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When and Where to Cherry Pick? Temporal and Spatial Dimensions of Price Search (06-120)

Dinesh K. Gauri, K. Sudhir, and Debabrata Talukdar

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When and Where to Cherry Pick? The Temporal and Spatial Dimensions of Price Search

Dinesh K. Gauri, K. Sudhir, and Debabrata Talukdar

Store managers need to understand consumer cherry picking across stores and across time. This study offers insights on both dimensions of price search behavior. They also find that, despite cherry picking, most consumers are profitable to retailers. Less than 2% of consumers engage in "extreme" cherry picking that yields net negative profit.

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Report Summary
Given the price variation across weeks within a store and across stores within a week, consumers can save on groceries by effective cherry picking through (1) price search over time (temporal search) and (2) price search across stores (spatial search). Yet, the extant literature has considered only the spatial dimension of price search.

Here, Gauri, Sudhir, and Talukdar introduce the notion that consumer price search, or cherry picking, has both temporal and spatial dimensions and seek answers to the following research questions: (1) What variables determine a household's price search on the temporal and spatial dimensions? (2) Which of the search patterns are most efficient for taking advantage of price variations in the market? (3) What is the impact of price search on store profits?

The authors make use of survey data from households whose actual purchasing behavior they were granted access to by a participating retailer. This unique combination of data enables them to compare and contrast findings about price search from surveys and revealed-purchase data.

They find that the spatial configuration of store and household locations serves to predict a household's price search pattern (that is, whether household members employ temporal search, spatial search, both, or neither). Interestingly, they find that pure temporal search by a store-loyal household yields as much savings as a pure spatial search by cross-store cherry pickers who do not search temporally. They also find that cherry picking does not have as adverse an impact on retailer profits as has generally been believed, with all search patterns (even spatio-temporal search) being profitable on average and less than 2% of the population engaging in extreme cherry picking that yields a net negative profit. ■

Introduction

Due to supermarkets' use of promotional pricing, there is considerable price variation across weeks within a store and across stores within a week. While a household is unlikely to find it cost-effective to exploit this price variation by searching for better prices on any particular grocery item, the household can achieve significant savings in terms of its overall basket of grocery purchases by making diligent price searches across time (temporal searches) and across stores (spatial searches).[1]

There is a long tradition in marketing (see extensive literature reviews in Newman 1977 and Beatty and Smith 1987) that focuses on the spatial (cross-store) dimension of price search for durable goods. The relatively limited literature on price search in grocery markets (e.g., Carlson and Gieseke 1983; Putrevu and Ratchford 1997; Fox and Hoch 2005) has also focused on the spatial dimension. This focus is restrictive, because one typically finds that promotions and pricing have weak or nonexistent effects on store traffic effects in grocery markets (e.g., Walters and Rinne 1986; Walters 1991; Bucklin and Lattin 1992), except in higher-cost categories (Kumar and Leone 1988; Grover and Srinivasan 1992).

Many consumers do not search across stores; there is considerable evidence of store loyalty among consumers (e.g., Bell, Ho, and Tang 1998; Bell and Lattin 1998). Consumer surveys corroborate this in that they find that the proportion of consumers who shop at multiple stores on a regular basis is only around 10-15% (Urbany, Dickson, and Key 1991; Slade 1995). Nevertheless, retail executives tend to disproportionately emphasize cross-store effects of promotions and treat promotions primarily as an offensive weapon to draw customers from the competing stores (Urbany, Dickson, and Key 1991; Urbany, Dickson, and Sawyer 2000).

Studies that focus on within-store choice find evidence that many consumers change their purchase timing (purchase acceleration or delay; for purchase delay see Hendel and Nevo 2005) and purchase quantities (stockpiling) within a store in response to price promotions. Thus they can get lower average prices for goods consumed over time merely by shifting their purchase timing or quantities, without cross-store shopping (e.g., Neslin, Henderson, and Quelch 1985; Gupta 1988). In the context of durable goods, Conlisk, Gerstner, and Sobel (1984) discuss how firms can use price promotions to distinguish consumers who can shift purchases over time from those that cannot. We refer to this as the temporal dimension of price search. Intertemporal price search is manifested in household choice data as changes in purchase timing (acceleration or delay) and quantities (stockpiling on deals; reducing purchase quantities when prices are high). Price promotions can help a retailer obtain a higher wallet share from even its price-sensitive shoppers who for a variety of nonprice-related reasons (e.g., location, preference for offered assortment, etc.) have a preference for shopping at its stores. At the same time, the retailer can obtain greater returns from its price-insensitive customers who do not restrict their purchases only to promotional periods. From this perspective, price promotions serve as a defensive weapon to retain a store's price-insensitive customers rather than as an offensive weapon that serves to attract customers from competing stores (Little and Shapiro 1980; Walters and MacKenzie 1988). Little and Shapiro (1980) note that prices in retail stores tend to be low relative to what the short-term price elasticities suggest because retailers price defensively to prevent their loyal consumers from shifting to competitors over the long run.

Given the dual use of price promotions (to draw consumers from other stores and to discriminate between price-sensitive and insensitive customers), a store manager needs to understand the price search behavior not only of cross-store shoppers, but also of those shoppers who shift their purchase timing in order to take advantage of promotions at their preferred store. The extant literature on price search has paid little attention to this temporal dimension. We therefore expand the focus on price search in the extant literature to include temporal price search by characterizing price search in grocery shopping along both the temporal (when to buy?) and spatial (where to buy?) dimensions. Given the temporal and spatial dimensions of price search, there are four possible price search patterns: (1) spatial (cross-store) price search, (2) temporal (store-specific over time) price search, (3) both, and (4) neither.

