

An Empirical Analysis of Price Endings with Scanner Data

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Several consumer behavior theories have been offered to explain the preponderance of prices that end in the digit 9. This study attempts to incorporate these proposed behaviors into the implicit utility function of consumer choice models, resulting in both a more accurate tool for managerial decision making and additional insights into how consumers actually behave toward price endings. An attempt is made to compensate for both level effects (those effects in which consumers may underestimate the value of a price) and image effects (those effects in which consumers may infer meaning from the right-hand digits). The models are estimated using scanner panel data for two frequently purchased products, tuna and yogurt. The results support the importance of accounting for the digits in consumer choice models, providing evidence for both image effects and level effects.

When consumers evaluate the price of a good, they may consider the whole price, as assumed by most marketers and economists, or they may use some heuristic to simplify the task. In an effort to explain the frequent use of prices that end in 99, academics have frequently proposed that consumers round prices down, essentially ignoring the right-hand digits. Other potential explanations are that consumers discern meaning from prices that end in 9 and that consumers compare prices from left to right. This article explores these possible price-ending effects through a unique approach of using scanner data to model consumers' behavior toward price endings. The results of the models estimated in this article demonstrate that the price-ending effects exhibited by consumers can be significant, and they provide implicit information about how consumers process the digits of a price. These models may also result in improved managerial pricing decisions.

Is understanding how consumers process the digits of a price, especially the right-hand digits, important? The simple answer is yes. Every time a manager sets a price for a product, s/he also determines, either implicitly or explicitly, the right-hand digits of that price. Many studies have found that the right-hand digits may have a significant effect on sales (Blattberg and Neslin 1990; Dalrymple and Haines 1970; Ginzberg 1936; Nagle 1987; Schindler and Kibarian 1996). In two of these studies (Ginzberg 1936; Schindler and Kibarian 1996), the negative effects

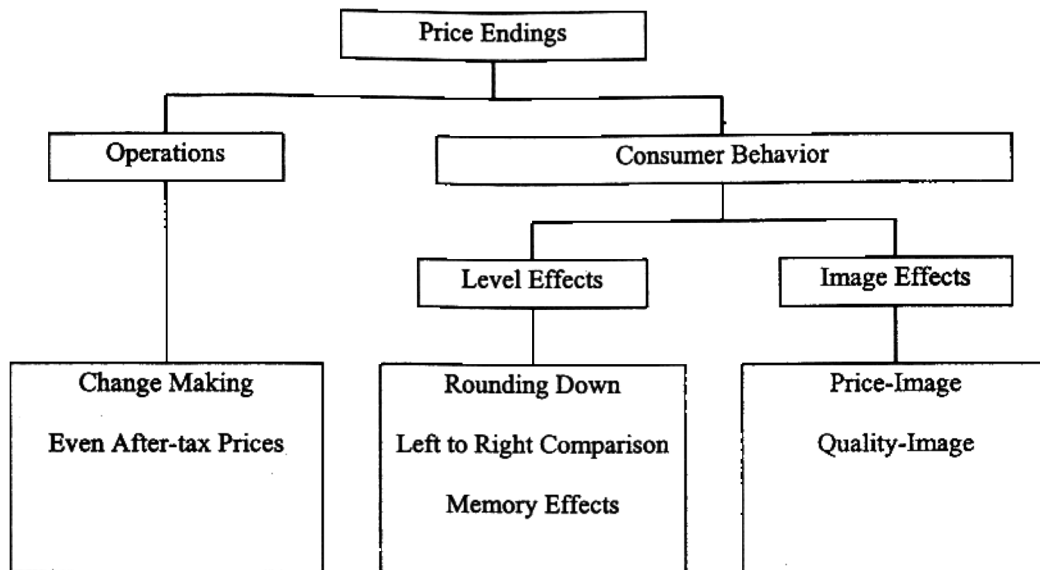
of using a digit other than 9 in the right-most column were substantial enough to motivate the firms involved to cancel any further trials for fear of substantially and negatively affecting sales.

Managers apparently set prices in a manner consistent with the premise that the last digit of a price has a significant impact on sales. Several surveys on what price endings managers actually use have been conducted, and all of these surveys support the premise that firms set prices to appear that they are just below a round number. For lower-priced goods, 9 is by far the most common right-most digit used in pricing (Friedman 1967; Kreul 1982; Rudolph 1954; Schindler and Kirby 1994; Twedt 1965), while for higher-priced goods, greater than \$5.00 (Rudolph 1954) or \$7.00 (Kreul 1982), 5 is the most common digit, owing to the frequent use of 95 as the last two digits. This practice of setting prices just below a round number is sometimes called "odd pricing" (see, e.g., Knauth 1949; Monroe 1979). This article will use the terms "odd price" and "just-below price" interchangeably. Similarly, the term "even pricing" is used to describe pricing at round numbers, typically represented by a price ending of zero (see, e.g., Georgoff 1972; Lambert 1975; Monroe 1979). In addition to a strong tendency toward just-below prices, these same price ending surveys found that the digits 0, 5, and 9 were used in actual prices over 74 percent of the time and up to 99 percent of the time, depending on the survey. This is additional support for the claim that managers behave in a manner consistent with the belief that price endings are important.

