise buyer who is an expert in fashion forecasting or a movie rental retailer may employ a counter-clerk who is knowledgeable about movies. But, customers may not be able to observe this service immediately. Thus, a retailer may try to use its price to signal its service cost and, thereby, the level of services.

**Separating Equilibrium**

Following the long tradition of signaling models (e.g. Milgrom and Roberts 1986, Funderberg and Tirole 1991, Chu 1993, Simester 1995), we search for a separating equilibrium in which a firm undergoes a costly action in order to signal its true type. In our particular model, the retailer that may be willing to signal its true type depends on customer preferences. Specifically, if customers prefer ‘no-frills’ service (i.e. \( s > 1 \)), a low service cost retailer may want to signal that it

---

4 However, over time customers can depend on prior information or reputation. Note that even in such cases customers are only observing a retailer’s prior service level not the current service level.
offers ‘no-frills’ service by charging a low price. On the other hand, when customers prefer ‘luxury’ service (i.e. \( s < 1 \)), a high service cost retailer may want to signal that it offers ‘luxury’ service by charging a high price. In either case, a separating equilibrium exists only if the signal is credible, i.e., the other retailer type cannot profitably mimic the signal.

To solve for the separating equilibrium, we follow Stiving (2000) with the adjustment proposed by Shoemaker et al. (2004). Therefore, we include all separating equilibria irrespective of whether it changes the behavior of a signaling retailer (in comparison to the full information scenario) or not.

We assume that a proportion \( \alpha \) of the population observes the retailer’s true service type (henceforth referred to as the informed segment). A proportion \((1-\alpha)\), referred to as the uninformed segment, does not observe the retailer’s type, but, when a separating equilibrium exists, is able to infer the retailer’s type through its price level. Let \( \Pi_{c} \) be the profit earned by a retailer whose true service cost is \( c (= L, H) \) and signals that its service cost is \( C \). For example, a retailer with a high service cost earns a profit of \( \Pi_{HH} \) if the uninformed customers also believe its service cost is high, but earns a profit of \( \Pi_{HL} \) if the uninformed customers believe it has low service cost.

Appendix 1 provides the details for deriving a separating equilibrium if it exists (both for \( s > 1 \) and \( s < 1 \)). Next, we use two illustrations to provide the intuition of this analysis.

Figure 2 provides an example of a separating equilibrium when customers prefer to shop a ‘no-frills’ retailer (using the parameter values \( M = 150, c_{H} = 40, \gamma = .8, s = 1.2, \) and \( \alpha = .4 \)). Under full information, a high service cost retailer maximizes \( \Pi_{HH} \) by pricing at \( P_{H} = 99 \) and thus earning a profit of \( \Pi_{HH_{Max}} = 3115.2 \), while a low service cost retailer prices at 89 and earns a profit
of 6882.67. However, with incomplete information, these prices do not form a separating equilibrium because a high service cost retailer could also price at 89 (fooling uninformed customers into believing that it has low service cost) and earn a higher profit (3504.48>3115.2) as indicated by the $\Pi_{HL}$ curve. A high service cost retailer would profit from mimicking a low service cost retailer as long as $P_L > P^*$. For the specified parameter values, $P^* = $78. Thus, when there is incomplete information, a low service cost retailer maximizes $\Pi_{LL}$ s.t. $P_L \leq 78$, which leads to the optimum price of 78 and a profit of 6734. A high service cost retailer prices at $P_H = 99$ in the separating equilibrium – the apex of the $\Pi_{HH}$ curve – knowing that even the uninformed customers will recognize it to be a high service cost retailer. Notice that the presence of an uninformed segment has a negative effect on the profit of a low service cost retailer. For this outcome to be a valid equilibrium, a low service cost retailer must be willing to incur the cost, i.e. sending a credible signal must be more profitable than not sending a credible signal. The appendix outlines the required condition. But, it is important to note that the analysis, similar to Simester (1995), assumes that in the absence of a credible signal uninformed customers will base their purchase decisions on expected costs, i.e. the belief that a retailer of unknown type has low service cost is equal to $\eta$, the actual probability that a randomly-selected retailer has low service cost.

Figure 2 here please

Figure 3 illustrates the case where $s < 1$ (using the parameter values $M = 150$, $c_H = 10$, $\gamma = .6$, $s = .5$, and $\alpha = .4$.) which was previously analyzed in Stiving (2000). Since customers prefer the shopping at a “luxury” retailer, a low service cost retailer has an incentive to falsely signal that it has high service cost. For a high service cost retailer to credibly signal that it offers a ‘luxury’ service environment, it must price at least as high as $P^*$ ($= 100$), which is higher than the full
information profit-maximizing price of 79. Facing this constraint, in the separating equilibrium, a high service cost retailer chooses a price of 100.

Figure 3 here please

Pooling Equilibrium

Under incomplete information, there is another possible outcome: a pooling equilibrium. In this case, a retailer chooses the same price regardless of its underlying service cost structure and the uninformed segment remains uncertain of whether a retailer has low or high service costs.

Let \((P_L^p, P_H^p)\) be the pooling equilibrium prices. In this equilibrium, a retailer chooses the same price \((P_H^p = P_L^p)\) regardless of its service costs. For a pooling equilibrium to exist, a retailer must willingly choose this price \(P_L^p\), i.e. a deviation to an alternate price must not increase its profit.

Appendix 2 provides the steps for obtaining a pooling equilibrium.

PRICE-ENDINGS IN EQUILIBRIUM

The focus of this paper is on retailers’ use of price-endings. Thus, in this section, we examine the price-endings in the equilibria identified in the earlier section, paying particular attention to when a retailer is most likely to deviate from using 9-endings.