The first substantive research question that we address is: Why do consumers choose different modes of price search? More specifically, what variables predict which of the four price search patterns a household will adopt? We generate our hypotheses about the predictors of price search patterns based on the economic tradeoffs of price search. If price search behavior is an outcome of consumers' trading off the benefits of price search against the opportunity costs of time for undertaking search (e.g., Urbany, Dickson, and Kalapurakal 1996; Putrevu and Ratchford 1997), then the relative location of the consumers with respect to the stores, the distances between stores, and the per-unit-of-time opportunity cost of search should be very important in explaining search behavior.

Surprisingly, geographic location has received limited attention in the empirical literature on price search, even though theoretical models (e.g., Hotelling's model) routinely assume geography to be the underlying source of differentiation between stores. Many store choice models that use revealed-preference data treat this as a form of unobserved heterogeneity. Others that use stated-price data ask questions about motivations and attitudes of consumers, but do not ask questions about consumer locations, relative to stores. Gravitation or attraction models of store or mall choice (Huff 1964) and derivative models (e.g., Cooper and Nakanishi 1988) focus only on relative distances between the stores and the individual. Hoch et al. (1995) consider distances between supermarkets and households and distances between households and the warehouse store in estimating store price elasticities, but do not consider distances between stores. Fox and Hoch (2005) account for both distances between the stores and the individual and the distance between stores in their investigation of cross-store price search, but treat these as having independent effects on price search.

In this paper, we argue that the relative locations of consumers with respect to stores and the distances between the stores interact with each other, and based on that assumption we generate a rich set of location-based hypotheses about search behavior along the two dimensions of price search. We find strong support for our rich set of location hypotheses. We also test and find support for the effects of household characteristics, personality traits, and attitudes (e.g., unit opportunity cost, perceived search skill, and market mavenism) as predictors of segment membership.

The second research question we address is: What are the relative gains from search for different price search segments? We develop an objective metric called "price search efficiency" to calibrate these gains. Briefly, it is the ratio of the actual savings realized relative to the maximum possible savings that a household could obtain by perfect cherry picking. The analysis helps us to answer interesting research questions. For example, how much of the potential savings does a person who does not search either temporally or spatially save simply by chance? Which is more cost effective: pure temporal search by store-loyal households or pure spatial search by store switchers? How much does one gain by engaging in both temporal and spatial search?

This research question is also important from a methodology perspective. Extant research on price search uses exclusively survey data or revealed-purchase data. Examples of survey-based papers are Urbany, Dickson, and Kalapurakal (1996) and Putrevu and Ratchford

(1997), which measure *stated* search propensity and investigate its antecedents, but do not verify whether actual price search is consistent with the stated search measures. Examples of papers based on revealed purchases are Carlson and Giseke (1983) and Fox and Hoch (2005), which find that consumers who purchase more across stores indeed find greater savings. Survey data provide not only insights about search behavior, but also about the underlying motivation behind search. But because survey data cannot be linked to actual behavior, we cannot understand the revenue and profit implications of price search from this data. In contrast, inferences about price search from revealed-purchase data give insights about revenues and profits, but not about the motivation behind search.

An open question is whether the two types of data are likely to lead to similar conclusions. That is, are consumers' self-reported measures of search consistent with their actual behavior? Putrevu and Ratchford (1997) highlight the importance of this issue when they state:

We have not addressed the related issue of whether the perceived behavior of consumers is a good measure of their actual behavior. Since studies have documented differences between self-reported and actual search behavior (Newman and Lockeman 1975), and perceived and actual knowledge (Brucks 1985), it is not clear that self-reported measures of grocery shopping and its antecedents of the type employed in this study will accurately track actual behavior. This is an issue for further research. (p.478)

To address this question, we collected survey data from households whose actual purchasing behavior we also had access to. It is unusual to be able to obtain that information, because widely available panel data tend to be historic, but a retailer's cooperation gave us access to purchase transactions in real time. We were able to survey households and track their purchases over time, and we compared the prices they paid at the focal retailer with the prices a competing retailer charged during the same period. By comparing prices across two competing retailers over multiple weeks, we were able to make inferences about the gains from spatial and temporal price search. In all, through direct field observations, we obtained prices on about 8,500 distinct product items over three week-long time windows (i.e., over 25,000 observations). We provide more details about the data collection later in the paper. This labor-intensive data collection method made it possible to compare and contrast stated-search data and revealed-purchase data for the first time in the literature.

Our third research question is: How does price search along the temporal and spatial dimensions affect store profits? This question has hitherto not been addressed in the literature because typical scanner data sets have no information on profit margins.[2] Further, most scanner data sets have information only on a limited number of categories (even the Stanford basket database does not cover all categories), rendering a complete analysis of customer profitability for a store infeasible. Currently there is speculation that price-sensitive grocery shoppers' cherry-picking behavior can adversely impact retail profitability significantly (e.g., Mogelonsky 1994; Drèze 1999), but there is no empirical evidence. We address this question using our unique data set, which provides information on both profit margins and all purchases (over a one-year period) at the cooperating retailer.

In summary, our study is unique in the price search literature because it explicitly takes into account how well households take advantage of *both* temporal and spatial price variations in the market. The study addresses three substantive research questions (What variables determine a household's price search on the temporal and spatial dimensions? How efficiently do households following different search patterns take advantage of price variations in the market? What is the impact of price search on store profits?) and one methodological research question (Are findings from survey-based research comparable to results from objective revealed-purchase data?)