The objective of this article is to present a new method of including price in choice models, producing three distinct results. First, the models presented here are more

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FIGURE 1
EXPLANATIONS FOR PRICE ENDINGS



accurate predictors of consumer behavior than the traditional price model, potentially enabling better decisions by marketing managers. Second, the results of the models provide strong evidence that consumers do not always process all of the numerical information contained in the price, as typically assumed by marketers and economists. Third, the evidence suggests that consumers process prices digit by digit, beginning with left-hand digits and frequently ignoring right-hand digits.

Conceptual Background

Several theories have been proposed to explain the preponderance of odd prices. Figure 1 lists several of these theories and broadly categorizes them into operations and consumer behavioral explanations. The operations theories revolve around procedural issues internal to the firm, typically in an effort to reduce costs. For instance, it is commonly believed that prices were originally set with a 9 in the right-most digit to force clerks to make change, thereby ringing up sales on the cash register. Otherwise, it was too easy for the customer to pay the exact amount and the clerk to simply pocket the money (Hower 1943; Schindler and Kirby 1997). The opposite explanation can also be offered. Noah's Bagels is one example of a local firm in California that sets prices so that the price is a round number after taxes are added. This could lower the time it takes to make change and allow the employee to serve the next customer quicker. Although these and other operational explanations for price endings may have merit, the emphasis of this article is on the consumer behaviors that drive specific price-setting strategies.

The consumer behavior theories propose that consum-

ers' interpretations of right-hand digits affect the demand curve, thus motivating firms to use certain price endings. As shown in Figure 1, proposed consumer behavior theories used to explain the dominance of odd prices can be categorized into "level effects" and "image effects." Level effects, also known as underestimation effects, refer to the behaviors or underlying processes that cause a consumer to distort their perception of the price. For example, one common hypothesis about level effects is that consumers tend to round numbers down, causing a consumer to believe that \$2.99 is much lower than \$3.00. Image effects, on the other hand, are those that cause a consumer to believe something about the product, store, or competition, on the basis of the right-hand digits of the price. For example, consumers may believe that a product with a price that ends in 99 is on sale. Each of the proposed level effects is a description of the way consumers process information about the digits of a price (i.e., their mental arithmetic), completely independent of firm behavior. On the other hand, the image effects are concerned with consumers' perceptions of firm behavior. Consumers may strategically attempt to discern firms' intentions when setting certain prices, or they may, over time, subconsciously learn the correlation between price endings and quality or discounted products. A thorough understanding of both level and image effects is required to develop models to capture these behaviors.

Level Effects

The original and most common explanation for underestimating an odd price is that consumers tend to round prices down (Alpert 1970; Gabor and Granger 1964;

Georgoff 1972; Hollander 1966; Lambert 1975; Schindler 1984; Schindler and Warren 1988; Whalen 1980). For example, they may round the price \$2.99 to \$2.00 or maybe to \$2.00 and some change. Lambert (1975) designed a study to directly test this hypothesis. He put together cards that listed four products and their prices. On some cards he used even prices and on others he used odd prices. He then told each respondent that they had a 50 percent chance of winning what was on the card (or the cash equivalent) or else they could take a certain amount of money. The respondents were asked at what level of certain cash would they be indifferent between the gamble and the sure thing. If consumers really do round down odd numbers, Lambert expected to see the average amount of the certain cash to be lower for the cards that used odd prices than for those that used even prices. His results were mixed. After running the study with five groups of subjects, he obtained results as expected in two of them, no significant results in two of them, and in the last he obtained results that contradicted his hypothesis. Alpert, McGrath, and Alpert (1984) repeated this study with a slightly improved design, but the results were still inconclusive. Schindler and Kibarian (1993) also attempted to demonstrate this phenomenon using consumers' recall of prices shortly after they observe the actual price, both in a laboratory setting and at a major supermarket. They expected to find significantly more underestimation in the recall of prices ending in 9 than in the recall of other prices, but no conclusive underestimation was found in either circumstance.

If consumers actually round down prices, firms would have a great incentive to use just-below prices, providing an explanation for the observed price endings. For example, using this heuristic, consumers would round down both \$.73 and \$.79 prices to simply \$.70. Since demand would be the same for both prices, the firm would obviously select \$.79 in order to maximize profits.