Table 1 gives simulation results for endings of equilibrium prices under both complete and incomplete information. As in Stiving (2000), Table 1 is constructed by making 10000 draws of parameters where \(M\) is set equal to 150, \(\alpha, \gamma, \) and \(\eta\) are uniformly distributed between .1 and .9, and \(c_H\) is uniformly distributed between 10 and 75. We consider the scenario where customers prefer ‘no-frills’ service in Table 1a \((s \sim U[1.0, 1.9])\) and where customers prefer ‘luxury’ service in Table 1b \((s \sim U[0.1, 0.9])\). “LL” and “HH” represent the full information case for a low service
cost and a high service cost retailer respectively. In Table 1a, “LS” gives the results for a signaling low service cost retailer in the incomplete information case when a separating equilibrium exists. Similarly, in Table 1b, “HS” gives the results for a signaling high service cost retailer. Note that in a separating equilibrium, when \( s > 1 \) a high service cost retailer continues to employ the “HH” price and when \( s < 1 \) a low service cost retailer continues to employ the “LL” price. The “Pooling” column shows the pricing distribution for existing pooling equilibria.

Table 1 here please

Table 1 shows that when customers prefer ‘no-frills’ service, i.e., \( s > 1 \), the price-endings used by a low cost retailer signaling ‘no-frills’ service are more likely to be random, i.e. less likely to be 9-ending and very unlikely to be 0-ending. For example, in Table 1a, non 9-endings are employed in less than 1% of the trials when there is full information or in a pooling equilibrium. But in a separating equilibrium, a signaling low service cost retailer uses random-ending prices in more than 40% of the trials. In contrast, when customers prefer ‘luxury’ service, i.e., \( s < 1 \), the price-endings used by a high cost retailer signaling ‘luxury’ service are more likely to be 0-ending. For example, in Table 1b, 0-endings only are used by a signaling high service cost retailer who uses them in more than 8% of the trials.\(^5\)

Stiving (2000) provides the intuition behind the prevalence of 0-ending prices when \( s < 1 \). Essentially, a signaling retailer is often required to use a price at or above a 9-ending, i.e. \( P^* \) is likely to be a 0-ending price. To see this, refer back to Figure 3. Due to the shape of the \( \Pi_{LH} \) curve, any horizontal line at \( \Pi_{HH\text{Max}} \) is most likely to intersect RHS of \( \Pi_{LH} \) at one of its downward jumps between a 9-ending price and a 0-ending price. Therefore, a signaling high service cost

\[^5\text{The prevalence of 0-endings would be even larger if we imposed restrictions similar to condition 2 in Stiving (2000). Instead, we follow Shoemaker et al. (2004) and do not exclude the “cheap” separating equilibria, i.e. where the full information solution also serves as a separating equilibrium.}\]
retailer is likely to choose a price equal to $P^*$, i.e. a 0-ending price, if one is far enough from the apex of the $\Pi_{HH}$ and profit is diminishing in price, or to choose the next highest 9-ending price. However, this reasoning no longer holds when $s > 1$. See Figure 2. On the LHS of $\Pi_{HL}$, the leftmost intersection of a horizontal line at $\Pi_{LL_{Max}}$ is essentially a random variable. Thus, $P^*$ could be characterized by any ending\(^6\) and a signaling low service cost retailer is likely to choose either $P^*$ or the next lowest 9-ending price that yields higher profits.

We now explore how the strength of customers’ preferences for shopping in a ‘no-frills’ vs. ‘luxury’ service environment will affect retailer price-endings. Table 2 records the price-endings used in a separating equilibrium as the intensity of preferences varies.\(^7\)

Table 2 here please

These numerical simulations in Table 2 suggest that when customers prefer ‘no-frills’ service (i.e. $s > 1$), as the intensity of this preference increases ($s$ increases), a low service cost retailer becomes more likely to use random-ending prices and less likely to use 9-ending prices. In contrast, when customers prefer ‘luxury’ service (i.e. $s < 1$), as this preference increases ($s$ decreases), a high service cost retailer becomes more likely to use 0-ending and less likely to use 9-ending prices. Thus, 9-ending prices are less likely to be used by a signaling retailer especially when a (credible) signal has a large impact on demand (i.e., $s$ differs significantly from 1).

**Developing Empirical Propositions**

Using the intuition developed from the simulation results, we can now develop key

\(^6\) Actually, higher-value endings are somewhat more likely than lower-valued ones.
\(^7\) Each column reports the results from 10000 simulations, holding $s$ constant throughout all draws and allowing the other parameters to vary randomly according to the same distributions used for Table 1. The price-endings for the pooling equilibria and for a non-signaling retailer in the separating equilibria are not recorded in Table 2 since 9-endings are used predominately (99% -100% of the trials) in these cases.
propositions that one might expect to hold in a more realistic environment, e.g. when more than two potential cost levels exist and when retailers cater to different segments of customers with different preferences for retail services. We will then test these propositions in the next section of this paper.

The model suggests that a retailer’s service cost impacts its decision to signal its services through price and, thereby, indirectly affects its price-endings. Retailers offering less service presumably target customers who prefer ‘no-frills’ service. Therefore, among these retailers the ones that consistently have lower service costs would want to signal that they are truly ‘no-frills’ stores. Our simulations show that these signaling retailers are more likely to have random-ending prices and are less likely to have 9-ending prices than the average retailer. On the opposite end of the spectrum, full service retailers are more likely to target a service-sensitive segment. Among these retailers, the ones that consistently have higher service costs would tend to signal that they are truly ‘luxury’ stores. In our simulation, these signaling retailers are more likely to have 0-endings and are less likely to have 9-endings than the average retailer. Of course, all the other retailers should use 9-ending prices so as to take advantage of the psychological processes of customers that are described in the first section. Therefore, we propose:

**Proposition 1a:** The incidence of random-ending prices is higher for retailers with relatively lower service costs.

**Proposition 1b:** The incidence of 0-ending prices is higher for retailers with relatively higher service costs.

**Proposition 1c:** The incidence of 9-ending prices is lower for retailers with relatively lower service costs as well as retailers with relatively higher service costs.