Conceptual Framework and Research Hypotheses

Types of price search patterns

Consider a duopoly grocery retail market in which price variations occur both temporally (across weeks, since cycle time for price changes is weekly) within a store and across stores. The duopoly assumption is reasonable and consistent with reality in many U.S. markets (Fox and Semple 2002), including the market we study. Given temporal and spatial price variations in the market, consumers can benefit from both temporal and spatial price search. We split consumers into high or low types along the temporal and spatial price search dimensions. This leads to four price search patterns among grocery shoppers (see Figure 1 below).

Some shoppers do not search actively either temporally within a store or spatially across stores. But they can still get low prices on promoted products when the products happen to be available on sale at their preferred store when they want to purchase them. We label this search pattern *incidental price search*.

A second type of shopper tends to be loyal to a preferred store and therefore does not take advantage of spatial price variations across stores. These shoppers shift purchases over time to avail themselves of promotions at their preferred store. We label this search pattern *temporal price search*.

Figure 1
Segmentation by Price Search Patterns

Cross-Store Price Search	Intertemporal Price Search: Low	Intertemporal Price Search: High
Low	Incidental price search	Temporal price search
High	Spatial price search	Spatio-temporal price search

A third type of shopper takes trips across stores on any given shopping trip to take advantage of cross-store spatial price differences. This segment is the focus of the study by Fox and Hoch (2005). This segment may be less loyal to a particular store than the previous two segments, though it is quite possible these shoppers buy most of their (nondeal) purchases at a preferred store and buy only low-priced items at the competing store. We label this search pattern *spatial price search*.

The fourth type of shopper takes advantage of both spatial and temporal price variations by making regular weekly shopping trips to both stores. These shoppers will switch between the two stores and shift their purchase timing in order to get the best price deals across stores and over time for a grocery item. We label this search pattern *spatio-temporal price search*.

What variables determine a household's price search pattern?

We start with the premise that consumers choose the search pattern that maximizes potential savings for the household, net of their costs. We use a cost-benefit framework that focuses on consumer and store locations and opportunity costs to help develop hypotheses about the choice of consumer search patterns (e.g., Urbany, Dickson, and Kalapurakal 1996; Putrevu and Ratchford 1997). We also consider certain stated personality characteristics and attitudes that can affect search behavior.

Benefits of price search

Financial Benefits. A common measure of price dispersion in a market is *information value*, which is the range of prices in a market. This measure reveals the maximum possible savings (and therefore potential benefit) from price search given perfect price information (Baye, Morgan, and Scholten 2003). Several papers have quantified the benefits of price search (information value) in durable goods markets (e.g., Brynjolfsson and Smith 2000; Clemons, Hann, and Hitt 2002; Ratchford, Pan, and Shankar 2003), but the benefits of price search in grocery markets have been a source of debate because of the low prices of grocery products (Urbany, Dickson, and Sawyer 2000).[3]

The information value (maximum potential savings) in the grocery market is based on price dispersion in both the temporal and spatial dimensions; such savings are available to consumers who do spatio-temporal price search. Mathematically, the information value for a household *i* based on all the items purchased across multiple shopping trips n_i is given by:

$$\text{Information Value}_i = \sum_j^{n_i} BV_{ij}^{\max} - \sum_j^{n_i} BV_{ij}^{\min},$$

where

$BV_{ij}^{\max} = \sum_{k=1}^{m_j} Q_{ijk} P_{ijk}^{\max}$ = Maximum possible dollar value that could have been paid by household *i* for the shopping basket purchased on trip *j*, across stores and across time.

$BV_{ij}^{\min} = \sum_{k=1}^{n_j} Q_{ijk} P_{ijk}^{\min}$ = Minimum possible dollar value that could have been paid by household *i* for the shopping basket purchased on trip *j*, across stores and across time.

In the above formulation, Q_{ijk} is the purchased quantity of item *k*, $P_{ijk}^{\max}$ is the maximum market price for item *k*, and $P_{ijk}^{\min}$ is the minimum market price for item *k*.

Since it would also be useful to identify the potential benefits from other types of price search patterns, we quantify the information values from temporal price search and spatial price search by measuring the price dispersion purely along the temporal and spatial dimensions, respectively. Thus, for the temporal search, $BV_{ij}^{\max}$ and $BV_{ij}^{\min}$ are based on basket values only across time within the store, while for spatial search, the basket values are computed only across stores on the week of the trip.

Clearly the greatest potential benefit will be from *spatio-temporal price search*. It is not a priori clear (without looking at the relative level of price variation within and across stores) whether spatial price search or temporal price search leads to greater savings. This study should shed some light on that question.

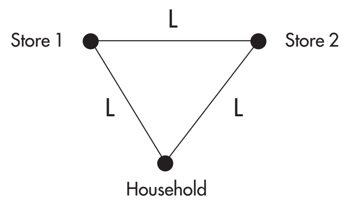
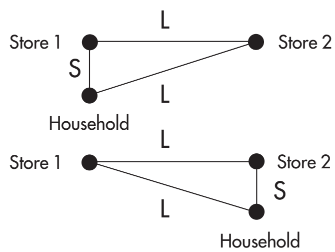
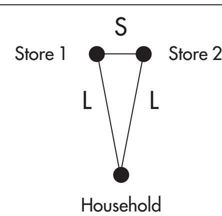
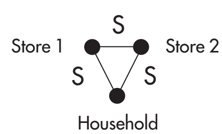
Personality-related Benefits. Some consumers may derive utility from price search. For example, market mavens are shoppers who benefit from the psychosocial returns gained by sharing relevant market information with others as much or more than they benefit from direct financial returns. Hence they collect relevant market information with the intent of sharing it with others (Feick and Price 1987; Urbany, Dickson, and Kalapurakal 1996). Urbany, Dickson, and Kalapurakal (1996) found that market mavens do more price search than others. We expect this trait to be least associated with incidental price search and most associated with spatio-temporal price search.

