What Affects Price and Price Cue Elasticities? Evidence from a Field Experiment

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Evidence from a Field Experiment

We conduct a large scale field experiment that includes eighteen stores and 192 products from different categories to investigate how consumers' respond to discounts and price cues. The results reveal how price and price cue elasticities vary with product and store characteristics. On products for which consumers are more knowledgeable about prices there is a larger response to discounts, but a smaller response to price cues. Over the seventeen weeks of our study, price discounts become at least 55% more effective but there is no change in the effectiveness of price cues. The response to discounts and price cues is greater when they are more distinctive, there is greater availability of substitute products and consumers are less focused on convenience goals. We also find that price cues are more effective on products that are more difficult to find in a store.

1. Introduction

The response to price discounts and semantic price cues, such as "Sale" signs, are among the most well-studied topics in marketing. However, we do not have a robust understanding of the market factors that moderate the response to either of these marketing actions. Reviews of the existing research illustrate some of the challenges in studying these issues (Tellis 1988; Bijmolt, Van Heerde and Pieters 2005, Krishna, Briesch, Lehmann and Yuan 2002). Broad generalizations are difficult because empirical studies generally include only a small number of categories or products. Moreover, elasticity estimates are often plagued by endogeneity and omitted variable biases.

We conduct a large-scale field experiment that is designed to overcome many of these challenges. The study measures the sales response to regular price discounts (henceforth "discounts") and price cues for 192 products drawn from a wide range of product categories. The randomized, balanced design overcomes measurement concerns, such as endogeneity. The breadth of the study enables us to draw generalizations about consumer responses to discounts and price cues. We test a series of predictions regarding the role of dynamics, availability of substitutes, shopping goals, price knowledge, consumer search and distinctiveness.

We find that discounts are more effective when there is greater availability of substitutes, consumers have better price knowledge and the discounts themselves are more distinct. In contrast, discounts are less effective in stores where more consumers are focused on convenience. Our experimental discounts remain in effect for 17 weeks, which gives us a unique opportunity to measure dynamic effects. We find that discounts become 55% more effective over the time horizon of our study, which is consistent with customers gradually learning about the lower prices.

While many studies have used field data to estimate price elasticities, estimates of the response to price cues are generally obtained from the lab. For example, three previous meta-analysis studies of price cues (and price framing) rely largely on lab experiments (Biswas, Wilson and Licata 1993, Compeau and Grewal 1998; and Krishna, Briesch, Lehmann and Yuan 2002).

These studies show that price cues can be an effective tool for increasing consumers' perceptions of value and influencing purchase intentions. The results we report are distinguished by the use of actual consumer transactions to identify moderators of price cue effectiveness. We find that price cues are less effective when consumers have better price knowledge, consumers are focused on convenience, and there is more incentive to search. But, price cues are more effective when customers can choose from a wider range of substitute products, difficulty of search is high, and the price cues themselves are more distinct.

Together, these findings contribute to our understanding of factors that affect price and price cue elasticities. In particular, this is the first study to empirically measure the moderating role of price knowledge on price and price cue sensitivity. While it has been hypothesized that good price knowledge positively moderates discounts and negatively moderates price cues, previous studies have not had sufficient data to evaluate these predictions.

The paper proceeds in Section 2 with a review of the literature, which provides motivation for the analysis that follows. In Section 3 we describe the design of the field experiment and present initial results. In Section 4 we describe how we measure the variation in store and product characteristics, and then present findings in Sections 5 and 6. The paper concludes in Section 7 with a discussion of the findings, managerial implications and opportunities for future research.

2. Predictions

Our theoretical predictions are motivated by prior literature that we categorize into six topics. The hypotheses are summarized in Table 1, which is located at the end of the section.

Dynamics

Consumer learning has received considerable attention from both behavioral and quantitative researchers in marketing (see for example Hoch and Deighton 1989; Akcura, Gonul and Petrova 2004; and Villas-Boas 2004). The focus of much of this research is on consumers learning about differences in product features. However, learning may also apply to discounts, with consumers learning about their availability over time (Eskin and Baron 1977; Hoch, Drèze and

Purk 1994).[1] If so, we might expect the response to discounts to increase over time, as more consumers learn of lower prices and transfer their purchases from other products or stores.

The behavioral pricing literature suggests that we can expect the opposite outcome for price cues, particularly if they are placed on non-discounted products for an extended period. There is evidence that price cues are less effective when retailers either use them too often (Sawyer and Dickson 1985; Winer 1986; Gurumurthy and Little 1987; Krishna 1991; and Lichtenstein and Bearden 1989) or use them on too many products (Anderson and Simester 2001). Explanations for these effects can be traced to both attribution theory and source credibility. Under attribution theory, when the cues are used more often they become less distinctive and consumers are more likely to disregard them.[2] The credibility argument predicts that the more frequently price cues are used, the less credible they become, and the less consumers will rely on them.

Availability of Substitutes

Standard economic models predict that price sensitivity will vary according to the availability of substitutes (see for example Bakos 1997; Nagle and Hogan 2006). Intuitively, if products are more differentiated (less substitutable) consumers are less likely to respond to a price change by purchasing an alternative product. The availability of substitutes may also moderate the response to price cues. However, the mechanism is slightly different. With discounts customers respond to changes in prices, while with prices cues they respond to perceptions that prices are low. In either case, we expect customers to be more responsive when there is a greater availability of substitutes.

Consumer Shopping Goals

The literature on goals demonstrates both that consumers' shopping goals vary over time and that they influence how consumers respond to marketing actions, including price promotions. For example, in a series of field experiments Lee and Ariely (2006) show that once consumers have reached the back aisles in a store, they are less likely to be influenced by coupons than

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[1] As we will discuss, Eskin and Baron (1977) find evidence of a positive time interaction, while Hoch, Drèze and Purk (1994) do not find any evidence of time interactions.

[2] We discuss the role of distinctiveness later in this section.

consumers who receive the coupons before entering the store. They conclude that consumers are more likely to be influenced by marketing actions if their goals are less concrete.

Other research on consumers' shopping goals has highlighted the importance of convenience (Arnold, Ma and Tigert 1978; Arnold Oum, and Tigert 1983; Arnold, Roth and Tigert 1981; Arnold and Tigert 1982; and Briesch, Chintagunta and Fox 2009). On shopping visits motivated by convenience we expect that consumers will be less likely to search for low prices (see for example: Scholderer and Grunert 2005).[3] We conclude that consumers are less likely to respond to discounts and price cues once their shopping goals are fixed, and particularly so if these goals are focused on convenience.

Consumer Price Knowledge

A common rationale for why price cues are effective is that they provide information to help consumers evaluate prices. If consumers are poorly informed about prevailing prices they may use the cues to help evaluate whether a price offers good value (Inman, McAlister and Hoyer 1990; Grewal, Marmorstein and Sharma 1996). This explanation requires that consumers are poorly informed about prices; if consumers can evaluate prices, they have no need for the price cue, and instead will be more sensitive to changes in the price itself. Under this reasoning, if more consumers can evaluate whether a price is low then aggregate demand will be *more* sensitive to discounts, but *less* sensitive to price cues (Hagerty, Carman and Farley 1988).

The literature also offers at least one additional prediction. If price cues provide information to help evaluate prices, then the effectiveness of any individual price cue may diminish when there are multiple cues duplicating the same information. There are at least two documented examples. Gupta (1988) reports that price promotions are less effective when the product is located at an end-of-aisle display. He concludes that the negative interactions "suggest a possible overlap or substitutability among different promotional instruments" (at page 348). There is a growing literature demonstrating that 9-digit price endings may serve as price cues,

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[3] This result also follows from a standard model of customer search behavior. For a review of this literature see Ratchford (2009). Hagerty Carman and Russell (1988) make what appears to be the opposite prediction. They show that among firms in the PIMS database price elasticities are larger in categories in which customers do not search. However, "search" in their study reflects customers' efforts to acquire information about product differentiation, rather than information about prices. Their rationale for why prices are more elastic is that the products are less differentiated, which corresponds more closely to our discussion of the *Availability of Substitutes*.

signaling to consumers that a price offers good value.[4] Anderson and Simester (2003) show that the effectiveness of these cues diminishes when there are other cues present. Both results suggest that price cues may be more effective at increasing demand when used in isolation.