Proposition 1 is stated at the level of an individual retailer. In reality, each retailer sells many different products. One might argue that unobserved differences in these products and not
the retailer price signal could lead to the same relationships identified in Proposition 1. If Proposition 1 is indeed a result of the signaling process then the same pattern should be observed holding the product constant. Therefore, one should find similar differences in price-endings used by retailers with different service costs for an identical product. In particular, retailers with relatively lower service costs and, thereby, relatively lower prices for a particular product should use random-endings more than other retailers. Also, retailers with relatively higher service costs and thereby relatively higher prices should use 0-endings more than other retailers. Consequently, the number of 9-ending prices should be lower at both ends of the price spectrum. Therefore, for an identical product available with different retailers:

**Proposition 2a:** *The likelihood of random-endings will decrease with lower relative prices.*

**Proposition 2b:** *The likelihood of 0-endings will increase with higher relative prices.*

**Proposition 2c:** *The likelihood of 9-ending prices will decrease for both higher and lower relative prices.*

**EMPIRICAL EVIDENCE**

**Data**

To examine Proposition 1, we obtain data on price-endings and service costs for a wide variety of retailers. Fortunately, the Internet is a rich data source for prices and price-endings. However, the cost data are only available for publicly traded companies which are usually large and well-known retailers. We used the *Stores* magazine of the National Retail Foundation, the world’s largest retail trade association, to arrive at the list of Top 100 retailers. For 61 of these retailers, we could obtain retail prices on the Internet. Next, we used the EDGAR database to obtain the sales and general administration costs of these stores as a percent of total revenue. We use this ratio to operationalize service costs of the retailers. Our final data consists of 55 of the
top 100 retailers after excluding the stores that are privately held (e.g., Toys ‘R Us), or have since been taken over by other stores (e.g., May Department Stores), or in countries with different currency denominations (e.g., in Japan, 1 yen coins are not commonly available). The data covers a wide range of retailers, including supermarkets (e.g., Safeway and Kroger), pharmacies (e.g., CVS and Walgreens), discount stores (e.g., Wal-Mart and Target), home improvement stores (e.g., Home Depot and Lowes), specialty apparel stores (e.g., The Gap and Victoria’s Secret), and department stores (e.g., Sears and Nordstrom). In some cases, a company includes a number of retailers. If this occurs, we include the price data from the largest store to represent that company. For example, we include data from Macy’s to represent Federated Department Stores and T J Maxx to represent the TJX Company.

For each of these 55 retailers we collect a sample of 50 prices using the following multistage random sampling procedure. We select one category in the initial menu using a table of random numbers. We proceed in this manner for each subsequent menu until we reach a page exhibiting products and prices. We select a maximum of 5 different prices from each page and then return to the main menu to start the process again until we reach a total of 50 prices for each retailer. In the end, this data (referred to as store-level data) contain 2750 prices for 55 retailers along with their service costs.

To test Proposition 2, we use the comparative prices provided by cnet.com. Cnet.com reviews 19 different product categories and reports the comparative prices of popular branded products (at the model level) in various retail outlets. We collect the comparative prices of up to 5 “most popular” products that are available with at least 10 retail stores for 13 out of the 19 product categories reported by cnet.com. We choose the “most popular products” since they are more likely to be available from multiple retailers. We do not include ‘service-based’ (like cellular
phones and internet services) and ‘intermediate-component’ product categories (like graphic cards and software) since they are often priced as a bundled offering with other products or services. To be able to compare across products we use a relative (to the average) transformation of the prices for every product. For example, the digital camera model Canon Powershot A620 is available with 12 different retailers at an average price of $267.22. For a retailer selling this digital camera model, the relative price of this item is the price of the retailer relative to the average price. Therefore for the retailer buy.com with a sale price of $259.99, the relative price is $259.99/$267.22 or 0.9729. Overall, this data (referred to as product-level data) contain 935 prices of 55 different product items.

Definition of price-endings:

There does not appear to be a consensus in the literature about exactly what constitutes a 9-ending price, especially as one begins to consider more expensive items. For example, one definition terms a price as 9-ending only when it ends in 99 cents (Schindler 2001). Another definition expands the definition to include all prices that end in 9 in the cents position (Stiving and Winer 1997). Still others consider a price as 9-ending if the last dollar digit is 9 (Anderson and Simester 2003). Since we consider a wide variety of products, we have to adopt a definition that could be applied to a wide range of prices. Also, since we consider deviations from 9-ending prices, to be conservative we should have a relatively more inclusive definition of 9-endings. We consider a price as 9-ending, when it (i) ends in 99 cents, or (ii) is less than $10 with a 9 in the cent position, or (ii) is between $10 and $100 with a 9 in the dime position or (iii) is over $100 with a 9 in the rightmost dollar position. Therefore, in addition to $2.99, $2.49, $24.95, and $249.50 are also categorized as 9-ending. If a price is not 9-ending, we consider it as 0-ending if it (i) contains no cents, or (ii) is less than $10 with a 0 in the cent position. Therefore in addition
to prices like $4.00 or $45.00, a price like $4.50 is also categorized as 0-ending. If a price is not 9-ending or 0-ending, we categorize it as ‘random’ ending. Based on this classification, we arrive at the proportion of 9-ending, 0-ending, and ‘random’-ending prices for each of the 55 retailers. 

### Descriptive Results

In Table 3 we report the pattern of price-endings at the store and at the product level. We find that even though most retailers overwhelmingly use 9-ending prices, other price-endings also exist. In the first retail-level dataset, the mean percent of 9-ending prices used by a store is about 54%. At the product-level too, we obtain similar results with the percent usage of 0-endings and random-endings together at about 36%. Thus, 9-endings are not as “ubiquitous” as commonly believed (Kalyanam and Shively 1998, p. 16). So as to understand the differences across retailers, in Tables 4 and 5, we provide the distribution of price-endings and the distribution of service costs across the 55 retailers in our first data set.

Table 4 shows that while the average extent of the usage of random-ending and 0-ending is high, the extent of use varies significantly as depicted by the high standard deviation. 8 out of the 55 retailers in our data use 0-endings for more than 80% of their products. Similarly, 5 out of the 55 retailers use random-endings for more than 80% of their products. Thus, in spite of the nearly even split between 9-endings and others, price-endings within a store are remarkably similar. In fact, 49 out of the 55 retailers use a specific type of price-ending (i.e., 9-ending, 0-ending, or random-ending) for over 60% of their prices. 18 of these retailers use the same type of

---

8 We use other definitions of 9-endings to check the robustness of our findings. For example we consider only prices ending in 99 to be 9-endings (Stiving 2001) or all prices ending in 9 in the cent position to be 9-endings (Stiving and Winer 1997). We find that our key results are not sensitive to these changes in the definition.
price-ending for over 90% of their prices.