Costs of price search

Time-related Costs. The cost of search is the opportunity cost of time involved in performing the search. Let W be the unit opportunity cost of travel time and T be the travel time to perform search. The travel time to perform search may be further decomposed into $T = D/S$, where D is the distance traveled to perform search and S is the speed of the typical mode of transport for grocery shopping. Then the cost of search (C) is given by $C = WT = W(D/S)$. In the context of grocery shopping in suburban markets in the United States, S can be assumed to vary little across consumers due to widespread car ownership in these markets. Hence we focus on two variables: (1) D, the distance traveled to perform search and (2) W, the unit opportunity cost of the household's time.

Unlike earlier studies (e.g., Fox and Hoch 2005) that treat the distance between the consumer and the store and the distance between stores as having independent effects on consumer price search patterns, we argue that these distances interact in determining a household's choice of search patterns. We denote a consumer's geographic location and the distances between the consumer and the two closest stores (and between

Table 1
Likely Spatial Layout and Price Search Pattern

<table>
<tr><th>Price Search Pattern</th><th>Spatial Layout of Most Likely Segments</th></tr>
<tr><td>Incidental</td><td>
</td></tr>
<tr><td>Temporal</td><td>
</td></tr>
<tr><td>Spatial</td><td>
</td></tr>
<tr><td>Spatio-temporal</td><td>
</td></tr>
</table>

the two stores) using a three-dimensional vector (D_{12}, D_1, D_2), where D_{12} is the distance between the two stores, D_1 is the distance between the consumer's home and Store 1, and D_2 is the distance between the consumer's home and Store 2. To facilitate exposition, we treat distance as a dichotomous variable: large (L) or small (S).[4] We represent the relevant distances using a three-dimensional vector $D_{12}D_1D_2$, i.e., if there are households that are situated such that $D_{12}= L$, $D_1= S$, $D_2= L$, we will refer to that segment as ***LSL*** segment. We will explain the rationale behind how the spatial configurations of the household and stores affect the household's choice of price search patterns. The pictorial descriptions in Table 1 can be helpful in understanding the logic of the hypotheses.

Households of type LLL, which are far away from both stores, which in turn are far away from each other, are most likely to adopt incidental price search because they can't visit either store often to take advantage of intertemporal price variations and because they find it costly to perform spatial price search.

Households of types LSL or LLS, which are close to one of the stores, are likely to be loyal to the closer store (this would be their primary store) and to perform temporal price search at their closest store because they can visit it often. They are not likely to perform much spatial price search due to the large distance between stores.

Households of the SLL type, which are far away from the two stores, which are close to each other, are likely to engage in spatial price search. As discussed earlier, this is the behavior that Fox and Hoch (2005) focus on, and indeed, they find that larger distances to the stores and shorter distances between stores lead to greater cherry-picking behavior. Our study nests this hypothesis in a broader set of hypothesis.

Finally, we expect that households of the SSS type would most likely indulge in spatio-temporal price search to take advantage of both the spatial and temporal price variation, given their close proximity to the stores as well as the short distances between stores.

Personality-related Costs. We expect that an increase in unit opportunity cost of time for a household will reduce the likelihood of spatio-temporal price search most and will increase the likelihood of incidental price search most. The net effect on the likelihood of choosing the two intermediate price search patterns cannot be ordered, but should lie between the two extreme patterns.

For shoppers who have a greater ability to remember prices and organize information, the cost of taking advantage of market price variations through price search is lower. Shoppers who

Table 2
Summary of Hypotheses and Empirical Results

Consumers' Stated Cherry-picking Behavioral Pattern	Determinants of Cherry-picking Patterns: Most likely consumer-store spatial pattern	Market mavenism	Opportunity cost of time	Perceived search skills	Effect of Cherry-picking Patterns on Price Search Efficiency and Profit Margins: Observed price search efficiency	Profit margin
Incidental cherry picking	LLL √	most negative √	most positive √	most negative √	lowest √	highest √
Temporal cherry picking	LSL or LLS √					
Spatial cherry picking	SLL √					
Spatio-temporal cherry picking	SSS √	most positive √	most negative √	most positive √	highest √	lowest √

Note: √ indicates support of a hypothesis based on our empirical results at $p < .05$.

have greater price search skills and who are more efficient in their price search are least likely to engage in incidental price search and most likely to engage in spatio-temporal price search.

The above hypotheses are summarized in Table 2 under the heading "Determinants of Cherry-picking Patterns."[5]

How efficient are households with different price search patterns?

We use an objective metric called *price search efficiency (PSE)* to capture the realized savings from price search. The idea behind the construct is similar to that developed in studies of durable goods (e.g., Ratchford and Srinivasan 1993) in that the return on price search is the ratio of realized price savings relative to maximum potential savings given the price dispersion in the market. Specifically, we use the following construct of *PSE* for a household i based on all the items purchased across multiple shopping trips n_i tracked over about a month:

$$PSE_i = \frac{\textit{Actual Savings Captured for Tracked Trips}}{\textit{Maximum Potential Savings for Tracked Trips}} = \frac{\sum_j^{n_i} BV_{ij}^{\max} - \sum_j^{n_i} BV_{ij}^{*}}{\sum_j^{n_i} BV_{ij}^{\max} - \sum_j^{n_i} BV_{ij}^{\min}}$$

where $BV_{ij}^{\max}$, $BV_{ij}^{\min}$ are as defined earlier, and BV_{ij}^{*} is the actual dollar value that household i paid for the shopping basket purchased on trip j.