Left-to-right comparison, another proposed explanation for the level effect, concerns the direct comparison of two numbers, possibly two prices displayed on the shelves at the grocery, or a shelf price with a reference price being held in memory. It has been theorized that consumers tend to compare two numbers by considering the digits from left to right. A convincing piece of anecdotal evidence for this explanation is provided by Monroe (1979) and discussed by Nagle (1987). Look at the following two pairs of prices: (\$.89, \$.75) and (\$.93, \$.79). For which of the two pairs is the lower price more of a bargain? Most people believe that \$.79 is the better deal, but the difference between each pair is identical (\$.14), and, in fact, the difference for the first pair is a higher percentage of the original value. One explanation for this phenomenon is that consumers compare prices from the left digit to the right digit. Consumers may compare the first digits of each price, like the 8 and 7 of the first pair and the 9 and 7 of the second pair, and then not go any further. By reasoning that the difference between the first pair's first digits (i.e., $8 - 7 = 1$) is less than the difference

between the second pair's first digits (i.e., $9 - 7 = 2$), the consumer may assume the better deal is with the second pair. An alternative way of looking at this phenomenon is that consumers may estimate the difference between two prices by simply subtracting left-hand digits when they are different and subtracting right-hand digits when the left-hand digits are the same. No formal study has been done to prove or disprove this concept. In a similar vein, Poltrock and Schwartz (1984) used the response time from respondents determining which of two four-digit numbers was larger to support the hypothesis that consumers compare numbers from the left digit to the right. They found that respondents seem to compare numbers from left to right and they ignore right-hand digits once they find different left-hand digits. However, in this experiment the respondents did not need to determine the relative difference between the two numbers as s/he might have to do when deciding which of two products to purchase.

Although the consumer behavior explanations for rounding down and left-to-right comparison may not seem similar, they are actually closely related. When the left-hand digits are different, left-to-right comparison and rounding down are indistinguishable, yielding identical results. However, when the left-hand digits are the same, rounding down makes no statement about which price a consumer may prefer, while left-to-right comparison does. Therefore, left-to-right comparison can be considered a modified version of rounding down. As such, it is not difficult to imagine that if consumers use the left-to-right comparison heuristic, firms still have an incentive to use just-below prices. As long as the dimes digits for two competitors are different, consumers ignore the pennies, motivating firms to use 9 price endings. For example, assume competitor A is charging \$.69 and competitor B is choosing between \$.73 and \$.79. Consumers using left-to-right comparison would estimate the difference between the competitor A's price and competitor B's price as \$.10, regardless of which price competitor B chooses, so competitor B would obviously choose \$.79.

A third explanation for level effects is based on the limited memory capacity of humans (Brenner and Brenner 1982). Since consumers are continuously barraged with information, including prices and other numbers, they most likely remember only the first digits of a price. Thus, when faced with the price \$14.99, they may only remember the 14. Elaborating on this theory, Schindler and Wiman (1989) proposed that during recall of numbers in which only the left-hand digits were remembered, consumers may guess what they think is most likely for the right-hand digits. In the example of \$14.99, if a consumer remembers the 14 and guesses for the right-hand digits anything other than 99, s/he will underestimate the actual price. In laboratory studies it has been shown that consumers have a poorer memory for odd prices than for even prices (Schindler 1984) and that recall errors for odd-priced products are more likely to be underestimates than the recall errors for even-priced products (Schindler

and Wiman 1989). It has also been demonstrated that left-hand digits are correctly recalled more frequently than right-hand digits, and that overestimates of prices that end in a digit other than 9 typically come from consumers guessing that the last digit is 9 (Schindler and Kibarian 1993). In a choice situation, such as what the consumer faces at the supermarket, s/he does not need to remember prices. Since the study in this article uses consumer choice data from a supermarket, the memory effects explanation is not a feasible alternative.

Image Effects

Several possible meanings implied by price endings have been proposed (see Schindler [1991] for a review) that can be further categorized into two topics: price image and quality image. The different price images or meanings that have been attached to prices that end in 99 include assumptions that the product is on sale (Berman and Evans 1992; Kotler 1991; Raphael 1968), that the price has been reduced, possibly from the next higher even price (Alpert 1971; Friedman 1967; Knauth 1949), and that this price is the lowest price around (Bliss 1952; Mason and Mayer 1990). The quality images proposed include assumptions that odd prices indicate low-quality merchandise (Kreul 1982), while even prices connote high-quality products (Wingate, Schaller, and Miller 1972), other quality products in that retail store (Nagle 1987), and the level of class or prestige of the retailer (Alpert 1971; Feinberg 1962; Raphael 1968; Spohn and Allen 1977).