Table 5 shows that there is considerable heterogeneity among stores in terms of service costs (as a percent of revenue). The mean service cost is 23.7% (of sales) with a standard deviation of 8.1%. While the difference in service costs between ‘no-frills’ warehouse clubs (e.g., 8.7% for Costco) and ‘luxury’ department stores (e.g., 37.0% for Burberry) is not surprising, there are also significant differences between retailers that are generally thought to be similar (e.g., Publix and Safeway, CVS and Walgreens, Amazon and Barnes and Noble).

Test of Proposition 1

Our first proposition suggests specific associations between the extent of 9-endings, 0-endings, and random-endings, with the service cost of a retailer. In particular, the extent of 0-endings should be positively related to the service cost, and the extent of random-endings should be negatively related to the service cost. The extent of 9-ending should be negatively related to the absolute value of the deviation of the service cost from average for the retailer.

In Table 6, we report the results of the store-level regression of (i) the percent of random-endings and 0-endings (i.e., R and Z) on the service cost (C) of a retailer, and (ii) the percent of 9-endings (N) on the service cost deviation of a retailer. The coefficient for service cost on the incidence of random-ending prices in a store is negative, as predicted, at an overwhelmingly significant level (p<0.001). The coefficient for service cost on the incidence of 0-ending prices in a store is positive, as predicted, also at an overwhelmingly significant level (p<0.001). And, as predicted, the extent of 9-endings is significantly associated (p<0.05) with the absolute deviation of service costs from average, since retailers at both the extremes of the cost spectrum are likely to use less 9-ending prices. Furthermore, these simple one-variable models have an average fit of over 25%. To check the predictive power of the price-endings, we classify the retailers in terms of
a median split of the service costs and use a binary logistic regression to identify the retailers in
the lower median given the price-endings. The extent of random-ending and 0-ending prices
correctly identifies the lower service cost retailer more than 77% of the time.

Table 6 here please

While these results strongly support our service signaling theory, there still may be two
concerns regarding the nature of our first data set. First, the data only consists of relatively large
and well-known retailers. We argue that including large retailers is likely to make the empirical
test conservative since well-known retailers are even less likely to use signaling. For example,
office supplies retailer Staples is widely known to provide ‘no-frills’ service – therefore it has a
lower need to signal this fact other than using the signal to reinforce existing perceptions. The
second concern relates to the differences between numerous product categories and the effect of
these differences on price endings. Proposition 2 directly address this concern. Also, the prices
collected from cnet.com to test this proposition are from retailers of different sizes that partially
mitigate the first concern.

Test of Proposition 2

Table 7 provides a percentile split of the 935 relative prices obtained from cnet.com along
with the frequency of random-ending, 0-ending, and 9-ending prices. For example, there are 85
‘random’-ending prices for the lowest quintile, i.e., the lowest 20% of the prices, 46 for the
second lowest quintile, etc. In general, apart from a few aberrations, this price-ending pattern
depicted in the quintile split fits our theory remarkably well. Particularly, for random-endings and
9-endings, the pattern is exactly as predicted. Incidence of random-endings decreases with
increasing relative prices, while the incidence of 9-endings is higher for moderate relative prices. We also get similar results using a quartile split indicating the robustness of this pattern.

Table 7 here please

As a statistical test, we ran a binary logistic regression of the dummy variables ‘random-ending’ (R) and ‘0-ending’ (Z) using ‘relative price’ (P) as the independent variable. We also ran a binary logistic regression of the dummy variable ‘9-ending’ with the independent variable ‘relative price deviation from average’ (P_dev). The results of these regressions are in Table 8. Both the models for random-ending (R) and 9-ending (N) are significant at p<0.01. The model for Z is marginally significant at p<0.1. Propositions 2a and 2c are strongly supported while there is only directional support for Proposition 2b. One reason for the weak result for 0-endings may be the nature of the data. Since these data are for internet retailers listed on cnet.com, it is possible they compete more on price than services. Also the target customers (i.e., those who are internet-savvy and make more online purchases) may be the ones who are more price-sensitive and less service-sensitive. As a result, few retailers will likely use high price to signal luxury service which is why the result on 0-endings is not strong. In this regard, also note the overall incidence of 0-endings in the product-level cnet.com data is about 10% lower than the store-level data (see Table 3).

Table 8 here please

In sum, our empirical evidence on the incidence of different price-endings is highly consistent with our service signaling theory. These findings, particularly the one that shows incidence of 9-endings initially increases as retail services (as reflected in higher service cost) increase, may be counterintuitive but explain many of the ‘price-ending’ aberrations reported in
recent surveys of managers (Schindler et al. 2003; Schindler 2001). It also explains anecdotal differences in price-ending behavior of retailers like Amazon and Barnes and Noble.

CONCLUSIONS

In this paper, we modified and extended Stiving (2000) for retailers using price to signal their services so as to increase their profit (compared to the no signaling case). We discussed circumstances when a retailer can credibly signal ‘no-frills’ and ‘luxury’ service environments and developed conditions for such separating and pooling equilibrium strategies. These signaling strategies, along with a demand function kinked at 9-ending price points, lead to price-endings different from the commonly observed ‘9’s.

In particular, when customers prefer a ‘no-frills’ service environment, conditions exist such that a lower service cost store will signal its lower costs through prices lower than the ‘normal’ profit-maximizing price. Likewise, when customers prefer a ‘luxury’ service environment, conditions exist such that a higher service cost store will signal its higher costs through prices higher than the ‘normal’ profit-maximizing price. The central thesis of this paper is that 9-ending prices will be less frequent under a signaling scenario for both lower service cost and higher service cost stores compared to a non-signaling store whose profit is almost always maximized at a 9-ending price.

To provide empirical evidence in support of our model, we collected a sample of 2750 retail prices for 55 large retailers. Additionally, we collected 935 prices for 55 specific product items available from multiple retailers. The empirical pattern of price-endings in our data provides

---

9 For example, (i) lower prices for a specific product are less likely to be 9-ending and (ii) managers believe that customers truncate prices but still choose not to use 9-ending prices.
10 For example, among the top 100 books listed, the number of 9-ending prices for Amazon.com is 11 and that for BarnesandNoble.com is 32.
strong support for our service signaling model. In particular, we find that:

1. For the two data sets in our study, about 60% of the prices are 9-ending, 18% of the prices are 0-ending, and 22% of the prices are random-ending.