For computing $BV_{ij}^{\max}$ and $BV_{ij}^{\min}$, we use both spatial (across the cooperating and competing chains) and temporal (across monitored weeks) market price dispersion for all the items under consideration that are in the shopping basket for trip j. Thus, we compute each household's maximum potential savings as if they did spatio-temporal price search. This enables us to evaluate the efficiency of all households on a comparable basis. If a household captures all the potential savings, its price search efficiency is 100%. On the other hand, if the household purchased every item at the highest price and thus realized no savings, its price search efficiency is 0%.

Are stated search patterns consistent with observed behavior?

If consumers' stated search patterns are consistent with observed behavior, then consumers who claim to search more will get lower prices on average. The self-declared spatio-temporal households should pay the lowest prices on average (because they have the highest price search efficiency) and the self-declared incidental price search households should pay the highest prices (because they have the lowest price search efficiency) on average. The other two segments should pay the intermediate level of prices. It is of empirical interest whether temporal households or spatial households are more efficient and obtain better prices on average.

Above we hypothesized that a household's spatial relation to available stores affects the cherry-picking pattern the household chooses. If, as hypothesized, the SSS segment is most likely to use the spatio-temporal cherry-picking pattern, it should also have the greatest price search efficiency. By the same logic the LLL segment should have the lowest price search efficiency. The LSL and SLL segments should have intermediate levels of price search efficiency.

Impact of price search patterns on retailer profits

We expect incidental cherry pickers to generate the highest profit margins for the retailer and spatio-temporal cherry pickers to generate the lowest profit margins. For the other two segments, the profit margins will be intermediate; which of the two will generate a higher profit margin is an empirical question.

Our hypotheses relating to the effects of cherry-picking patterns on price search efficiency and store profits are summarized on the right-hand side of Table 2.

While we state specific hypotheses about the relative levels of profit margins accruing to the different search patterns, we do not have specific hypotheses about the average profits from households with the different search patterns. We expect that either the incidental cherry pickers (highest margins) or the temporal cherry pickers (highest loyalty and therefore greatest wallet share) should generate the best aggregate profits. But the specific ordering of these two segments is an empirical question.

Data

Data collection strategy

The data are from four suburban areas of a mid-size city in the northeastern United States in 2003-2004. In each area two regional competing grocery chains account for more than 85% of market share. We obtained the cooperation of one of the retail chains, which provided us "live" access to data on customer transactions at its stores on a daily basis. We label this cooperating chain "Chain A" and the other chain "Chain B."

We selected a group of four of Chain A's stores, paying special attention to the relative geographic distance between those stores and the corresponding nearest stores from Chain B. Specifically, we chose two Chain A stores that had competing Chain B stores within three-tenths of a mile and another two Chain A stores that had competing Chain B stores more than 2 miles away. This ensured that there was significant variation in interstore distances in the data to test our hypotheses.

Given our research purposes, we augmented the transactional data obtained from Chain A in two ways. First, we surveyed customers at Chain A about their search behavior and other relevant attitudes toward grocery shopping. Second, through direct observation we collected Chain B's prices for the products purchased in Chain A in any given week.[6]

We began with a survey of a random sample of customers on their visits to the four selected Chain A stores over three months during September-November 2003. We staggered the surveys over three months due to constraints on the number of available interviewers.

The interviewers met shoppers at random while they were leaving the selected Chain A stores after their shopping trips and used filter questions to determine whether they qualified for inclusion in the sample for our study. The qualifying criteria were (1) that the intercepted shopper had to be the primary grocery shopper for his or her household and (2) that he or she had a loyalty card from Chain A. The second criterion ensured that we had identifier information (the loyalty card number) that we could use to scan the transaction database of Chain A for shopping visits by the respondent. If the intercepted shoppers met the qualifying criteria, the interviewer collected the following information about them: (1) loyalty card number, (2) which store the shopper considered his or her primary store, and (3) relative expenditure levels at the two competing chains. The interviewers then gave the qualified shoppers a detailed survey questionnaire containing relevant behavioral, attitudinal, and demographic questions and requested the shoppers to return the finished questionnaires in prepaid return envelopes. If the responses were not returned within a month, we sent a reminder. We obtained responses from 255 shoppers, a response rate of slightly less than 50%.

After we received the completed mail-in survey from a shopper, we used the identifier information (loyalty card number) to scan the transaction database of Chain A for shopping visits by this respondent on a daily basis. Once we detected a shopping trip by this respondent, we obtained the prices for all the items in the respondent's shopping basket over that week and the two following weeks. We obtained the contemporaneous price data from Chain B for all products in that basket by visiting the competing Chain B store in the same week and the following two weeks.[7] This systematic (and labor-intensive) data collection approach ensured that we collected complete information on actual prices paid by the shopper as well as the intertemporal (over three weeks) and cross-store (across the two competing retail chains) price variations for all the items purchased on any particular shopping trip.

For each mail-in survey respondent, we went through the same process of obtaining price information for purchased items in their baskets for multiple trips. For most households we obtained information for three trips. For a few households, we were able to obtain data on only two trips within the data collection period. Overall, we collected price data on about 8,500 distinct items over 710 shopping trips purchased by the 255 households who responded to our survey. Because each item needed to be tracked over three weeks at Chain B by direct observation, we collected over 25,000 price observations manually during a period of about six months in 2003 and 2004.

As discussed earlier, having the directly observed price information from both chains helped us develop measures of households' revealed-price search efficiency. The information from the mail-in surveys allowed us to compare households' revealed-price search efficiency with their self-stated price search propensity, so that we could assess the comparability and validity of the two data-collection methods (observation versus surveys) for collecting information on price search. We also used the information from the mail-in surveys to construct other attitudinal and personal-characteristics measures.