Consumer Search

When consumers engage in more search they may become better informed about competing prices (Stigler 1961). Therefore, increased willingness to search is expected to lead to improved knowledge of market prices and increase the effectiveness of discounts. We predict the opposite effect for price cues; if more consumer search leads to better consumer price knowledge then we expect that price cues will become less effective.

An alternative explanation for the effectiveness of price cues is that they attract consumers' attention to products they would not otherwise consider or find. This prediction is consistent with the role of attention as a moderator of exploratory search (Janiszewski 1998). Notice that this explanation does not require that the price cues serve a signaling or information role. It is sufficient that they draw attention, in a similar manner to brightly colored shelf talkers or displays. It seems likely that attracting attention will be particularly important when the risk of overlooking the product is high, and so we predict that price cues are more effective on products that are otherwise difficult to find.

Distinctiveness

Our final predictions focus on awareness of the treatments themselves. If consumers do not notice the discounts or the presence of the price cues they cannot react to them. Therefore we would expect both treatments to be more effective when they are more distinctive (Lichtenstein and Bearden 1989; Lichtenstein, Burton and Karson 1991; and Burton, Lichtenstein and Herr 1993). This theory of distinctiveness can be traced to earlier work on attribution theory; the more distinctive the treatments, the more likely consumers are to elaborate on them (Jones and McGillis 1976; and Kelley 1973). It can also be motivated by the extensive work on salience. This research suggests that decision-makers attribute more weight to salient features than non-salient features (Taylor and Fiske 1978; and Taylor et al. 1979).

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[4] See for example: Thomas and Morowitz 2005; and Berman and Evans 1992.

Table 1 about here

We summarize each of these predictions in Table 1. Notice that the *Availability of Substitutes* and *Consumer Shopping Goals* are expected to moderate the response to discounts in the same direction as the response to price cues. However, we expect the moderating effects to be in different directions for *Dynamics*, *Price Knowledge*, *Search* and *Distinctiveness*.

In the next section we introduce the field experiment and summarize both the design and initial results.

3. Design of the Field Experiment

The study was conducted with the cooperation of a large chain of convenience stores. The stores sell a typical array of products in the grocery, health and beauty and general merchandise categories. The stores are smaller than most supermarkets and are located in convenient residential and urban locations. At the time of the study the firm also operated an Internet channel, but few consumers purchased through this channel.

Eighteen of the chain's stores participated in the study. The stores are located within approximately five miles of each other in the metropolitan area of a major US city. We manipulated prices and price cues on 192 Test Products that were available in all eighteen stores. These items were randomly selected from almost 20,000 SKUs sold by the retailer. In choosing these SKUs we were concerned that the field test manipulations on one product could affect demand for one of the other 192 products. For example, if a shampoo is discounted, it may affect demand for both substitutes (other shampoos) and complements (conditioners). We selected products to minimize the risk of this occurring. We began with the retailer's classification of products into almost one thousand categories and within each category randomly selected a single SKU. A team of retail managers, the authors and research assistants then independently reviewed all of the candidate products. If there was a possibility that two products were close substitutes or complements, we randomly removed one of the products.

The design included three experimental conditions:

Price Cue: A "LOW prices" sign was attached to the shelf.

Price Discount: The regular price was reduced by 12%.

Control: No change.

In the price cue condition a 2” x 2” sticker was affixed to the front of the shelf immediately under the location of each product and right beside the product’s price information. The price cue sticker had the words “LOW prices” in a red circle on a yellow background, as depicted in Figure 1. In the discount condition the price was reduced by 12%, while in the Control condition it was left unchanged.[5] There was no sticker or other announcement of a price change in either the control or discount conditions. The size of the price discount was determined by company managers and was outside the control of the research team.[6]

The price was left unchanged in the price cue condition (at the regular price) and for this reason the sticker does not claim that the price of that product was reduced.[7] We expect the *LOW prices* cue to affect consumer price perceptions (Dickson and Sawyer 1990) and recognize that a more explicit discount claim, such as “Sale”, may have a larger impact on demand. However, our focus is on comparing the relative impact of the price cue *across* products and not on the magnitude of the main effect. Since we used the same sticker on each product, the *LOW prices* cue does not limit our ability to compare outcomes across products. Similarly, use of a 12% price reduction in the Discount condition would be expected to yield different demand effects than either smaller or larger price reductions.

Figure 1 about here

The 12% price discounts were unannounced price reductions; there were no “LOW prices” stickers or any other indications that the price had changed. For this reason, the response to

[5] The price in the Control price was the same price that the firm was charging for these products in a large number of other stores.

[6] Management had recently tested a 12% price reduction in an unrelated, large-scale price test, and this may have contributed to this decision.

[7] Claiming that a price is low raises ethical concerns if it misleads consumers about true price levels. While beyond the scope of this paper, study of the inherent ethical issues is called for. Such a review would be particularly valuable given the very widespread use of price cues in both retail and industrial settings. We certainly do not intend that readers interpret our results as a recommendation that firms engage in unethical practices.

these discounts should be interpreted as regular price elasticities rather than promotional price elasticities. This is consistent with calls for more research recognizing that firms can separately vary regular prices and promotional cues (Shankar and Krishnamurthi 1996; and Blattberg and Neslin 1990).

Ideally we would have included a fourth condition, in which prices were discounted *and* the "LOW prices" sticker was used. This would have allowed us to measure interactions between the prices and price cues. From a practical perspective, managerial constraints prevented us from including this additional condition. Also, a fourth condition would reduce the statistical power of our measures since we would have fewer stores allocated to each treatment. Finally, our predictions in Table 1 are about individual effects (price or price cue) not the joint effects (price and price cue).

To control for product and store effects we used a balanced experimental design that rotated the experimental treatments. The 192 products were randomly assigned to six "product groups" and the stores were randomly assigned to three "store groups". We then rotated the experimental treatments across the product and store groups as illustrated in Table 2.

Table 2 about here

It is possible that the discount and LOW prices treatments may prompt consumers to increase their purchase quantities to take advantage of the actual or perceived discounts by "stocking up" for future consumption. This introduces the possibility of inter-temporal substitution in demand. To control for this possibility we maintained the experimental manipulations for 4-months (17-weeks) between April, 2006 and July, 2006.[8] The treatments did not vary over these seventeen weeks and regular visits by the research team to the stores ensured compliance with the experimental design. This design also allows us to evaluate the impact of consumer learning by measuring how the response to the two treatments varied across the 17-weeks.

[8] The length of this treatment period is similar to the 16-week periods used by Hoch, Drèze and Purk (1994) in their pricing experiments at Dominick's Finer Foods.

Overall Results

More than 600,000 units of the 192 Test Products were purchased during the 17-week treatment period. We received transaction data describing the number of units of each product purchased in each store in each week, together with the price paid and the wholesale cost of those purchases. In Table 3 we report preliminary results.

Table 3 about here

As expected, the discount and LOW prices sticker both resulted in significant increases in unit sales. Lowering prices by 12% led to an average increase of 13.2% units sold. This is equivalent to an elasticity of approximately -1.1. This sales increase was offset by the price reduction, and so overall revenue increased by just 2%. Overall, the retailer's profits were actually lower in the discount condition than in the Control. When using the LOW prices sticker, unit sales increased by an average of 8.4%. This sales increase was achieved without changing prices and so revenue increased by 3.4%. Moreover, because margins were maintained, profits also increased in this condition.