2. Retailers are remarkably consistent in terms of price-endings. 49 out of the 55 retailers in our data use one type of price-ending for more than 60% of the products.

3. Retailers are less likely to use 9-ending prices when they intend to use prices to signal their level of service (either high or low).

4. The extent of different price-endings is significantly associated with the service cost of a retailer.

Managerial Implications

As discussed earlier, price-endings, per se, are not explicit signals but are artifacts of the service signaling process. Even then, we reckon that over time customers may have developed associations between services and price-endings. A similar point was made by Stiving (2000). However, unlike Stiving (2000), we show that 9-endings can have different associations for different types of stores. For example, for relatively higher service cost stores, 9-endings can be associated with a relatively lower price (and a lower level of service) since the full information 9-ending price and the pooling equilibrium 9-ending price are both lower than the separating equilibrium price. Likewise, for relatively lower service cost stores, 9-endings can be associated with higher price since the full information 9-ending price and the pooling equilibrium 9-ending price is higher than the separating-equilibrium price. Real-life examples abound. Among mall stores, Macy’s and Nordstrom use 0-ending prices connoting higher service (and consequently higher price) than J.C.Penney and Sears who use more 9-endings. On the other hand, among strip-mall discount stores, Wal-Mart prefers random-endings connoting lower service (and consequently lower price) than Target and K-Mart who use more 9-ending prices. This is contrary to the common belief in the marketing literature that 9-ending prices necessarily signal low price.
In our model, low-service firms use random-endings while high-service firms use 0-endings, and those in between almost exclusively use 9-endings. Even though these price-endings are merely artifacts of the signal, customers can potentially associate these price-endings based on observations over time. To examine this conjecture, we surveyed student subjects about their perceptions of stores for three different profiles of price-endings – random-endings, 0-endings, and 9-endings. The set of prices for the profiles were carefully chosen such that the mean and variance of the prices were the same. Subjects were explicitly informed that (i) each profile represents a different retail store, (ii) the prices are randomly drawn from the weekly featured products of these stores, and (iii) though the retailers sell similar product categories, individual prices across the stores are not for identical products and, therefore, not comparable. They were also informed of a range of services that retailers could provide. Subjects were then asked to predict for each profile the likely service level of the store. 23 out of the 42 subjects chose the random-ending profile to be the most likely to represent the retailer with the least service level while the corresponding response for the 9-ending and 0-ending profiles were 10 and 7 respectively. This finding, though preliminary, leads us to suspect that price-endings may implicitly contain information on the level of retail services provided.\textsuperscript{11}

In light of this finding, some stores may need to amend their price-ending strategies. It seems particularly necessary for stores trying to reposition. For example, currently Wal-Mart has a service cost of 17.8\%, which is much lower than its direct competitors, K-Mart (21.3\%) and Target (22.2\%). Now, if K-Mart is able to reduce this cost gap and signal it through low prices, it should also use more random-endings so as to take advantage of the associations developed by customers. Similarly, if Wal-Mart is seeking to be more ‘fashion’-savvy (Wall Street Journal

\textsuperscript{11} More details of this survey instrument and results are available with the authors on request.
2005), it may need to signal this through relatively higher prices with more 0-endings.

Another key implication pertains to the effect of price-endings on profitability. Using the earlier example, if competitors catch up with Wal-Mart in terms of costs, it might be rational for both Wal-Mart and its competitors to use a pooling equilibrium strategy in pricing with more 9-ending prices. Given its current pricing strategy and usage of price-endings, it seems that Wal-Mart believes the benefits of the ‘no-frills’ signal outweigh potential gains of a 9-ending price. But, in view of the size of the potential profit, retailers should conduct more pricing and price-ending experiments. In contrast, several surveys find that most retailers merely treat price-endings as customary and rooted in tradition rather than logic (Schindler et al. 2003; Shoemaker 2004).

**Directions for future research**

Our study’s findings as well as its limitations provide several opportunities for future research. In particular, the empirical evidence is based on aggregate store-level data and focuses on the overall service costs of the retailer. The theoretical model, however, shows the extent of 9-endings also depend on several customer-level variables. These include the percent of customers truncating price, the percent of customers knowledgeable about retailer costs, and more importantly, the preference of customers regarding a ‘no-frills’ or a ‘luxury’ shopping environment. For example, our model suggest that retailers at either end of the cost spectrum will become even less likely to employ 9-endings as fewer customers are informed about a retailer’s true cost structure and as more customers consider the full price (see Appendix 3; also see Basu 2006). Future research can hypothesize on these customer-level variables and empirical tests can

---

12 If Wal-Mart were to increase all its prices to the next 9-ending cent, the pre-tax profits (at the current sales level) could increase by as much as $300 million or about 10% of its current profits.
be conducted through controlled experiments or by examining price-endings among (i) different product categories, (ii) different channels of distribution, and (iii) different countries and cultures. Thus a common theoretical basis can be developed to explain the differences in the usage of price-endings in different contexts as reported in various studies (Lambert 1975; Ratfai 2003; Suri et al. 2004; Van Raaij and Van Rijen 2003). This can also help a retailer to develop targeted price-ending strategies at the individual and segment levels.