An abundance of support is accumulating for the price-image effect. Statistically significant results have been found that support several claims: consumers do believe that odd prices indicate that the price has not been raised recently (Schindler 1984), they believe that prices that end in 99 indicate that the product is on sale (Quigley and Notarantonio 1992; Schindler and Kibarian 1996), and they believe that prices ending in 99 imply that the product is at the lowest price around (Schindler and Kibarian 1996). A field study conducted using 90,000 mail-order catalogs with price endings of 88, 99, and 00 resulted in the catalog with the price endings of 99 outperforming by over 8 percent both of the other catalogs (Schindler and Kibarian 1996). These results are consistent with the explanation that price endings of 99 indicate a good deal. Note that these results are not consistent with any of the level effects described above, as none of the level effects offer an explanation for a higher price, \$.99, yielding a higher demand than a lower price, \$.88. This does not indicate that level effects do not exist, only that in the context of this study, the image effects were strong enough to be noticed over any level effects.

The one study that attempts to demonstrate the quality-image effects of even prices (Schindler and Kibarian 1993) produced insignificant results when looking for differences in the following areas: the overall quality of the product being advertised, the quality of the other items

in the store, and the image of the store itself. An additional justification for consumers associating even prices with higher quality is if consumers associate high prices with high quality and higher prices tend to be even, then consumers could learn to believe that even prices are indicators of higher quality.

It is relevant to note that almost all image effects surround the digits 0 and 9, the two most commonly used price endings. The digit 0 has been suggested as a signal of higher quality, presumably enhancing the desirability of a product. The digit 9 has been proposed as both a signal of lower quality and a signal of a good price, confounding any a priori predictions of the digit 9 as an image effect.

Previous Price-Ending Models

A few previous attempts have been made at including price-ending effects in models. The first was a simple variant of the classic econometric supply-and-demand model with simultaneous equations (Dalyruple and Haines 1970). Included in the demand equation was a variable that was 1 if the price was even and 0 if the price was odd. The 82 even prices were even dollar amounts, and the 222 odd prices ended in either 5, 7, or 9. When estimated as a linear model, the coefficient of the price-ending variable was positive, indicating that demand was higher when prices were even. This result was opposite of what was expected. However, when estimating the same equations as log models, the sign of the price ending variable became negative, implying that consumers prefer odd prices. Obviously, no conclusive results can be drawn from this study.

Blattberg and Wisniewski (1987) used scanner data to model how a price ending of 9 affects promotions. They use market share as the dependent variable and develop a model that includes a dummy variable that is 1 only when the price promotion ends in the digit 9. Analyzing 20 product categories, they find that using a price ending of 9 for promotions provides an average of 10 percent sales increase over not using a 9. This is a significant finding consistent with the price-image effect proposing that prices that end in 9 are good deals.

The study conducted by Little and Gines (1987) using scanner data on pancake syrup is most similar to what is presented here in that they also used a logit model to look for price-ending effects. In their study they included a variable for price and also included a dummy variable for each of the digits 0 through 8. They were looking for significant effects of prices ending in 9 that would be observed through negative and significant coefficients of each of the dummy variables. This would indicate that the digit 9 is preferred by consumers in the choice of pancake syrup. They found significant results indicating that the digit 9 is preferred over the digits 0, 1, 2, 3, and 5. The effect of ending with one of the remaining digits was not significantly different from ending with the digit 9, making those results inconclusive.

Each of these models demonstrates that price endings do have some significant effect on consumer decisions. However, none of these models is consistent with the theory on level effects or image effects. In each case, the results achieved by the researchers could be explained using either one or a combination of the two effects. This article analyzes models of consumer choice developed directly from consumer behavior theory, beginning first with level effects and then including possible image effects.

THE DATA

The empirical analysis is conducted on two scanner panel data sets for the products tuna and yogurt. Each record in a scanner panel data set includes a household identification number, the product purchased, the price paid, and many other characteristics about the purchase event. Several attributes of these data sets enhance their attractiveness: the prices of the products are always under a dollar (two-digit prices), the number of coupons redeemed for these products is minimal, and these products are purchased enough to build complete and accurate store data files.¹ Accurate store data files are extremely important since estimating rather than simply using the correct level of the price for nonpurchased brands would detract from the ability to test the effects of price endings. Another attribute critical to this study is that there is a reasonable spread of price endings represented in the data. If all prices ended in 9, the data would not be able to reveal consumers' behavior toward price endings. As a last criterion required to test the left-to-right comparison explanation, the data must have some prices for which the value of the dimes digits for the two brands is equal, and other prices for which they are different.

The tuna data is for the 6.5-ounce size of water-packed chunk light tuna and is limited to two major national brands, Chicken of the Sea and Starkist, which make up over 80 percent of the purchases in this category. For these brands, the data include 12,385 purchase events (excluding purchases with coupons) covering 123 weeks in three stores. The parameters are estimated for 1,702 households with 9,300 observations, while the remaining 567 households were used as a holdout sample. Of the 24,770 prices in the data set (one for each brand purchased and not purchased for a given purchase occasion), 50.5 percent ended in the digit 9 and none ended in 0, leaving 12,260 prices ending in one of the other digits (1–8). The dimes digits of the prices are equal for the two brands in 40.6 percent of the purchase events.