We also estimate these results directly using a multivariate approach. This will later prove helpful when we investigate how the outcome is moderated by product and store characteristics. Because demand is measured as a "count" of the number of units sold, our multivariate analysis uses Poisson regression (which is well-suited to count data) to separately estimate the following two equations:[9]

$$\ln(\lambda_{its}) = \alpha + \beta_1 Discount_{is} + \sum_{s=1}^{18} \eta_s store_s + \sum_{i=1}^{191} \tau_i product_i \tag{1a}$$

[9] In doing so we assume that the number of units of product *i* sold in week *t* in store *s* (Q_{its}) is drawn from a Poisson distribution with parameter λ_{its}:

$$\text{Prob}(Q_{its} = q) = \frac{e^{-\lambda_{its}} \lambda_{its}^{q}}{q!}, \quad q = 0, 1, 2, \ldots$$

where: $\ln(\lambda_{its}) = \boldsymbol{\beta}\mathbf{X}_{its}$. The $\mathbf{X}_{its}$ term denotes the independent variables, while $\boldsymbol{\beta}$ denotes the estimated coefficients.

$$\ln\left(\lambda_{its}\right)=\alpha+\beta_1 LOW\ prices_{is}+\sum_{s=1}^{18}\eta_s store_s+\sum_{i=1}^{191}\tau_i product_i \qquad (1b)$$

The variables are defined as:

$Discount_{is}$	Equal to 1 if product *i* was discounted in store *s* and zero otherwise.
LOW $prices_{is}$	Equal to 1 if product *i* had a "LOW prices" sticker in store *s* and zero otherwise.
$Store_s$	Equal to 1 if store *s* and zero otherwise.
Product i_i	Equal to 1 if product *i* and zero otherwise.

Under this specification, the β_1 coefficients measure the percentage change in demand attributable to the discounts and *LOW prices* stickers (respectively). The store and product fixed effects control for demand factors that are common either to the products or to the stores. Inclusion of these fixed effects is only possible because the treatments for each product are randomized across the stores. Notice that because the treatments were randomized across stores, the identity of the control stores and treatment stores varies across products.

We estimated this model using weekly sales across all seventeen weeks. Each model included observations for the eighteen stores and seventeen weeks and across the 192 products this provided a sample size of 39,168 observations for each model. The results are reported in Table 4. Product and store fixed effects are included in the model but omitted from the table to ease exposition. Overall, the discount led to an estimated 13.7% increase in demand, compared to a 4.8% increase for the LOW prices cue. These findings replicate the univariate analysis.

Table 4 about here

We can compare these initial findings with both previous field experiments and previous review papers. We begin by a comparison with previous field experiments.

Previous Field Experiments

Early examples of using large-scale field experiments to estimate price elasticities include Curhan (1974) and Eskin and Baron (1977). Curhan (1974) experimentally varied prices, newspaper advertising, and display variables for sixteen fresh fruit and vegetables in four supermarkets. The 10% price reductions yielded average category-level sales increases ranging from 1% on hard fruit to 18% on soft fruit.

Eskin and Baron's (1977) report the findings from four industry-implemented experiments, each involving a single product. Prices were increased across stores by amounts ranging from 15% or 40%. The price changes led to significant sales increases in three of the four studies, with brand-level elasticity estimates ranging from -0.85 to -1.85.

More recently, Hoch, Dreze and Purk (1994) report the findings from two studies conducted at 86 Dominick's Finer Foods stores in Chicago. These studies involved category-wide price changes that led to either an average price increase of 10% or price decrease of 10%. In their first study the price changes were rotated across stores, while in the second study all categories within the store received the same treatment. Their two studies yielded similar findings: price decreases yielded a unit demand increase of approximately 3% and price increases lowered unit demand by approximately the same amount. These findings suggest a price elasticity of -0.4 (after accounting for temporary promotions), which indicates considerably less elastic demand than our study. The most obvious explanation for this difference is that Hoch, Dreze and Purk (1994) vary all prices within a category and report category-level elasticities. This experimental design will tend to reduce within-category substitution and reduce the observed elasticities.[10] In contrast, we restrict the price changes to a single product in each category.

Previous Review Papers

Tellis (1988) and Bijmolt, Van Heerde and Pieters (2005) use large-scale meta-analysis methods to summarize elasticity estimates in previous studies. Both papers evaluate how estimates are affected by the estimation approach. Tellis (1988) identifies 367 elasticity estimates from 220 different brands and markets. The mean price elasticity is -1.76, with a standard deviation of 1.74. His results confirm that these estimates are influenced by a range of method-induced biases. After accounting for these biases, the "unbiased" mean price elasticity is approximately -2.5. Seventeen years later, Bijmolt, Van Heerde and Pieters (2005) are able to expand the

[10] Neslin and Shoemaker (1983) compare elasticity estimates from twelve studies. They report average elasticities in the range of -1.74 to -1.90 for individual brands, and -0.52 to -0.70 for category-level elasticities. Similarly, Bolton (1989b) compares elasticities from three brand elasticity studies and seven category-level studies and finds that elasticities are typically higher when calculated at the brand level (than at the category-level).

sample of elasticity estimates to 1,851. The average elasticity in their sample is -2.62. They also report that these estimates are strongly influenced by method-induced bias.

Two sources of bias are particularly worthy of mention. First, econometric studies that use historical variation in prices to evaluate the impact of prices on sales risk introducing bias if they do not account for the causes of the historical price variation. This issue has attracted increasing attention in more recent years and Bijmolt, Van Heerde and Pieters (2005) find that it has a strong influence on elasticity estimates. Papers that explicitly account for the endogeneity in prices tend to yield significantly larger elasticity estimates. Because prices in our study are exogenously varied between conditions, the elasticity estimates in our study are not susceptible to this bias.

The second source of bias is common to meta-analysis studies. The so-called “file-drawer” bias suggests that there may be many elasticity estimates that are unpublished because “their results are not consistent with the expectation of a significantly negative price elasticity” (Tellis 1988 at 337). The distribution of price elasticities reported by Tellis (1988) and Bijmolt, Van Heerde and Pieters (2005) are both consistent with this: they reveal strong negative skewness, suggesting that many small (and positive) elasticity estimates go unreported. In this study we use the elasticity estimates for our entire population of 192 products, which ensures that the distribution of price elasticities is not distorted by censuring. This may help to explain why the average price elasticity is lower in our study.

There are also at least three previous meta-analysis studies of the impact of price cues and price framing: Biswas, Wilson and Licata (1993); Compeau and Grewal (1998) and Krishna, Briesch, Lehmann and Yuan (2002). The results of the studies are consistent, confirming that price cues can be an effective tool for increasing consumers’ perceptions of value. However, there is an important difference between those studies and this study. Most of the earlier work in this area is conducted in the laboratory using perceptual measures of the response to price framing and price cues. The dependent measures typically include perceived value, perceived savings, and purchase intentions. In contrast, the results we report use actual purchasing behavior from the field. The difficulty of mapping perceptual measures to sales means that we are not able to directly compare the magnitude of our findings with the findings in these earlier studies.

While these preliminary results serve as a reassuring manipulation check, they are not the primary focus of this paper. Instead we focus on understanding how the impact of the two experimental treatments varied over the 17-week treatment period and across different product and store characteristics. In the next section we describe how we will measure these moderating effects.

4. Variables to Measure and Estimate the Moderating Effects

We develop a series of variables that allow us to operationalize the constructs discussed in Section 2. We then incorporate these variables in a model to test the predictions in Table 1. Summary statistics for each variable are reported in the Appendix together with a table of pairwise correlations.

Dynamics

To investigate the dynamic variation in the response to the two treatments, we constructed a continuous *Trend* variable that ranges from 1 in the first week of the treatment period to 17 in the final week. Recall that we predict that the discounts will become more effective in the later weeks, but that the *LOW prices* sticker will lose credibility and become less effective over time.

Availability of Substitutes

We anticipate that both treatments will be more effective when there is a wider range of substitutes available for consumers to choose from. In our field test setting, the most obvious opportunity for substitution is to other products in the store, particularly when the store offers a wider range of products in that category. Therefore, we constructed a variable measuring the number of products in the same category as each of the products in the field test (*Category Size*).

Although *Category Size* measures the number of substitutes, it does not describe the degree of differentiation between those substitutes. Parker and Neelameghan (1997) suggest a less direct measure, which may also help to measure the degree of differentiation: the stage in the product's life cycle. They argue that consumers will become more price sensitive later in a product's life cycle because the product faces closer substitutes (see also Hagerty, Carman and Russell 1988). Simon (1979) makes the opposite prediction. He presents evidence that consumers become more loyal and less price sensitive as the product matures. To distinguish between these opposing predictions, we constructed a variable (*Stage in Product Life Cycle*) to measure the number of days (in thousands) between the date that the retailer first sold each product and the start of the field test.