Finally, in spite of the empirical evidence, we still believe our results to be tentative. Future research should replicate our study in different market contexts to arrive at more robust theoretical and empirical findings. For example, a switchover of currency (such as the change to ‘Euro’ in European markets or currency rescaling in Turkey) might serve as a natural experiment to see if, and how quickly, credible signaling is re-established.
Table 1
Simulated Price-Endings under Complete and Incomplete Information\(^a\)

<table>
<thead>
<tr>
<th>Price-Ending</th>
<th>LL</th>
<th>HH</th>
<th>LS</th>
<th>Pooling</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0%</td>
<td>0%</td>
<td>.15%</td>
<td>0%</td>
</tr>
<tr>
<td>1</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>8.19%</td>
</tr>
<tr>
<td>2</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.26%</td>
</tr>
<tr>
<td>3</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.42%</td>
</tr>
<tr>
<td>4</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.24%</td>
</tr>
<tr>
<td>5</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.39%</td>
</tr>
<tr>
<td>6</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.47%</td>
</tr>
<tr>
<td>7</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.44%</td>
</tr>
<tr>
<td>8</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>1.34%</td>
</tr>
<tr>
<td>9</td>
<td>100%</td>
<td>99.33%</td>
<td>59.60%</td>
<td>100%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Price-Ending</th>
<th>LL</th>
<th>HH</th>
<th>LS</th>
<th>Pooling</th>
</tr>
</thead>
<tbody>
<tr>
<td>(b) 0.1 &lt; s &lt; 0.9</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>0%</td>
<td>0%</td>
<td>8.19%</td>
<td>0%</td>
</tr>
<tr>
<td>1</td>
<td>0%</td>
<td>0%</td>
<td>1.26%</td>
<td>0%</td>
</tr>
<tr>
<td>2</td>
<td>0%</td>
<td>0%</td>
<td>1.20%</td>
<td>0%</td>
</tr>
<tr>
<td>3</td>
<td>0%</td>
<td>0%</td>
<td>1.42%</td>
<td>0%</td>
</tr>
<tr>
<td>4</td>
<td>0%</td>
<td>0%</td>
<td>1.24%</td>
<td>0%</td>
</tr>
<tr>
<td>5</td>
<td>0%</td>
<td>0%</td>
<td>1.39%</td>
<td>0%</td>
</tr>
<tr>
<td>6</td>
<td>0%</td>
<td>0%</td>
<td>1.47%</td>
<td>0%</td>
</tr>
<tr>
<td>7</td>
<td>0%</td>
<td>0%</td>
<td>1.44%</td>
<td>0%</td>
</tr>
<tr>
<td>8</td>
<td>0%</td>
<td>0%</td>
<td>1.34%</td>
<td>0%</td>
</tr>
<tr>
<td>9</td>
<td>96.14%</td>
<td>99.36%</td>
<td>80.59%</td>
<td>99.13%</td>
</tr>
</tbody>
</table>

\(^a\) Values for \(s\), \(c_H\), \(\alpha\), \(\gamma\) and \(\eta\) are drawn randomly, with 10000 sets drawn. For each draw, we find (i) the price-ending under full information (labeled “LL” and “HH”), (ii) the price-ending for a low service cost retailer if a separating equilibrium (labeled “LS”) exists for \(s > 1\), (iii) the price-ending for a high service cost retailer if a separating equilibrium (labeled “HS”) exists for \(s < 1\), and (iv) the price ending for both retailers if a pooling equilibrium exists (labeled “Pooling”). The frequency of each ending is tabulated across all draws and reported as a percentage of draws.
Table 2
Price-endings for the Signaling Retailer in a Separating Equilibrium

<table>
<thead>
<tr>
<th>Price-Ending</th>
<th>s = .1</th>
<th>s = .3</th>
<th>s = .5</th>
<th>s = .7</th>
<th>s = .9</th>
<th>s = 1.1</th>
<th>s = 1.3</th>
<th>s = 1.5</th>
<th>s = 1.7</th>
<th>s = 1.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>14.22%</td>
<td>14.77%</td>
<td>7.17%</td>
<td>2.40%</td>
<td>0.24%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.12%</td>
<td>0.45%</td>
<td>1.03%</td>
</tr>
<tr>
<td>1</td>
<td>2.69</td>
<td>2.01</td>
<td>1.46</td>
<td>0.49</td>
<td>0.18</td>
<td>0.00</td>
<td>0.31</td>
<td>1.33</td>
<td>2.43</td>
<td>3.29</td>
</tr>
<tr>
<td>2</td>
<td>3.52</td>
<td>2.35</td>
<td>1.44</td>
<td>0.63</td>
<td>0.15</td>
<td>0.07</td>
<td>0.96</td>
<td>2.95</td>
<td>5.49</td>
<td>7.02</td>
</tr>
<tr>
<td>3</td>
<td>4.63</td>
<td>2.49</td>
<td>1.55</td>
<td>0.57</td>
<td>0.31</td>
<td>0.28</td>
<td>1.84</td>
<td>5.09</td>
<td>7.34</td>
<td>8.96</td>
</tr>
<tr>
<td>4</td>
<td>5.31</td>
<td>2.93</td>
<td>1.25</td>
<td>0.83</td>
<td>0.40</td>
<td>0.49</td>
<td>3.64</td>
<td>8.70</td>
<td>10.36</td>
<td>10.18</td>
</tr>
<tr>
<td>5</td>
<td>7.11</td>
<td>2.66</td>
<td>1.40</td>
<td>0.74</td>
<td>0.43</td>
<td>1.04</td>
<td>6.12</td>
<td>9.39</td>
<td>10.85</td>
<td>10.95</td>
</tr>
<tr>
<td>6</td>
<td>8.01</td>
<td>2.95</td>
<td>1.27</td>
<td>0.78</td>
<td>0.69</td>
<td>2.14</td>
<td>8.47</td>
<td>11.79</td>
<td>11.35</td>
<td>10.57</td>
</tr>
<tr>
<td>7</td>
<td>1.62</td>
<td>3.49</td>
<td>1.14</td>
<td>0.96</td>
<td>0.65</td>
<td>3.86</td>
<td>9.94</td>
<td>12.28</td>
<td>11.75</td>
<td>11.21</td>
</tr>
<tr>
<td>8</td>
<td>1.62</td>
<td>2.74</td>
<td>1.36</td>
<td>1.19</td>
<td>0.80</td>
<td>5.93</td>
<td>13.20</td>
<td>11.85</td>
<td>11.75</td>
<td>12.05</td>
</tr>
<tr>
<td>9</td>
<td>51.27</td>
<td>63.60</td>
<td>81.96</td>
<td>91.41</td>
<td>96.16</td>
<td>86.18</td>
<td>55.53</td>
<td>36.50</td>
<td>28.23</td>
<td>24.74</td>
</tr>
</tbody>
</table>