The second data set is for single serving sizes of yogurt (6–8 ounces) from a single store. Attention is again re-

stricted to the two dominant national brands, Yoplait and Dannon, for which 1,232 purchases (without coupons) were observed over the 137-week period of the data. For this data set, 259 households and 1,065 purchase events were used for calibration, while 64 households made up the holdout sample. Of the 2,464 observed prices, 36.1 percent end in 9 and 10.9 percent end in 0, leaving 1,306 prices that end with digits in the range of 1–8. The dimes digits are equal in 69.0 percent of the purchase events.

MODEL DEVELOPMENT

To explore the effect price endings may have on consumer choice, we use a binary logit model similar to the multinomial logit model used by Guadagni and Little (1983). This type of model provides the ability to propose different structures for the consumer's indirect utility function, to estimate the importance of different variables in this utility function, and to compare the proposed structures.² For example, we propose a utility function that assumes consumers holistically evaluate the price of a good (model A) and see how well it fits the data. We then do the same for a utility function that assumes consumers weight the pennies and dimes digits of a price differently (model B) and see how well it fits the data. Comparing the estimation results may provide enough information to determine which of these models is more consistent with the consumer behaviors that generate the data.

Each proposed utility function in this study consists of alternative-specific variables (AltSpec), variables for "display," "feature," and "loyalty," and some form of price variables. The alternative-specific variable is a dummy variable for either the Starkist brand of tuna or the Yoplait brand of yogurt. The display and feature variables are dummy variables indicating the presence of a special in-store display and/or a feature advertisement in a local newspaper, and loyalty is a dummy variable that is set to 1 if the brand under consideration is the same brand that the consumer last purchased. This method of estimating a loyalty variable has been used previously (e.g., Bucklin, Gupta, and Siddarth 1994; Winer 1986) and is a parsimonious alternative to the exponential smoothing technique proposed by Guadagni and Little (1983). Both of these techniques produce state-dependent variables attempting to capture consumer heterogeneity and nonstationarity. Fader and Lattin (1993) point out that the optimal value of the smoothing constant used in the exponential smoothing technique is dependent on the average length of the choice history of the household and that a more complex model is required to fully capture heterogeneity and nonstationarity. Since both the proposed loyalty variable and the exponential smoothing loyalty variable are at best reduced form estimates of the

¹Each purchase record provides the price of the product purchased but not the prices of the other choices. These prices are obtained by finding other purchase records in the same time period where a consumer purchased other brands in the same product category.

²Readers unfamiliar with logit models may want to see Guadagni and Little (1983) and Winer (1986), two papers that more thoroughly describe this type of model.

true behavior, we selected the parsimonious specification. The results, shown later in this article, demonstrate that the loyalty variable was not correlated at all with the variables of interest in this study.

For clarity, a common portion of the consumer utility function called U_{base} is defined as follows:

$$U_{\text{base}} = \beta_1 \times \text{display} + \beta_2 \times \text{feature} \\ + \beta_3 \times \text{loyalty} + \beta_4 \times \text{AltSpec.}$$

The coefficients of the display, feature, and loyalty variables are expected to be positive and significant. Notice that U_{base} does not include a price variable. Different formulations of price variables are what differentiate each of the models.

The first model to be estimated includes the variable "price," simply defined as the price the customer paid or, for the nonpurchased brand, the estimated shelf price of the product determined by looking for purchases by other consumers in the same time period. This is the usual method of incorporating price into choice models as demonstrated by Guadagni and Little (1983). This model assumes consumers use all of the numerical information contained in the price. We refer to this as holistic processing of the price:

$$\text{Model A: } U = U_{\text{base}} + \gamma_1 \times \text{price.}$$

Model B replaces the variable "price" with two variables, "dime" and "penny." These variables are generated by splitting the price of the product (what would have been in the variable "price") into its respective digits. For example, \$.37 would be split into a 3 for the dime variable and a 7 for the penny variable:

$$\text{Model B: } U = U_{\text{base}} + \gamma_2 \times \text{dime} + \gamma_3 \times \text{penny.}$$

This model is a nested version of model A since price = 10 × dime + penny, and restricting $\gamma_2 = 10 \times \gamma_3$ produces model A. Thus, comparing models A and B may provide insight into whether consumers put different weights on the different digits of the price. For example, if consumers process the price holistically, rather than process the digits individually, then model B should not fit better than model A. However, if all consumers simply round down prices, completely ignoring the pennies digits, then model B should be a better fit for the data, and the coefficient of the penny variable should be zero.