Consumer Shopping Goals

Although the nature of the field test means that we do not have a direct measure of individual consumer shopping goals, we do have an indirect measure. Five of the eighteen stores are open 24-hours. We might expect that these stores would have a higher proportion of consumers who have concrete shopping goals (e.g., late night medication for a sick child), making them less susceptible to discounts (Lee and Ariely 2006; Janiszewski 1998). In particular, many of these consumers are likely to be motivated by convenience rather than finding low prices. Consistent with this, the average basket size is significantly smaller at these stores than at other stores. We constructed an indicator variable identifying the stores that are open 24-hours (*Open 24-Hours*) and anticipate that the response to the discounts and *LOW prices* cues will both be lower in these stores.

Consumer Price Knowledge

Recall that the behavioral pricing literature suggests that price cues will be most effective (and discounts will be least effective) on products for which few consumers can evaluate prices. We constructed two measures of how well consumers can evaluate the prices of the 192 products used in the field experiment. First, we conducted an in-store survey to measure how accurately consumers could recall the prices of these products. Participants were shown one of the products and asked: "What is your best guess of the price that [store name] normally charges for this product?" We obtained 5,969 useable responses from 783 participants. From these responses we calculated how many consumers could accurately recall the price of each product (*Price Recall Accuracy*). This measure is defined as the percentage of consumers who recalled a price within 20% of the regular price.[11] The product for which consumers' price recall was most accurate: Arizona iced tea, with 70% of the responses falling within 20% of the correct price. In contrast, LA sports hair gel had only one response within the 20% threshold. We provide a more detailed description of the survey in the Appendix.

Our second measure is motivated by the extensive literature on measuring price knowledge.[12] A common finding is that consumers' abilities to recall prices are closely related to the frequency with which they purchase the products. Therefore, we will use purchase frequency as an alternative measure of price knowledge (Hagerty, Carman and Russell 1988 propose a similar interpretation). Our *Purchase Frequency* variable was constructed by counting the number of times that product *i* was purchased (in tens of thousands) in a large sample of historical transactions.[13] As we would expect, the *Purchase Frequency* and *Price Recall Accuracy* measures are highly correlated (a complete table of pairwise correlations is provided in the Appendix).

We also identified a related prediction: price cues are less effective when there are other price cues present. For example, Anderson and Simester (2003) show that 9-digit price endings are less effective when products have sale signs. Across the 192 products in our field setting we have an analogous situation: 102 of the products had (regular) prices ending in 99-cents. If this price ending acts as a price cue, then adding the *LOW prices* sticker to these products may be less effective than adding them to the other 90 products. Therefore, we constructed a binary variable (*99-cent Price Ending*) to identify products with 99-digit price endings.

Consumer Search

We focus on how consumer's willingness to search and difficulty of search moderate the effectiveness of discounts and price cues. One measure of the willingness to search is the

[11] The standard for evaluating accuracy (20%) is somewhat arbitrary and so for completeness we repeated the analysis using different thresholds (e.g., 10%). This revealed that the accuracy threshold has little effect on the findings.

[12] Examples of academic studies include: Gabor and Granger (1961); Allen, Harrell and Hutt (1976); Conover (1986); Dickson and Sawyer (1990); Lee and Monroe (1999); and Vanhuele and Drèze (2002). Industry studies include: Progressive Grocer (1964 and 1977).

[13] These historical transactions include over 40 million shopping trips made by a randomly selected sample of over 800,000 consumers, who had all purchased from one of the 18 stores involved in the field test. The transactions include every purchase made by these consumers using the store's frequent shopping card in the 20-months preceding the field test, including purchases at stores other than these 18 stores.

Regular Price of the product (the price charged in the control and *LOW prices* conditions). We expect that consumers will be more motivated to find lower prices on higher priced products (Curhan 1974). Recall from our earlier discussion of consumer price knowledge, this suggests that discounts will become more effective and price cues will become less effective.

We also predict that difficulty of search will moderate the effectiveness of price cues. If price cues attract attention to a product, then they are more likely to be effective on products that are difficult to find. We construct two measures of the difficulty of finding a product. The first measure focuses on the size of each product (in square inches), which is calculated by multiplying together the physical height and width (*Physical SKU Size*). We anticipate that larger products will be easier to find and so their demand will be less responsive to the *LOW prices* sticker. This is consistent with the evidence that larger advertisements are more likely to be selected for viewing and that the physical size of an advertisement explains considerable variation in readership (Adams 1917; Strong 1914).

Our second of the difficulty of finding a product was obtained somewhat fortuitously. As preparation for the field test, we sent a team of research assistants to locate the products in two of the chain's stores. The team initially had difficulty finding 39 of the 192 products. We identify these 39 hard-to-find products using a binary variable (*Hard to Find*).

Distinctiveness of the Discounts

We have two measures of the distinctiveness of the discounts. The first measure is motivated by research that demonstrates consumers often truncate prices and focus on the leftmost digit. For example, Thomas and Morowitz (2005) show that price ending effects occur only when the leftmost digit in price changes (see also Stiving and Winer 1997, who review the price-ending literature). In the discount condition, the 12% discount resulted in a change in the left digit on some products but not on others. For example, a 12% discount from \$3.27 to \$2.88 does result in a change in the left digit, while a 12% discount from \$3.47 to \$3.05 does not. Of the 192 products, the 12% discount resulted in a left digit price change for 63 (32.8%) of them. We identify these products by a binary variable (*Left Digit Price Changed*).[14]

[14] Notice that we only observe variation in this variable in the discount condition.

Our second measure is the *Regular Price* of the product. Recall that the percentage discount was the same for all products (12%). This represents a larger dollar discount on products with higher regular prices: 12% off a $10 product is a $1.20 discount, but only a 12-cent discount on a $1 product. The importance of the discount magnitude is highlighted in several studies. Darke, Freedman and Chaiken (1995) conclude: "it is the absolute amount of discount rather than the percentage discount that shoppers want to avoid missing out on" (at page 583). Similarly, Grewal, Marmorstein and Sharma (1996) and Krishna et al. (2002) report that consumers are more responsive when a discount is larger in dollar terms. Lalwani and Monroe (2005) present evidence of similar effects and conclude that increasing the depth of discounts increases their "discriminability," which increases their salience and attracts more attention.[15] Using the size of the discount to measure distinctiveness is also consistent with previous research indicating that larger discounts are more salient, and are therefore more likely to induce a response (Krishna and Johar 1996).

Note that we also predict that consumers' may be more motivated to find lower prices on higher priced products. We include *Regular Price* as a measure under both headings (Consumer Search and Distinctiveness of the Discounts) and recognize that both interpretations are plausible.

Distinctiveness of the *LOW prices* Cue

We have a single measure of the distinctiveness of the *LOW prices* sticker: the physical size of the store (*Store Size*). This is measured in thousands of square feet using data obtained from the retailer. In larger stores the *LOW prices* sticker compete with a great range of visual stimuli, and so we might expect that they would be less effective.[16]

Table 5 about here

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[15] These results are related to a stream of literature in which researchers demonstrate that the salience of either the frequency or magnitude of numerical stimuli can be independently manipulated, changing where participants allocate attention (see also Panksy and Algom 1999 and 2002).

[16] Previous research has also studied the interaction between shelf location and price sensitivity (Wilkinson, Mason and Paksoy 1982; Lemon and Nowlis 2002; Gupta 1988; Papatla and Krishnamurthi 1996; Shankar and Krishnamurthi 1996; and Bolton 1989a). We might expect that the *LOW prices* stickers were more distinctive if they were placed on items located at eye level. Unfortunately the shelf heights of the items vary across stores, and we do not have a reliable measure of the location of the items in each store.

Summary

We summarize the moderating variables and our predictions in Table 5. Our experimental design introduces exogenous variation in both prices and in the use of the *LOW prices* cue. This variation ensures that we obtain accurate measures of demand elasticity in response to these two treatments. However, we do not exogenously manipulate the moderating variables listed in Table 5. This has important implications for the interpretation of our results.