Finally, in order to address the question of the impact of price search on a chain's profits, we obtained information about the profits and profit margins generated for Chain A by the 255 sample households over the 52 weeks of 2002. We also obtained profit and margin data for all loyalty card customers (21,963) from two of the sample stores of Chain A in order to do an in-depth investigation of how cherry picking affects customer profitability.

Measures

We used self-reported consumer data to construct the various attitudinal and behavioral measures. The appendix presents a complete list of the items used in each scale along with the corresponding scale reliability coefficients. It also notes the specific sources when items were drawn

Table 3
Information Value from Price Search in Grocery Markets

Shopping Basket Value	Average Values of Maximum Potential Savings (std. dev.)		
	Spatial	Temporal	Spatio-temporal
< $30	$2.98 (2.90)	$3.60 (5.90)	$5.04 (4.13)
$30–$60	$9.64 (5.79)	$11.47 (9.14)	$16.35 (9.29)
$61–$90	$16.41 (7.45)	$19.94 (9.87)	$27.36 (10.25)
> $90	$28.02 (11.56)	$31.02 (18.1)	$45.05 (19.34)
sample average: $31.22	**$7.20 (5.65)**	**$8.49 (6.45)**	**$11.99 (9.39)**

from past research. We developed the new measures based on our conceptual framework and then modified them based on personal interviews with a convenience sample of 14 grocery shoppers. We used another convenience sample of 68 grocery shoppers to make initial assessments of the reliabilities of all the multi-item scales used and to make any necessary adjustments in terms of dropping and/or modifying items.

We drew on Feick and Price (1987) and Urbany, Dickson, and Kalapurakal (1996) to construct the market mavenism measure. The "perceived search skills" construct is based on Putrevu and Ratchford (1997) and Urbany, Dickson, and Kalapurakal (1996). We used two constructs to distinguish between consumers' stated temporal and spatial price search propensities. We drew on existing research for the five items used in the spatial price search propensity scale and developed the five items used in the temporal price search propensity scale.

We performed a two-segment cluster analysis (using Ward's method with squared Euclidean distances) of consumers' temporal and spatial price search propensity measures to classify consumers into high and low types along each dimension.[8] The average scores for temporal price search propensity for the high and low segments were 3.6 (s.e. = .039) and 2.1 (s.e. = .054) on a five-point scale. The large difference and the low standard errors indicate a high degree of discrimination between the high and low types on the temporal dimension. The corresponding scores for spatial price search propensity are 4.01 (s.e. = .038) and 2.32 (s.e. = .064), indicating a high degree of discrimination between the high and low types on the spatial dimension as well.

As Putrevu and Ratchford (1997) point out in their study, it is very difficult to develop a multi-item scale that exhibits high scale reliability for a unit opportunity cost measure. On the other hand, using respondents' actual wage rate as a measure requires us to impute a wage rate for those who do not work. We followed Marmorstein, Grewal, and Fishe (1992) and Putrevu and Ratchford (1997) in using a single-item measure that asked respondents at what hourly wage rate they would be willing to undertake an extra hour of work suitable to their skills.

We represented the spatial patterns with three variables: distance of household to closest Chain A store ($\boldsymbol{D}_1$), to closest Chain B store ($\boldsymbol{D}_2$) and distance between the two stores ($\boldsymbol{D}_{12}$). We found that an analysis based on a binary classification of distances into "small" and "large" fit the data better than an analysis that input the distance as continuous variables directly into the regressions.[9] We used the delimiting distances of less than three-tenths of a mile ($\boldsymbol{D}_{12} < .3$) and greater than 2 miles ($\boldsymbol{D}_{12} > 2$) to determine whether the distance between stores was small or large. For distance between the household and the store, we used a median split (1.8 miles) to classify distances as large or small. We found that the results are robust to changes in the split threshold (e.g., at 2 miles).

Empirical Analyses and Results

The benefits of price search

Table 3 shows the information value (i.e., the maximum potential savings) from the different price search patterns based on the 710 tracked shopping baskets in our data. To gain insight into how basket size affects the potential benefits

Table 4a
Stated Cherry-picking Patterns

Distance between Stores	*N*	Incidental %	Spatial %	Spatio-temporal %	Temporal %
< .3 miles (close)	156	22	21	46	11
> 2 miles (far)	99	37	3	20	40
Average	**255**	**28**	**14**	**36**	**22**

Table 4b
Observed Location Patterns

Distance between Stores	*N*	LLL %	SLL %	LSL+LLS %	SSS %
< .3 miles (close)	156	0	47	0	48
> 2 miles (far)	99	23	0	67	0
Average	**255**	**9**	**29**	**26**	**30**

(Percentages do not add to 100% because we omitted observations with other infrequent location patterns)

of search, we also report these values grouped by basket sizes.

As expected, we found that the average information value is greater for larger baskets across the four different search patterns. In fact the information value is convex in relation to basket size, that is, the savings from larger baskets are more than proportionately greater than the savings from smaller baskets. On basket values greater than $90, with spatial-temporal price search, a household could potentially save $45 on average. For basket values of $60-$90, the average potential savings drop to about $27. The corresponding average is about $16 on basket values of $30-$60, and only about $5 on basket values less than $30.

Not surprisingly the average potential savings from search across all basket sizes is greatest ($11.99) when consumers search along *both* the temporal and spatial dimensions, as seen in the column for the spatio-temporal price search. Interestingly, the average potential savings of $8.49 from price search on the purely temporal dimension is greater than the $7.20 savings from search on purely the spatial dimension. It is interesting and somewhat surprising to consider that there is apparently greater potential for savings by being loyal to a store and cherry picking temporally than by shopping across stores each week without cherry picking temporally.

What variables determine a household's price search pattern?