A third model is developed to provide insight into the assumption that consumers selectively ignore the pennies digit. More specifically, an attempt is made to model the left-to-right comparison behavior. Recall that in left-to-right processing, consumers ignore the pennies digits whenever the dimes digits are different, but when the dimes are the same, they use the pennies digits. To model this, a new variable, δ , is defined to be a dummy variable that takes on the value of 1 only when the dimes variables of the two brands under consideration are equal; otherwise it is 0. Thus, model C adds the variable $\delta \times \text{penny}$ to model B. The $\gamma_3 \times \text{penny}$ term remains in the model to

make this a nested version of model B and to provide insight into how consumers consider the pennies when the dimes are not equal.³ If consumers use the left-to-right processing heuristic exclusively, then model C will fit better than model B, the coefficient of the penny variable will be zero, and the coefficient of $\delta \times \text{penny}$ will be negative and significant:

$$\text{Model C: } U = U_{\text{base}} + \gamma_2 \times \text{dime} \\ + \gamma_3 \times \text{penny} + \gamma_4 \times \delta \times \text{penny.}$$

Missing from models A, B, and C is any compensation for image effects. Blattberg and Wisniewski (1987) found that including a dummy variable when the right-most digit is 9 significantly increased the performance of their model, possibly capturing the image effect of this digit. Little and Ginese (1987) similarly found that right-most endings of the digit 9 were significantly better than several other price endings, again possibly the result of image effects. In the Image Effects section above, it was noted that both 9 and 0 price endings have been hypothesized to affect consumers' image of the product or price, so in an attempt to capture these effects, each of the above models is reestimated with dummy variables for prices that end in 0 or 9. Toward this end, two new variables are defined, "zero" and "nine," which take on the value of 1 if the right-most digit of the price is a 0 or a 9, respectively. Models A*, B*, and C* are defined as follows:

$$\text{A*}: U = U_{\text{base}} + \gamma_1 \times \text{price} \\ + \gamma_5 \times \text{zero} + \gamma_6 \times \text{nine};$$

$$\text{B*}: U = U_{\text{base}} + \gamma_2 \times \text{dime} + \gamma_3 \times \text{penny} \\ + \gamma_5 \times \text{zero} + \gamma_6 \times \text{nine};$$

$$\text{C*}: U = U_{\text{base}} + \gamma_2 \times \text{dime} \\ + \gamma_3 \times \text{penny} + \gamma_4 \times \delta \times \text{penny} \\ + \gamma_5 \times \text{zero} + \gamma_6 \times \text{nine.}$$

Since consumers prefer to pay less for any given good, it is expected that the coefficients of the price, dime, penny, and $\delta \times \text{penny}$ variables should be negative. The variable zero is predicted to have a positive coefficient consistent with the claim that prices that end in 0 are a signal of quality. No a priori prediction about the variable nine is made, since it has been hypothesized to be both an indicator of a good deal and a signal of poor quality.

EMPIRICAL RESULTS

We used both likelihood ratio and *t*-statistic tests to analyze the results. The likelihood ratio test provides a

³A simpler way of modeling this is to omit the penny variable in model C, which does not change the substantive results. However, this is not a nested model of B and so the results are not as easily compared.

TABLE 1
ESTIMATION RESULTS: TUNA DATA

	Model A		Model B		Model C	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Display	.85	7.8	.86	7.8	.80	7.4
Feature	.74	12.5	.74	12.4	.71	11.9
Loyalty	.74	24.4	.74	24.4	.74	24.4
Starkist	.34	11.5	.34	11.4	.37	12.2
Price	-.16	-41.5				
Dime			-1.57	-36.2	-1.69	-35.1
Penny			-.17	-8.8	-.06	-2.7
$\delta \times$ Penny					-.39	-8.2
Log likelihood		-4,021.9		-4,021.6		-3,983.4
	Model A*		Model B*		Model C*	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Display	.87	8.0	.84		.81	7.5
Feature	.71	12.0	.71		.70	11.8
Loyalty	.74	24.5	.74		.74	24.3
Starkist	.37	12.4	.35		.37	12.1
Price	.15	-38.7				
Dime			-1.54	34.7	1.83	-33.5
Penny			-.07	-2.9	-.01	-.6 NS
$\delta \times$ Penny					-.27	-5.7
Nine	-.45	-8.1	-.56	-8.9	-.42	-6.3
Log likelihood		-3,988.3		-3,981.7		-3,963.7

NOTE.—NS indicates not significant at the 95 percent confidence level.

statistical comparison of the fit of two nested models. For the variables for which a direction was explicitly stated (display, feature, loyalty, price, dime, penny, $\delta \times$ penny, and zero) a one-tailed *t*-test is appropriate, and for the others (nine and the alternative specific variables) a two-tailed test must be used.