In some cases the moderating variables are expected to be exogenous (e.g., *Trend*) but in other cases the characteristics may be endogenous (e.g., *Regular Price*). Where the characteristics are endogenous it is possible that the moderating effects we estimate (if any) are caused by unobserved factors that contributed to the variation in these variables. Since all of the moderating variables are product and store characteristics, we partially control for endogeneity concerns via product and store fixed effects.

Even where the moderating variables are exogenous, there are at least two other potential limitations. First, the direction of causation is sometimes uncertain. For example, suppose we find that demand is more sensitive to discounts on products for which consumers have more information about prices. Better price knowledge may make it easier for consumers to recognize discounts but it is also possible that price sensitivity makes consumers more knowledgeable about prices.

A second limitation is that in some cases interpretation of the results may be confounded by multiple interpretations of the variables. For example, we will show that demand is more price elastic in categories that contain more products. This could reflect the increased availability of substitutes. Alternatively, it is possible that consumers have more reference prices against which to evaluate the price of the focal product.

Given these limitations it is important to be explicit about how to interpret the results. While we obtain accurate estimates of the demand elasticities, the variation in these elasticities are best viewed as measures of association. We rely upon the previous literature to motivate the results and speculate on possible causes but it is beyond the scope of this paper to draw firm conclusions about causation. Doing so may require additional data, including possibly data from the lab.

In the next two sections we describe the association between each variable and the response to the two treatments. In Section 5 we focus on the price elasticity results and in Section 6 we turn attention to the *LOW prices* cue.

5. Price Elasticity Results

To estimate the impact of each moderating factor we introduce interaction terms to our Poisson regression model:

$$\ln(\lambda_{its}) = \alpha + \beta_1 Discount_{is} + \beta_2 Discount_{is} * Moderator + \sum_{s=1}^{18} \eta_s store_s + \sum_{i=1}^{191} \tau_i product_i \qquad (2a)$$

The *Moderator* term denotes the moderating variable. When the variables reflect characteristics of the store or product, there is no need to include main effects as these are captured by the *store* or *product* fixed effects. For the analysis of the dynamic trend in the effects across the 17-week period we include the *Trend* variable as a main effect in Equation 2a.

We use two estimation approaches. In the first approach we estimate each interaction term separately. This approach has been widely use to separate out the effects of different moderating variables (see for example Biswas, Wilson and Licata 1993; Compeau and Grewal 1998). It has the advantage that the coefficients are not affected by collinearity with other moderating variables. We also estimate joint models in which we include all of the moderating effects in a single model. This approach is also widely used and offers an opportunity to see which effects survive after controlling for other sources of variation (see for example Tellis 1988; and Krishna et al. 2002). We report the estimated β_2 coefficients from Equation 2a in Table 6.

The coefficients are generally consistent between the joint and individual estimation methods. In some cases, the magnitude of a coefficient is smaller in magnitude in the joint model, but the coefficient typically retains the same sign and statistical significance. This is not unexpected given the collinearity of some variables. The one exception is *Price Recall Accuracy*, which is not significant in the joint model due to the high correlation with *Purchase Frequency*. A detailed discussion of each result follows.

Dynamics

There is evidence of a strong time trend in the response to the discounts, with a significantly larger response at the end of the 17-week treatment period than at the start. This result is consistent with customers learning about the price changes over time and gradually shifting their purchases to take advantage of the discounts.

Table 6 about here

We can further investigate this trend by grouping the treatment period into sub-periods and re-estimating the results. We construct dummy variables for four different sub-periods: weeks 1-5; weeks 6-9; weeks 10-13; and weeks 14-17. We then re-estimated Equation 1a separately for each sub-period and report the β_1 coefficients from each model in Figure 2 (joint estimation of the coefficients in Equation 2a yields similar results). They reveal that the discounts initially had a 10% - 11% impact on demand and this increased to over 17% in the last 4-weeks of the treatment period. This implies that the price elasticity started at approximately -0.9 and increased to -1.4 over the 17 weeks; an increase of 55%.

We interpret the moderating effect of the trend variable as evidence of consumer learning about discounts. If additional consumers learn about the discount each week, then more consumers will have learned about the discounts in week 17 than in week 1. We might also expect that the frequency with which products are purchased will moderate the rate of learning. To investigate this we estimated a model with a three-way interaction between *Discount*, *Trend* and *Purchase Frequency*. The results of this model (which are available from the authors) confirm a positive and significant interaction effect. This supports our learning interpretation; customers gradually learn about discounts and they learn at a faster rate for frequently purchased products.

Figure 2 about here

The dynamic trend we observe can be compared with two previous studies, both of which report the findings from field experiments. Eskin and Baron (1977) reported four field experiments in grocery stores and varied the prices across stores within the same city. Their experiments all had at least a 24 week duration. They also find evidence of a significant time trend in the response to the price changes, with a larger response at the end of the treatment periods. In contrast, Hoch, Drèze and Purk (1994) do not observe any time trend. Although their study was designed to last 16 weeks, some of the manipulations remained in place for over 40 weeks. Even after 40 weeks their results remained unchanged, with no shift in the basic pattern. There are many differences between the three studies and so reconciling these differences is difficult. One prominent difference in the Hoch, Drèze and Purk (1994) study is that they manipulate the prices of all of the products in the category. This yields category-level price elasticities, which contrast with the product-level elasticities reported in this study and Eskin and Baron (1977). However, it is not clear how this contributed to the difference in these results.

Availability of Substitutes

The discounts were significantly more effective at increasing demand in larger categories. This is consistent with the prediction that demand will be more price sensitive when the availability of substitutes is greater. We recognize that the variable *Category Size* may have other interpretations beyond availability of substitutes. However, we will later report results on price cues that provide convergent evidence for this interpretation (see Section 6).

We also find that demand is less price sensitive on older products that are in later stages of their product life cycles. Recall that the interaction between price sensitivity and the variable *Stage in Product Life Cycle* has been a subject of considerable debate. The negative result that we report was predicted by Simon (1979), who argues that customers become less price sensitive and more loyal as products mature. Bijmolt, Van Heerde and Pieters (2002) report the same findings, but Parker and Neelameghan (1997) and Hagerty, Carman and Russell (1988) find the opposite result.

Consumer Shopping Goals

The findings for the *Open 24 Hours* interaction are consistent with our prediction that a higher proportion of customers shopping at these stores have more concrete shopping goals, including a focus on convenience rather than searching for low prices. Thus, price discounts are less effective when customers are more focused on convenience.

Consumer Price Knowledge

The literature predicts that aggregate demand will be more sensitive to price changes when *more* customers can evaluate whether the price is low (Hagerty, Carman and Farley 1988). The results for both measures of customers' price knowledge are consistent with this. We see a bigger response to the discounts on products for which more customers can accurately recall the price and/or on products that are purchased more frequently. Because these two measures are highly correlated, including both of them in the joint model results in a loss of significance for the *Price Recall Accuracy* coefficient.

Previous work has identified a link between purchase frequency and price sensitivity (Hagerty, Carman and Russell 1988; Carman 1974). Perhaps surprisingly, our study is the first study to directly measure price knowledge and show how it affects the response to discounts. This reflects the challenge of measuring both price knowledge and price elasticity in the same study. Studies that measure the response to price changes (Hoch, Dreze, and Purk 1994) do not measure the role of price knowledge. Similarly, the price knowledge literature provide novel measures of customers' price knowledge (Dickson and Sawyer 1990; Vanhuele and Drèze 2002), but does not measure how these metrics moderate the response to price changes.

Consumer Search

The findings for the *Regular Price* interactions are not in the direction that we expected. Recall that we anticipated customers would be more motivated to search for low prices on higher priced products (Curhan 1974). The results reveal that demand is actually less sensitive to price changes on higher priced products. We investigated two possible explanations for this surprising result.

First, customers tend to under-estimate the prices when asked to recall the prices of products with higher regular prices. It is possible that the discounts are less effective on higher priced products because customers continue to think the prices are high, even after they are discounted. To investigate this possibility we included variables measuring the degree to which customers under-estimate prices of the different products.[17] The negative interaction between *Regular Price* and discounts survive even in the presence of this additional variable, which suggests that underestimating prices is not a complete explanation for this interaction.