To see how the distribution of price search patterns changes as a function of the distance between the Store A and Store B, we report what percentage of households adopted each of the four price search patterns (see Table 4a). When the two stores are far away from each other (greater than 2 miles), only 3% of the sample engage in pure spatial price search, but 20% of the sample engage in spatio-temporal price search. In contrast, when the two stores are close to each other, 21% engage in spatial price search and 46% engage in spatio-temporal price search. When stores are far apart, 40% of households engage temporal price search, but that falls to 11% when the stores are close by.[10]

Table 5

Multinomial Logit Regression: Determinants of Price Search Patterns

(spatio-temporal price search and SSS is the base case.)

	Incidental Estimate (std. error)	**Temporal** Estimate (std. error)	**Spatial** Estimate (std. error)
Intercept	3.06** (1.48)	–.10 (1.35)	–6.19*** (1.30)
LSL/LLS	1.96*** (.67)	2.59*** (.51)	–.54 (1.15)
SLL	.48 (.72)	.29 (.59)	2.55*** (.58)
LLL	5.52*** (.91)	2.59*** (.89)	–3.57*** (1.18)
Opportunity cost	.24*** (.03)	.14*** (.02)	.16*** (.03)
Market mavenism	–.70** (.32)	–.17 (.24)	.36 (.26)
Perceived search skills	–2.09*** (.49)	–.89** (.39)	.03 (.34)

*$p < .1$; **$p < .05$; ***$p < .01$

Note: We also included various demographic variables (age, sex, income, and household size) in the regression, but we do not include them in the regressions we report because none of them were significant.

The percentages of households in each of the spatial segments for stores that are adjacent to each other (< .3 miles) are: SSS (48%), and SLL (47%). In contrast, the percentages of households in each of the spatial segments for stores that are far away from each other (> 2 miles) are: LSL or LLS (67%), LLL (23%).[11]

We used a multinomial logit model to explain the household's choice of price search pattern. The main explanatory variables were the cost-of-search variables: (1) the location configuration of the households and stores and (2) unit opportunity costs. In addition, we incorporated individual-specific variables, such as perceived search skills, and shopping-related personality traits, such as the self-perception of being a market maven. The results are reported in Table 5.

The multinomial logit regression results are reported in three columns, one for each price search pattern (because each variable of interest has different effects on the likelihood that a certain price search pattern will be chosen). We have only three columns because we treat spatio-temporal price search as the base case, and the coefficients are relative to this base case. For the spatial-configuration variables, we treat SSS as the base case.

Our hypotheses about the role of location configuration on price search patterns are well supported by the data. Let us first turn to the spatial-configuration estimates across columns. The coefficient of LSL/LLS is highest (2.59) for temporal price search (relative to the other price search patterns), supporting the hypothesis that when the two stores are far apart and households are close to one of the stores, the households are most likely to do temporal price search. The coefficient of SLL is highest (2.55) for spatial price search, as expected. The coefficient of LLL is highest (5.52) for incidental price search, as hypothesized.[12]

Next, we interpret the spatial-configuration estimates within each column. Within the incidental price search column, LLL, as predicted, has the highest coefficient (relative to the other location variables), 5.52. Interestingly, both LSL/LLS and LLL have the highest coefficients (2.59) for temporal search, i.e., long distances between stores reduce cross-store shopping. But as we stated earlier, LSL/LLS households prefer temporal price search while LLL households prefer incidental price search most. Finally spatial price search has the highest coefficient (2.55) for SLL households, as expected.

Opportunity cost is significant and positive, as expected, for all price search patterns, suggesting that an increase in opportunity cost reduces the likelihood of using spatio-temporal price search relative to the other three types of price search. An increase in opportunity cost has the greatest impact on the likelihood of using incidental price search (.24) relative to the spatio-temporal price search. The marginal effect of opportunity cost on the probability of both temporal price search (.14) and spatial price search (.16) is not significantly different, though we expected the effect to be greater for spatial price search since that required an additional trip to a competing store at the same time.

The effect of perceived search skills on the price search pattern is as expected. People who perceive themselves as more skillful tend to do more spatial price search and less temporal (–.89) or incidental price search (–2.09). Perhaps the perceived search skill measure is more correlated with how well they can search for relevant price information across stores than within stores over time.

Shopping mavens tend to do spatial price search most and are least likely to do incidental price search (–.7), consistent with their need to be key informants to others about the best prices available in the market.

The U^2 for the model in Table 5 is .45. With the location variables removed, the U^2 drops to .33. With location and opportunity cost removed, the U^2 with the perceived price search skills and mavenism drops to .09. Thus while attitudinal variables do help to explain observed price search patterns, location and opportunity costs are more important factors.

How efficient are households with different price search patterns?

To address the question about actual savings from price search, we computed the observed price search efficiency of each household across multiple shopping trips (two to three trips) at Chain A. As these trips for each household are spread typically over a month, the observed efficiency can be interpreted as the price search efficiency of the household over a basket of monthly purchases at Chain A.

We regressed observed price search efficiency against the stated price search patterns of households, including as controls whether Chain A was the primary store and the average basket size (number of items) across tracked trips. The regression results are reported in Model 1 of Table 6.

As expected, the incidental cherry picker has the most inefficient price search, but even the incidental cherry picker is able to obtain 54% (the intercept) of the maximum potential savings. Interestingly, while the temporal cherry picker saves as much as 68% (intercept + temporal) of potential savings, the spatial cherry picker saves only 66% (intercept + spatial) of potential savings. However, households that combine spatial and temporal cherry picking are able to obtain as much as 76% (intercept + spatial-temporall) of the maximum potential savings.[13] Thus, spatio-temporal cherry pickers are 22 percentage points more efficient in their price searches than incidental cherry pickers; they are also 14% more efficient than pure (i.e., only within-trip) spatial cherry pickers and 13% more efficient than pure (i.e., store-loyal) temporal cherry pickers.[14]

The results show that a significant fraction of the maximum potential savings can be obtained by conscientious shoppers who shop at one store and shift their purchase timing to take advantage of price specials at their store of choice. At the same time, those who also engage in cross-store cherry picking increase their potential savings by an additional 8% of the average maximum potential savings. An interesting finding is that about 54% of the possible savings are obtained by households who do not search for low prices at all—in other words, price-insensitive shoppers are also benefiting from price promotions.