Values for \( c_H \), \( \alpha \), \( \gamma \) and \( \eta \) are drawn randomly, with 10000 sets drawn. Table 2 records the price-endings for a high service cost retailer in signaling equilibria that exist when \( s < 1 \) and those for a low service cost retailer in signaling equilibria that exist when \( s > 1 \).
Table 3
Share of Price-Endings

<table>
<thead>
<tr>
<th>Share of Price-Endings</th>
<th>Avg. Store</th>
<th>Avg. Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>% 9-endings</td>
<td>53.89 (36.04)</td>
<td>63.94 (17.31)</td>
</tr>
<tr>
<td>% 0-endings</td>
<td>24.14 (33.58)</td>
<td>13.23 (11.34)</td>
</tr>
<tr>
<td>% Random-endings</td>
<td>21.96 (29.12)</td>
<td>22.83 (17.56)</td>
</tr>
</tbody>
</table>

*Standard deviation in brackets
Table 4  
Distribution of different price-endings across stores

<table>
<thead>
<tr>
<th>Share of Price-Endings</th>
<th>9-endings</th>
<th>0-endings</th>
<th>Random-endings</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 % to &lt; 20 %</td>
<td>16</td>
<td>39</td>
<td>36</td>
</tr>
<tr>
<td>20 % to &lt; 40 %</td>
<td>6</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>40 % to &lt; 60 %</td>
<td>5</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>60 % to &lt; 80 %</td>
<td>8</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>80 % and over</td>
<td>20</td>
<td>8</td>
<td>5</td>
</tr>
</tbody>
</table>
Table 5
Distribution of service costs across stores

<table>
<thead>
<tr>
<th>Service Costs</th>
<th>No. of retailers</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 15 %</td>
<td>5</td>
</tr>
<tr>
<td>15 % to &lt; 20 %</td>
<td>13</td>
</tr>
<tr>
<td>20 % to &lt; 25 %</td>
<td>16</td>
</tr>
<tr>
<td>25 % to &lt; 30 %</td>
<td>12</td>
</tr>
<tr>
<td>30 % and over</td>
<td>9</td>
</tr>
</tbody>
</table>
### Table 6
Store-level Regression of Price-Endings

<table>
<thead>
<tr>
<th>Variables</th>
<th>Random-Ending</th>
<th>0-ending</th>
<th>9-ending</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>31.83 (5.41)***</td>
<td>-12.38 (6.20)**</td>
<td>31.33 (5.61)***</td>
</tr>
<tr>
<td>Service Cost</td>
<td>-20.85 (5.12)***</td>
<td>24.45 (5.88)***</td>
<td></td>
</tr>
<tr>
<td>Service Cost Deviation</td>
<td></td>
<td></td>
<td>-20.83 (10.69)**</td>
</tr>
<tr>
<td>$R^2$</td>
<td>32 %</td>
<td>25 %</td>
<td>21 %</td>
</tr>
</tbody>
</table>

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01; standard errors in parentheses.
Table 7
Relative Price and Price-Endings

<table>
<thead>
<tr>
<th>Percentile Split</th>
<th># Random-Endings</th>
<th># 0-Endings</th>
<th># 9-Endings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lowest Quintile</td>
<td>85</td>
<td>21</td>
<td>81</td>
</tr>
<tr>
<td>Second Lowest Quintile</td>
<td>46</td>
<td>26</td>
<td>115</td>
</tr>
<tr>
<td>Middle Quintile</td>
<td>41</td>
<td>24</td>
<td>122</td>
</tr>
<tr>
<td>Second Highest Quintile</td>
<td>25</td>
<td>29</td>
<td>133</td>
</tr>
<tr>
<td>Highest Quintile</td>
<td>26</td>
<td>31</td>
<td>130</td>
</tr>
<tr>
<td><strong>TOTAL</strong></td>
<td><strong>223</strong></td>
<td><strong>131</strong></td>
<td><strong>581</strong></td>
</tr>
</tbody>
</table>
Table 8:
Product-level Logistic Regression Results

<table>
<thead>
<tr>
<th>Variables</th>
<th>R</th>
<th>Z</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.39 (0.76)***</td>
<td>-1.83 (0.92)**</td>
<td>0.38 (0.094)***</td>
</tr>
<tr>
<td>P</td>
<td>-3.60 (0.77)***</td>
<td>3.70 (2.94)</td>
<td></td>
</tr>
<tr>
<td>P_dev</td>
<td></td>
<td></td>
<td>-1.5 (0.85)*</td>
</tr>
<tr>
<td>Log-Likelihood</td>
<td>-501.58</td>
<td>-670.45</td>
<td>-618.74</td>
</tr>
</tbody>
</table>

* p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01; standard errors in parentheses.
Figure 1:
Demand and Profit Functions under Price Thresholds
Figure 2:
Separating Equilibrium under Price Threshold for $s > 1$
Figure 3:
Separating Equilibrium under Price Threshold for $s<1$

![Graph showing separating equilibrium under price threshold for $s<1$]
APPENDICES

Appendix 1: Steps to obtain a separating equilibrium

For $s > 1$,

1. Let $P_{HH} = (\delta_{HH} + \rho_{HH})$ maximize $\Pi_{HH}$ and define $\Pi_{HH}\text{Max}$ as this maximum attainable profit.