Second, it is possible that consumers who purchase higher priced products from this retailer are systematically different than consumers who purchase lower priced products. In particular, customers who purchase higher priced products may be less price sensitive. The rationale is that on higher priced products customers have a greater motivation to search for lower prices elsewhere, but these customers choose to purchase them from a convenience store.[18] To investigate this explanation we calculated the average number of discounted products purchased by each customer in our historical sample. This data confirmed that higher priced products are more likely to be bought by customers who purchase fewer discounted items, which is consistent with the conjecture that higher priced items are purchased by less price sensitive customers. However, the interactions with the *Regular Price* again survive when we add controls for the variation (across products) in this customer characteristic. It appears that this is also not a complete explanation for the result.

Distinctiveness of the Discount

There is a much larger increase in demand when the 12% discount results in a change in the left digit. This is what we would expect if customers focus on the left digit when evaluating prices. To further investigate this result, we re-estimated Equation 1a separately using (1) the 63 products for which left digit changed in the discount conditions and (2) the remaining 129 products. We illustrate the outcomes in Figure 3, where we report the β_1 coefficients for both models. On products for which the discounts led to a left digit price change the increase in demand was 20.8%, compared to just 6.1% for the other 129 products.

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[17] The variables measure the difference between the regular price of each product and the average price recall response (for that product) from participants in our survey. We constructed measures of the difference in both dollar terms and in percentage terms.

[18] We thank Ram Rao for this suggestion.

Figure 3 about here

We also anticipated that discounts on higher priced products would be more distinctive, and therefore likely to generate a larger increase in demand (the same prediction may also result from a greater willingness to search for low prices on higher priced products). As we previously discussed, the findings yield the opposite result: demand was less sensitive to discounts on higher priced products.

Summary

We have described how the response to the 12% discounts varies across a range of store and product characteristics. The findings are consistent with most of our predictions with one notable exception: the results for the *Regular Price* interaction are in the opposite direction to what we expected. Although we investigated two possible explanations for this surprising result, neither explanation could fully explain the finding.

Our analysis and discussion have focused on the statistical significance of the interactions. It is also interesting to compare the relative magnitudes of the effects. To do so we must compare the six continuous variables separately from the two binary variables.[19] For the continuous variables we first standardize them, so that they have the same mean and standard deviation, and then evaluate the relative magnitudes of their interaction coefficients. The largest interaction is observed for *Category Size*, followed by the *Trend* and then *Regular Price*. The variables with the smallest effects are *Price Recall Accuracy* and *Purchase Frequency*, which are both designed to measure the role of consumer's price knowledge. Among the two binary variables, a *First Digit Price Change* has a much larger impact on price sensitivity than the *Open 24 Hours* variable. This is perhaps unsurprising given that *Open 24 Hours* is a relatively indirect measure of consumer shopping goals.

In the next section we evaluate how the various store and product characteristics moderated the response to the *LOW prices* sticker.

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[19] The six continuous moderating variables include: *Trend, Category Size, Stage in Product Life Cycle, Price Recall Accuracy, Purchase Frequency*, and *Regular Price*. The two binary variables are: *Open 24 Hours* and *Left Digit Price Change*.

6. Price Cue Results

To estimate the impact of each moderating factor we again extend our Poisson regression model to include interaction terms:

$$\ln(\lambda_{its}) = \alpha + \beta_1 LOW\ prices_{is} + \beta_2 LOW\ prices_{is} * Moderator_{is} + \sum_{s=1}^{18} \eta_s store_s + \sum_{i=1}^{191} \tau_i product_i \quad (2b)$$

We estimate the coefficients using joint and separate models and report the results in Table 7.

Table 7 about here

Dynamics

The response to these cues is very stable over time with no evidence of a systematic time trend (even when grouping the weeks into sub-periods). Recall that we expected that the LOW prices stickers would become less effective over time, as their credibility diminished. It is possible that the relatively ambiguous nature of the "LOW prices" claim may have contributed to this result. If the claim had been associated with a special event that customers perceived was limited in duration then there may have been greater erosion in credibility over time.

Availability of Substitutes

The results are consistent with the predictions. We see a larger response to the *LOW prices* stickers when the category size is large and for products that were more recently introduced to the store (*Stage in Product Life Cycle*). This is the same pattern of results that we observed for the 12% discounts.

An alternative interpretation of the *Category Size* variable is that customers have more price knowledge in larger product categories because they have more benchmarks against which to compare prices. This is consistent with the larger response to discounts (see Section 5) but cannot explain the larger response to price cues. Together, the results of the discount and price cue models are consistent with our interpretation of *Category Size* as a measure of the availability of substitutes.

Consumer Shopping Goals

There is a smaller response to the *LOW prices* stickers in the stores that are open 24 hours, which is consistent with our prediction. Recall that discounts are also less effective in 24 hour stores. Together, these results appear to confirm that point-of-sale marketing actions are less effective when consumer's goals are focused on convenience.

Consumer Price Knowledge

The results for the *Price Recall Accuracy* and *Purchase Frequency* interactions are the reverse of those reported for the discounts. When more customers can accurately recall the prices (or when the product is purchased more frequently) there is a larger response to the discounts, but a smaller response to the *LOW prices* stickers. This is precisely the pattern predicted by the literature. When customers have good price knowledge they can recognize when a price is low and respond to price changes. However, when they are unable to evaluate prices, customers use sale signs (and other low price claims) to evaluate whether to purchase.

We also see evidence that the *LOW prices* stickers are less effective when used on products that have 99-cent price endings. This replicates earlier findings (Gupta 1988; and Anderson and Simester 2003), which predict that the effectiveness of price cues will diminish when there are multiple cues providing similar information. We can highlight the difference in these results by estimating Equation 1b separately for the 102 products that had prices ending in 99-cents, and the remaining 90 products. We summarize the β_1 coefficients for both models in Figure 4. On products with 99-cent price endings there was a 3.9% sales increase, compared to a 9.2% increase on products without 99-cent price endings.

Figure 4 about here

Consumer Search

We find a smaller response to price cues on products with higher regular prices. This is in accordance with our prediction, which recognized that consumers have more incentive to search when prices are higher. We note that both this prediction and our result differ from findings in Krishna et al. (2002) who find that consumers evaluate deals more favorably on higher priced items.

The *LOW prices* stickers were more effective on products with smaller package sizes. This is consistent with the interpretation that the stickers serve to attract attention to products, and that this is more important on products that would otherwise not receive attention. There is also weak evidence that they are more effective on products that our research team initially had difficulty finding in the stores. However, the coefficient for this interaction (*Hard to Find*) is not significant in the joint model.

Distinctiveness of the *LOW Prices* Cues

The *LOW prices* stickers were more effective in smaller stores than in larger stores. Because the stickers compete with a larger range of visual stimuli in the larger stores, it is plausible that they were less distinctive in larger stores. While this finding is consistent with our prediction, we note that there is an alternative argument that suggests the opposite result. The *Store Size* variable may also describe how difficult it is for consumers to find the products. If the *LOW prices* stickers help consumers locate products we may see a greater response when they are used in larger stores. The empirical results suggest that the "distinctiveness of the cue" effect outweighs this alternative interpretation.

Summary

We can again extend the analysis to evaluate the relative magnitude of the effects. In the price cue analysis we evaluated eight continuous variables, and three binary variables.[20] After standardizing the continuous variables, the largest interaction coefficients are for *Regular Price*, *Category Size, Product Life Cycle* and *Store Size* (in that order). The smallest effects are for *Trend*, and the two price knowledge measures (*Purchase Frequency* and *Price Recall Accuracy*). The prominence of the *Category Size* and modest magnitude of the price knowledge interactions mirror the findings for the discounts in the previous section.

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[20] The eight continuous variables include: *Trend, Category Size, Stage in Product Life Cycle, Price Knowledge, Purchase Frequency, Regular Price, SKU Size, Store Size*. The three binary variables include: *Open 24 Hours,99-cent Price Ending,* and *Hard to Find*.

Among the three binary variables, *Open 24 Hours* and *99-cent Ending* are of very similar magnitudes, while the *Hard to Find* coefficient is small (and not significantly different from zero).

7. Conclusions

We have reported the findings from a large-scale field experiment involving 192 products. The field experiment provided measures of the demand response to both an exogenous price change and the use of a semantic price cue. By investigating how these reactions varied according to temporal, store and product factors we are able to characterize the environmental and market factors that are associated with variation in price and price cue elasticities.