The parameter values, *t*-statistics, and log-likelihood values for the models when estimated with the tuna data are presented in Table 1. Looking first at the models without the image-effect dummy variables reveals that model C is a much better fit than model B or model A ($p < .001$), but model B is not a significant improvement over model A. Comparing the image-effect models with their parsimonious counterparts indicates that in every case, the model that contains the dummy variable nine⁴ is a significantly better fit than the similar model that does not ($p < .001$). Looking within the image-effects models, B* is a better fit than A* ($p < .001$) and C* is a better fit than B* ($p < .001$). Thus, in the tuna data, C* is by far the best-fitting model estimated. All parameter values have the correct sign (if predicted) and, with 9,300 observations in the calibration sample, all of them are significant ($p < .05$), with the sole exception of the coefficient

of the penny variable in C*. Implications of these results will be discussed later.

The estimation results for the yogurt data are presented in Table 2. Likelihood-ratio tests indicate that model B is a better fit than model A ($p < .01$), but model C is not a better fit than model B. Like the tuna data, adding the zero and nine variables to each of these models yields a significantly better fit ($p < .001$). Within the image-effect models, B* is not a significant improvement over A*, but C* is significantly better than A* or B* ($p < .05$). Thus, C* is the best fitting model for both data sets. As before, the signs of the parameter estimates, when predicted, are all correct.⁵ However, in the yogurt data many more parameter estimates are not significant at the .95 level.

An additional test of the power of these results is to analyze the models on the holdout samples. The parameter estimates shown in Tables 1 and 2 were used to estimate consumers' utilities for the holdout samples, and the probabilities that consumers would choose the selected alternatives were calculated. These probabilities are then used to predict which choice the consumer will make, and these predictions are compared with the actual

⁴The variable "zero" is not included in these models, as none of the observed prices ended in the digit 0 in the tuna data set.

⁵The variable "display" is not included in these models, as none of the records in the yogurt data had a display.

TABLE 2
ESTIMATION RESULTS: YOGURT DATA

	Model A		Model B		Model C	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Feature	.63	3.2	.44	2.1	.42	2.0
Loyalty	1.52	13.7	1.51	13.6	1.51	13.6
Yoplait	.42	5.1	.47	5.5	.47	5.5
Price	-.06	-5.4				
Dime			-1.09	-5.6	-1.08	-5.4
Penny			-.03	-1.5 NS	-.04	-1.1 NS
$\delta \times$ Penny					.01	.3 NS
Log likelihood		-500.5		-496.0		-495.9
	Model A*		Model B*		Model C*	
	Parameter	t-statistic	Parameter	t-statistic	Parameter	t-statistic
Feature	.53	2.5	.56	2.6	.71	3.1
Loyalty	1.52	13.6	1.53	13.6	1.54	13.6
Yoplait	.40	4.6	.31	2.3	.34	2.5
Price	-.05	-2.3				
Dime			-.56	-2.4	-.48	-2.0
Penny			-.15	-1.4 NS	-.05	-.5 NS
$\delta \times$ Penny					-.10	-2.3
Zero	1.12	3.3	.76	1.4 NS	1.21	2.1
Nine	.43	3.3	.85	1.7 NS	.85	1.7 NS
Log likelihood		-483.1		-482.7		-480.1

NOTE.—NS indicates not significant at the 95 percent confidence level.

choice made by the consumer. The number of correct predictions made by each model for both data sets are shown in Table 3. Although no statistical test exists to compare these values, of specific interest is that model C* predicts correctly more frequently than model A and is at least as accurate as each of the other models for both data sets.

DISCUSSION

The purpose of this study was to present a unique method of modeling consumers' behavior toward prices while simultaneously looking for insights into how consumers may behave toward price endings. By starting

with the theoretical explanations for level effects, rounding down and left-to-right comparison, we were able to develop models that directly represented each potential explanation. Dividing the price into its digits and then enabling the right-most digit to be selectively ignored provided nested tests for each of the theories. The final step was to add dummy variables for 9 and 0 endings to capture the possible level effects. From a statistical fit point of view, model C* fits both data sets better than any of the other models, especially better than the traditional approach of simply using the variable price (model A). Model C* also correctly predicts more out of sample purchase events than model A and is no worse than any of the other models.

From a managerial decision-making point of view, the difference between using model A and model C* can be quite large. Imagine a manager at Starkist (Yoplait) determining the optimal price to charge when her/his competitor is charging \$.49 and there are no displays or features. As an example, consider only those consumers who chose the competitor's product on the last purchase occasion. Table 4 presents the choice share predictions made by models A and C* for both product categories. Considering the large differences between the predictions of the two models for both data sets, what is a manager to believe? Although neither model will be 100 percent accurate, C* provided a significantly better fit to the calibration data sets and was more accurate at predicting

TABLE 3
NUMBER OF CORRECT PREDICTIONS
FROM HOLDOUT SAMPLE

Model	Tuna	Yogurt
A	2,471	151
B	2,471	153
C	2,500	153
A*	2,492	151
B*	2,501	153
C*	2,502	153
Number of records	3,085	206