2. Find the maximum value, $P^* = (\delta^* + \rho^*)$, s.t. $\forall P_H \leq P^*$, $\Pi_{HL} < \Pi_{HH}\text{Max}$.

3. Calculate $P_{LS}$ as the price that maximizes $\Pi_{LL}$ subject to the restriction that $\delta_{LS} + \rho_{LS} \leq P^*$

4. The prices of $P^*_L = P_{LS}$ and $P^*_H = P_{HH}$ constitute a separating equilibrium that yields profits of $\Pi_{LL} (P_{LS}) \equiv \Pi^*_L$ for a low service cost retailer and $\Pi_{HH}\text{Max}$ for a high service cost retailer only if $\Pi_{LL} (P_{LS}) \geq \Pi^*_L$, where $\Pi^*_L$ is the maximum profit obtainable if a credible signal is not sent by a low service cost retailer. To calculate $\Pi^*_L$, assume that it is known with probability $\eta$ that the retailer is a low service cost type and with probability $1-\eta$ the retailer is a high service cost type. Thus, the expected value of $\theta$ is $\eta s + 1 - \eta$. If the uninformed segment bases decisions on “expected” costs and the informed segment knows the “true” cost structure, demand will be:

$$Q^*_L = \alpha \left( \gamma \max\left[ M - \frac{\delta + \rho}{s}, 0 \right] + (1 - \gamma) \max\left[ M - \frac{\delta}{s}, 0 \right] \right) + (1 - \alpha) \left( \gamma \max\left[ M - \frac{\delta + \rho}{\eta s + 1 - \eta}, 0 \right] + (1 - \gamma) \max\left[ M - \frac{\delta}{\eta s + 1 - \eta}, 0 \right] \right)$$

$$\Pi^*_L = \max_{\delta_L + \rho_L} \left[ Q^*_L \right]$$

(A1)

Similarly, for $s < 1$,

1. Let $P_{LL} = (\delta_{LL} + \rho_{LL})$ maximize $\Pi_{LL}$ and define $\Pi_{LL}\text{Max}$ as this maximum attainable profit.

2. Find the maximum value, $P^* = (\delta^* + \rho^*)$, s.t. $\forall P_L \geq P^*$, $\Pi_{HL} < \Pi_{LL}\text{Max}$.

3. Calculate $P_{HS}$ as the price that maximizes $\Pi_{HH}$ subject to the restriction that $\delta_{HS} + \rho_{HS} \geq P^*$

4. The prices of $P^*_L = P_{LL}$ and $P^*_H = P_{HS}$ constitute a separating equilibrium that yields profits of $\Pi_{LL}\text{Max}$ for a low service cost retailer and $\Pi_{HH} (P_{HS}) \equiv \Pi^*_H$ for a high service cost retailer only if $\Pi_{HH} (P_{HS}) \geq \Pi^*_H$, where $\Pi^*_H$ is the maximum profit obtainable if a credible signal is not sent by a high service cost retailer, i.e.,

$$Q^*_H = \alpha \left( \gamma \max\left[ M - (\delta + \rho), 0 \right] + (1 - \gamma) \max\left[ M - \delta, 0 \right] \right) + (1 - \alpha) \left( \gamma \max\left[ M - \frac{\delta + \rho}{\eta s + 1 - \eta}, 0 \right] + (1 - \gamma) \max\left[ M - \frac{\delta}{\eta s + 1 - \eta}, 0 \right] \right)$$

$$\Pi^*_H = \max_{\delta_H + \rho_H} \left[ Q^*_H \right]$$

(A2)
Appendix 2: Steps to obtain a pooling equilibrium

To determine the profit under deviations from this pricing equilibrium, we need to clarify how customers perceive such differences. Following the “intuitive criterion” utilized by Simester (1995), we conjecture the following beliefs for the uninformed segment for the relevant range of potential prices for $s > 1$ (an analogous set of assumptions are made for $s < 1$): ¹³

1. If the retailer prices less than or equal to $P^*$, then the retailer must have low costs (where $P^*$ is defined in step 2 of the Separating Equilibrium subsection).
2. If the retailer prices in the range $P^* < P \leq P_{LP}$, where $P_{LP}$ is the argmax of $P_L^DQ_{L^C}^P$, then with probability $\eta$ it has low costs.
3. If the retailer selects any other price, then the retailer must have high costs.

For a low service cost retailer to choose to price at $P_{LP}$, signaling that it has low service cost (i.e. choosing a price at or below $P^*$) must yield no more profit than what is earned in the pooling equilibrium. For this to be true, equation (A2) must hold:

$$P_{LP}^DQ_{L^C}^P \geq \Pi_L^S \tag{A2}$$

Furthermore, a high service cost retailer will price at $P_{LP}$ only if condition (A3) is satisfied:

$$\left(P_L^P - c_H\right)Q_{H^C}^D \geq \Pi_{HMax} \tag{A3}$$

Thus, a pooling equilibrium exists only if conditions (A2) and (A3) are both satisfied. A low service cost retailer earns a profit of $P_L^DQ_{L^C}^P$, where $Q_{L^C}^P$ is given in (A1). A high service cost retailer chooses the same price ($P_H = P_{LP}$) and earns a profit of $\left(P_L^P - c_H\right)Q_{H^C}^D$, where

$$Q_{H^C}^D = \alpha\beta\gamma\partial\eta\partial\gamma\alpha\partial\gamma\partial\eta\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\alpha\partial\gamma\a
Appendix 3: 9-endings and customer-level variables

Table A1 reports the percentage of 9-endings used by a low service cost retailer when a separating equilibrium exists. For each data point, we make 10,000 draws holding one of the customer level variables – proportion of informed customers (α) or proportion of non-truncating customers (γ) fixed, with the values of all other variables determined randomly using the same distributions as those used to construct Table 1a. For example, when only 10% of customers can observe the retailer’s true cost type (α=.1), a low service cost retailer will end up employing a 9-ending in approximately 52% of all simulated trials in which a separating equilibrium exists.

Table A1
% 9-Endings for a Lower Service Cost Retailer when s>1

<table>
<thead>
<tr>
<th>α</th>
<th>% of 9-Endings*</th>
<th>γ</th>
<th>% of 9-Endings</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>51.91</td>
<td>0.1</td>
<td>69.68</td>
</tr>
<tr>
<td>0.3</td>
<td>56.19</td>
<td>0.3</td>
<td>66.30</td>
</tr>
<tr>
<td>0.5</td>
<td>58.01</td>
<td>0.5</td>
<td>62.07</td>
</tr>
<tr>
<td>0.7</td>
<td>64.55</td>
<td>0.7</td>
<td>54.11</td>
</tr>
<tr>
<td>0.9</td>
<td>88.56</td>
<td>0.9</td>
<td>41.71</td>
</tr>
</tbody>
</table>
REFERENCES


______ (1997), “Why are so many goods priced to end in nine? And why this practice hurts the producers,” Economics Letters, 54, 41-44.


European Court of Justice (2005), Newsletters and Bulletins: Registration of Marks for Retail Trade Services in the European Union, May.