The results include several surprising findings. Overall, sales were significantly more responsive to the 12% discount than they were to the presence of a colorful 2" x 2" sticker proclaiming "LOW prices". Given the distinctiveness of the sticker we might have expected that it would attract a larger response. The high level of consistency between the predicted and observed interactions was also somewhat surprising. It is also reassuring, and suggests that our models of these response functions are generally well-founded.

The findings offer a unique test of the prediction that consumer price knowledge moderates the response to discounts and price cues in opposite directions. The reasoning in the literature is that customers will be more responsive to discounts when they have good price knowledge and are able to evaluate the price change. If their price knowledge is poor, customers will instead use the price cues to evaluate whether a price offers good value. This is exactly the pattern of findings that we observe.

In several cases the results help to distinguish conflicting predictions and thus contribute to ongoing debates in the literature. For example, previous findings differ as to whether discounts become more effective over time, and whether demand is more price sensitive once a product reaches a more mature stage in its life cycle.

The primary limitations have already been acknowledged. In particular, the interactions between the two treatments and the various product and store characteristics are best interested as measures of association. In most cases causal inferences are not appropriate because of endogeneity in those characteristics, multiple interpretations, or difficulty in assigning the direction of causality. Resolving these limitations will require additional data. We hope that the results in this paper motivate future researchers to seek that data.

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Table 1. Summary of Predictions

Dynamics
Discounts become more effective over time and price cues become less effective.

Availability of Substitutes
Discounts and price cues are more effective when there are more substitutes available.

Consumer Shopping Goals
Discounts and price cues are less effective when consumers' goals are more concrete and/or more focused on convenience.

Consumer Price Knowledge
Discounts are more effective and price cues are less effective when more consumers can evaluate prices.

Consumer Search
When consumers engage in more search, discounts are more effective and price cues are less effective.

Prices cues are more effective on products that are otherwise difficult to find.

Distinctiveness
Discounts and price cues are more effective when they are more distinctive.

Table 2. The Experimental Design

	Store Group 1	Store Group 2	Store Group 3
Product Group 1	Price Discount	Price Cue	Control
Product Group 2	Price Discount	Control	Price Cue
Product Group 3	Control	Price Discount	Price Cue
Product Group 4	Price Cue	Price Discount	Control
Product Group 5	Price Cue	Control	Price Discount
Product Group 6	Control	Price Cue	Price Discount

Table 3. Overall Results

	Price Discount	LOW prices Cue
Average Change in Unit Sales	13.2%**	8.4%**
Standard Error	2.8%	2.9%
Sample size	192	192

**Significantly different from zero, $p < 0.01$.

Table 4. Poisson Regression Results

	Discount Model	LOW prices Model
Discount	0.137** (0.003)	
LOW prices		0.048** (0.004)
Log likelihood	-160,841	-154,995
Sample size	39,168	39,168

The data in this table describe the coefficients from estimating Equations 1a and 1b on the 17-week treatment period. Asymptotic standard errors are in parentheses. Store and product fixed effects (and the intercept) are omitted from the table to ease exposition.
**Significantly different from zero, $p < 0.01$.
*Significantly different from zero, $p < 0.05$.

Table 5. Summary of the Variables and Predictions

Construct	Variable	Price Sensitivity	Price Cue Sensitivity
Dynamics	*Trend*	positive	negative
Availability of Substitutes	*Category Size*	positive	positive
	Stage in Product Life Cycle	ambiguous	ambiguous
Consumer Shopping Goals	*Open 24 Hours*	negative	negative
Consumer Price Knowledge			
Knowledge of Prices	*Price Recall Accuracy*	positive	negative
	Purchase Frequency	positive	negative
Presence of Other Price Cues	*99-cent Price Ending*		negative
Consumer Search	*Regular Price*	positive	negative
	Physical SKU Size		negative
	Hard to Find		positive
Distinctiveness			
Distinctiveness of Discounts	*Left Digit Price Change*	positive	
	Regular Price	positive	
Distinctiveness of Price Cues	*Store Size*		negative

Table 6. Price Elasticity Results

	Variable	Predictions	Separate Models	Joint Model
Dynamics	*Trend*	positive	0.0053^{**} (0.0007)	0.0053^{**} (0.0007)
Availability of Substitutes	*Category Size*	positive	0.0619^{**} (0.0068)	0.0544^{**} (0.0070)
	Stage in Product Life Cycle	ambiguous	-0.0390^{**} (0.0022)	-0.0154^{**} (0.0028)
Consumer Goals	*Open 24 Hours*	negative	-0.0396^{**} (0.0076)	-0.0369^{**} (0.0076)
Consumer Price Knowledge	*Price Recall Accuracy*	positive	0.3133^{**} (0.0169)	0.0340 (0.0292)
	Purchase Frequency	positive	0.0449^{**} (0.0022)	0.0175^{**} (0.0045)
Consumer Search	*Regular Price*	positive	-0.0139^{**} (0.0013)	-0.0046^{*} (0.0015)
Distinctiveness of the Discount	*Left Digit Price Change*	positive	0.1523^{**} (0.0071)	0.0985^{**} (0.0081)
	Regular Price	positive	see above	see above

The data in this table describe the coefficients from estimating Equation 2a. In the "Separate Models" the interaction effects are estimated in different models. In the "Joint Model" all of the interactions are estimated in the same model. All of the models have a sample size of 39,168. Asymptotic standard errors are in parentheses. The intercept, store and product fixed effects, and the main effect of *Trend* are omitted to ease exposition.
**Significantly different from zero, $p < 0.01$.
*Significantly different from zero, $p < 0.05$.

Table 7. Price Cue Results

	Variable	Predictions	Separate Model	Joint Model
Dynamics	*Trend*	negative	0.0003 (0.0007)	0.0003 (0.0007)
Availability of Substitutes	*Category Size*	positive	0.1316** (0.0067)	0.1078** (0.0070)
	Stage in Product Life Cycle	ambiguous	-0.0201** (0.0024)	-0.0415** (0.0029)
Consumer Goals	*Open 24-Hours*	negative	-0.0592** (0.0079)	-0.0694** (0.0079)
Consumer Price Knowledge	*Price Recall Accuracy*	negative	-0.2516** (0.0179)	-0.1836** (0.0293)
	Purchase Frequency	negative	-0.0290** (0.0024)	-0.0389** (0.0045)
	99-cent Price Ending	negative	-0.1076** (0.0079)	-0.0686** (0.0084)
Consumer Search	*Regular Price*	negative	-0.0086** (0.0013)	-0.0184** (0.0015)
	Hard to Find	positive	0.0327* (0.0130)	-0.0228 (0.0136)
	Physical SKU Size	negative	-0.0020** (0.0002)	-0.0019** (0.0003)
Distinctiveness	*Store Size*	negative	-0.0276** (0.0026)	-0.0304** (0.0026)

The data in this table describe the coefficients from estimating Equation 2b. In the "Separate Models" the interaction effects are estimated in different models. In the "Joint Model" all of the interactions are estimated in the same model. All of the models have a sample size of 39,168. Asymptotic standard errors are in parentheses. The intercept, store and product fixed effects, and the main effect of *Trend* are omitted to ease exposition.

**Significantly different from zero, $p < 0.01$.

*Significantly different from zero, $p < 0.05$.