TABLE 4
PROJECTED CHOICE SHARES

Price (¢)	Starbuck tuna (%)		Yoplait yogurt (%)	
	Model A	Model C*	Model A	Model C*
45	55.9	76.6	30.2	19.7
46	51.9	71.2	28.8	17.3
47	47.9	65.0	27.5	15.1
48	44.0	58.3	26.3	13.2
49	40.1	40.7	25.0	23.2
50	36.4	18.9	23.8	30.7
51	32.8	18.7	22.7	11.1
52	29.4	18.5	21.6	10.6
53	26.2	18.3	20.5	10.1
54	23.2	18.1	19.5	9.6
55	20.5	17.9	18.5	9.1

NOTE.—Calculations assume that Chicken of the Sea tuna and Dannon yogurt are priced at 49¢, there are no displays or features, and the consumer last purchased Chicken of the Sea brand tuna or Dannon yogurt.

choices in the holdout sample, so the manager will most likely be better off believing the results of model C* over those of model A.

In addition to managerial implications, these results also offer insight into the processes consumers may use when evaluating price in a choice situation. Although it is not possible to prove that consumers use some behavior over another on the basis of these modeling techniques, the results are supportive of both image effects and level effects. The significance of the image-effects models (A*, B*, and C*) over their counterparts (A, B, and C) in every case is consistent with the image-effects explanations. The variable zero was positive and significant as predicted in the yogurt results, supporting the theory of image effects. The variable nine, on the other hand, was negative and significant for the tuna data and was positive and significant for the yogurt data. Although it is possible that the variable nine is capturing quality-image effects for tuna and price-image effects for yogurt, it seems more likely that the image effects are not being fully captured by the dummy variables, making it difficult to draw conclusions.

As to level effects, the results are most consistent with the left-to-right processing explanation. Model C* was the best fitting model to the data sets, indicating that the variable $\delta \times$ penny is a significant contribution to the model. Also, the coefficient of $\delta \times$ penny was significant in both data sets, while the coefficient of the penny variable became insignificant in the C* results. This implies that consumers selectively ignore or consider the pennies digits, a result most consistent with the left-to-right processing explanation.

The relatively poor fit of model A indicates that consumers do not simply process the price as a whole, contrary to traditional marketing and economic thought. Is processing the digits of a price irrational behavior? Probably not in the sense that it is not irrational for consumers

to use heuristics to make complicated calculations simpler. If consumers compare prices from the left digit to the right, frequently ignoring the pennies digit, they may be implicitly weighing the mental cost of thinking about the pennies digit against the amount of additional information it provides. Since the information in the dimes digit is (in actuality, not in consumers' perceptions) 10 times more important than that in the pennies digit, it is likely that the choice decision made when using only the dimes digits would be the same choice made when using both digits. Therefore, consumers may act rationally by trading off the low likelihood of making a mistake against the cost of mentally processing the pennies digit. This is consistent with Shugan's (1980) theory where he proposes that, for each situation, consumers choose an "optimal" decision rule by trading off the accuracy of the rule against the mental cost of using it. Consumers do not try to optimize every decision; rather, they want to make a good decision with the least amount of mental processing. In the left-to-right comparison case, consumers may make reasonable decisions using only the dimes digit, without expending the extra mental processing effort of evaluating the pennies.

Limitations and Conclusions

This study has several limitations, most of which can be considered topics for future research. First, only very similar products were used. For both data sets, the analysis was limited to the high-quality national brands, not considering what models may best fit the situation in which consumers choose between national brands and much lower priced store brands. Second, only two brands were used for each product category. This restriction was driven by the desire to model the left-to-right comparison technique, requiring a direct comparison between the dimes digits of both brands. If more than two brands are used, the structure of the utility function and the value of δ or its equivalent are not clear.

Like all research of this type, the models tested cannot completely rule out alternative explanations. It is possible that an alternative explanation, one different from the left-to-right comparison hypothesis, represents the "true" consumer behavior, and the results we see in the models are simply an artifact of this behavior. Thus, an experimental approach to analyzing how consumers process the digits of a price could prove more conclusive.

In addition to addressing these limitations, there are other interesting areas for future research in this area, possibly approached by more empirical work or laboratory experimentation. For example, what happens when the price has more than two digits? With many digits, which digit becomes the right-most digit? In addition to looking at consumer choice, what effects do price endings have on purchase incidence?

Despite the limitations, this study makes several contributions to the marketing literature. First, it provides a framework for including price endings in choice models,

enabling more accurate share predictions by firms. Second, this study provides strong support for the claim that consumers typically process the digits of a price and not the price as a whole when making brand choices. And third, there is some evidence for the hypothesis that consumers process digits from the left to the right. There is still much we do not know about how consumers process and interpret the digits of a price, but further understanding of how consumers react to price endings is both academically interesting and relevant to firm decision making.

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