Figure 1. The "LOW prices" Cue

Figure 2. Response to the Discounts Across the Treatment Period

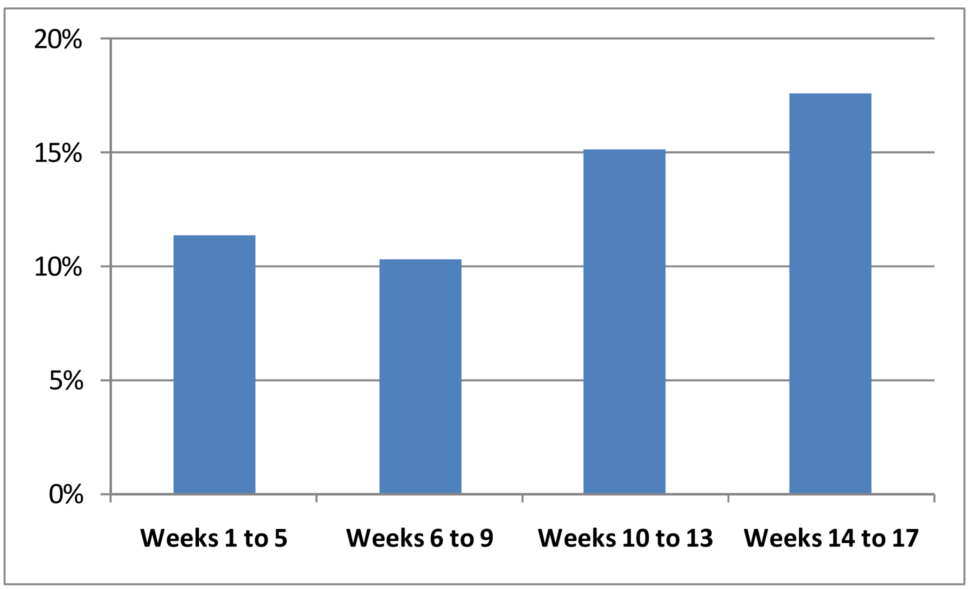


Figure 3. Left Digit Price Change and the Response to Price Discounts

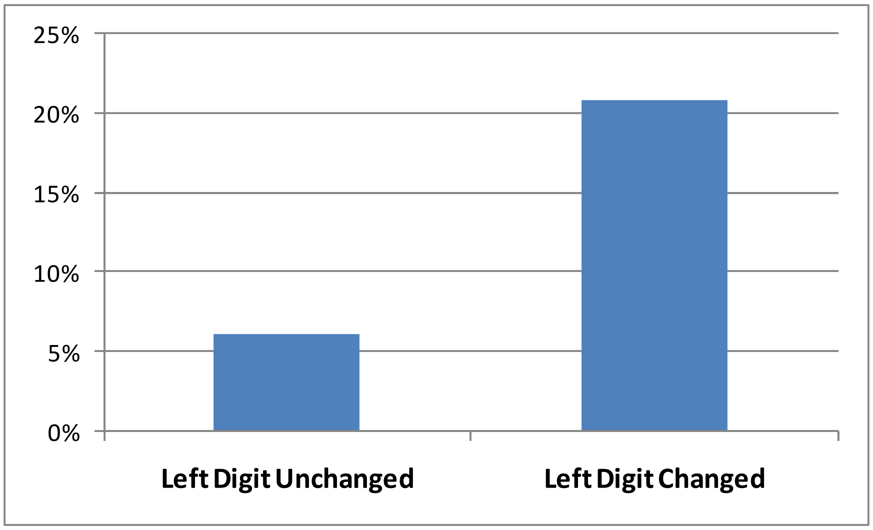
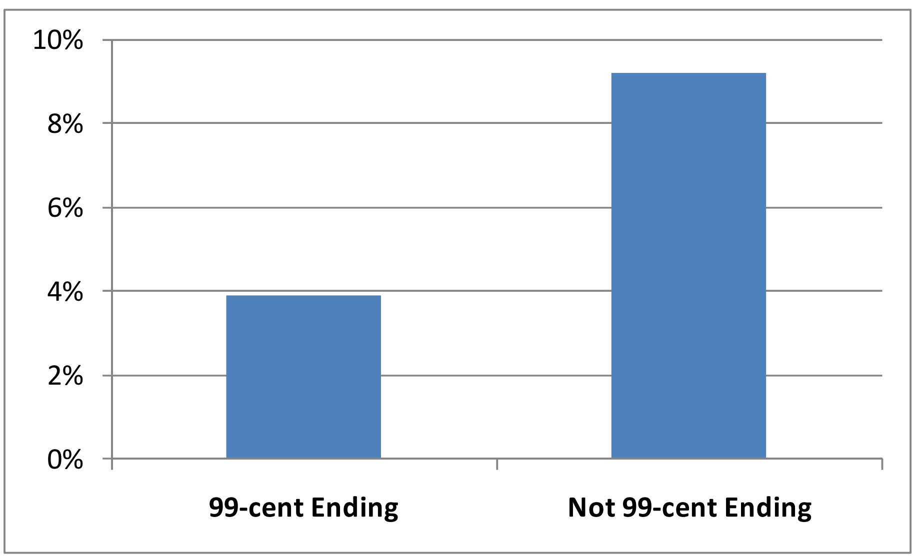


Figure 4. Response to the *LOW prices* Stickers

Items With and Without 99-cent Price Endings



Appendix

Price Recall Survey

We collected a measure of how accurately consumers could recall the prices of the 192 products used in the field experiment. The price recall measures were collected from a sample of actual consumers inside two of the chain's stores. A team of research assistants approached consumers standing in check out lines waiting to complete their transactions and asked them to participate in "a short survey about products and prices that takes roughly four and a half minutes". They were offered a free $5 gift card for participating. Pretests confirmed that the survey was generally completed in less than five minutes and approximately 60% of consumers who were asked to participate agreed to do so.

Respondents to the survey were each shown actual examples of eight of the Test Products and asked: "What is your best guess of the price that [store name] normally charges for this product?" Respondents in the pretest were asked to describe in their own words to the interviewer what was meant by this question. Their responses confirmed that they had little difficulty interpreting the question. Other questions in the survey asked consumers to indicate how often they purchased each product, the purpose of their visit to the store, and their overall perception of prices at the store (the complete survey is available from the authors).

The 192 Test Products were randomly sorted into groups of eight products, and these groups were then rotated across the respondents. Thus, each consumer provided price knowledge measures for eight randomly selected products. A total of 783 consumers participated in the survey and this yielded 5,969 usable price recall measures across the 192 Test Products. This represents an average of just over 31 responses per product. All products had at least 25 responses and no product had more than 32 responses (the variation reflects the random assignment of products to survey groups). Although the response measures were conducted during the same time period as the experimental treatments, we do not believe the measures were influenced by the treatments. Consumers were asked whether they had seen the prices of any of the products in the store on that visit. This occurred for just 1% (64) of the price recall responses and omitting these observations has no affect on the results.

Table A1: Summary Statistics

	Mean	Standard Error	Minimum	Maximum	Sample Size
Product Characteristics					
Category Size	0.49	0.04	0.02	4.89	192
Stage in Product Life Cycle	2.53	0.10	-0.06	4.10	192
Price Recall Accuracy	0.31	0.01	0.03	0.70	192
Purchase Frequency	0.27	0.04	0.01	4.01	192
99-cent Price Ending	0.53	0.04	0.00	1.00	192
Regular Price	4.94	0.36	0.50	39.99	192
Physical SKU Size	24.60	1.28	2.36	99.81	192
Hard to Find	0.20	0.03	0.00	1.00	192
Left Digit Price Change	0.33	0.03	0.00	1.00	192
Store Characteristics					
Open 24 Hours	0.28	0.11	0	1	18
Store Size (000 sq ft)	8.41	0.37	6.61	11.11	18

Table A2: Pairwise Correlations

Product Characteristics	Category Size	Stage in PLC	Price Recall Accuracy	Purchase Frequency	99-cent Price Ending	Regular Price	SKU Size	Hard to Find
Stage in Product Life Cycle	0.04							
Price Recall Accuracy	0.04	-0.12						
Purchase Frequency	-0.05	0.19	0.29**					
99-cent Price Ending	-0.05	-0.22	-0.19**	-0.07				
Regular Price	-0.07	-0.09	-0.13	-0.19**	0.15			
Physical SKU Size	-0.10	-0.13	-0.09	-0.01	0.06	0.14		
Hard to Find	0.12	-0.11	-0.01	-0.11	0.06	0.07	0.12	
Left Digit Price Change	0.11	0.07	0.11	0.10	0.41**	0.12	0.12	-0.01

Store Characteristics	Store Size
Open 24 Hours	-0.11

The table reports Pearson pairwise correlation coefficients. The sample sizes are 192 for the product characteristics and 18 for the store characteristics.

** significantly different from zero, $p < 0.01$.

* significantly different from zero, $p < 0.05$.