In Model 2, rather than using stated price search patterns as explanatory variables, we used the

Table 6
Regression Results for Observed Price Search Efficiency across Tracked Multiple Shopping Trips

	Dependent Variable: Observed Price Search Efficiency across Multiple Shopping Trips		
Explanatory Variable	**Model 1**	**Model 2**	**Model 3**
Stated cherry-picking behavioral pattern	Estimate (std. error)	Estimate (std. error)	Estimate (std. error)
Spatio-temporal	.221*** (.033)		
Temporal	.143*** (.039)		
Spatial	.129*** (.045)		
Incidental (base category)			
Consumer-store spatial patterns			
SSS		.327*** (.045)	
LSL/LLS		.250*** (.046)	
SLL		.230*** (.045)	
LLL (base category)			
Distance to the primary store			−.011* (.006)
Distance between stores			−.019** (.008)
Distance to primary store × Distance between stores			−.003* (.002)
Unit opportunity cost of time		−.003*** (.001)	−.003*** (.001)
Market mavenism		.007 (.015)	.001 (.015)
Perceived search skills		.011 (.023)	.031 (.022)
Primary shopper with respect to focal store	−.008 (.045)	−.086 (.047)	.032 (.045)
Average number of items per tracked shopping trip	.001 (.001)	.001 (.001)	−.000 (.001)
Intercept	.536*** (.051)	.516*** (.094)	.654*** (.098)
R^2	.164	.260	.222
N	228	222	222

*$p < .1$; **$p < .05$; ***$p < .01$
Note: We also included various demographic variables (age, sex, income, and household size) in the models, but we do not include them in the regressions we report because none of them were significant. Also, unit opportunity cost of time was not significant when included as a regressor in Model 1.

underlying drivers—location, opportunity cost, and attitudinal variables that we had identified earlier (see Table 2)—to explain stated price search patterns. The results are consistent with our hypotheses. We find that SSS households have the greatest price search efficiency (with the highest estimated coefficient, .327) and that LLL households have the lowest price search efficiency (all estimated price coefficients are positive when LLL is the base case). Interestingly, we find that these underlying location variables have greater explanatory power than the stated price search patterns themselves.[15] The R^2 of the model increases from 16.4% to 26% when the underlying determinant variables of stated price search pattern, as well as available and relevant demographic variables (age, sex, income, and household size), are included. But most of the explanatory power lies with the location and opportunity cost variables (24.9%), which together essentially capture the economic drivers of price search efficiency. Of the 24.9% R^2, 17.7% comes from the location variables and 7.2% comes from unit opportunity cost of time.[16]

Unfortunately, much of the recent research on store choice, which relies on scanner data for choice information, treats location and attitude or motivation variables as unobserved heterogeneity (e.g., Bucklin and Lattin 1992; Popkowski Leszczyc, Sinha, and Timmermans 2000) and focuses on only pricing differences between stores at a single category level (e.g., Bucklin and Lattin 1992). It is therefore not surprising that these papers are unable to explain store choice effectively. By contrast, research that uses Hotelling-type models and that takes consumer locations and opportunity costs into account covers what consumers consider the important tradeoffs.

In Model 2, we have included distances as a discrete variable (large and small). Shopping trips involve fixed costs of travel to the stores and the actual cost of shopping. The cost of shopping dominates total cost for short distances, while the travel to store dominates for larger distances. Hence we expect there to be threshold effects for the effect of distance on number of trips taken. Therefore a binary categorization of distances seems conceptually appropriate. However, it is necessary to check if the fit can be improved by using distance variables directly, which we did in Model 3, which used distances as continuous variables. As expected, we find that coefficients of distance between the household and primary store and of distance between primary and secondary store are negative, demonstrating that greater distances to the store and between stores reduce households' price search efficiency. Further, consistent with the interaction effects identified in Model 2, we find a negative and significant interaction effect between the two distances. However the R^2 for the model drops from 26% to 22.2%. Thus we conclude that Model 2, with its discretized distances, has greater explanatory power.

In none of the models do we find the average trip basket size to be significant. Although the potential benefits from effective searches increase as the basket values increase, the basket sizes do not, it appears, affect the efficiency of the search. Unlike Fox and Hoch (2005), who demonstrate that households shop across stores more often when they have larger baskets to purchase, we did not test the endogeneity of trip size. That was not a focus of our paper, and in any case we did not have data on whether consumers actually shopped at multiple stores.

Are stated search patterns consistent with observed behavior?

Overall, the results from Model 1 suggest that households' observed price search efficiency is consistent with their stated price search patterns. Therefore, we conclude that both survey data and objective behavioral data will provide broadly similar insights—which sheds some light on an unresolved question in the price search literature (Putrevu and Ratchford 1997).

We now explore the differences between survey and observed data. While stated price search pattern explains only 16% of the variance in price search efficiency, a combination of observed locations and opportunity cost explains 24.9% of the variance in observed price search efficiency.[17] Further, the three location variables alone explain as much as 17.7% of the variance. Thus, observed variables are better at explaining price search efficiency. Why is price search efficiency better explained by objective variables than by stated price search behavior?

Note that earlier we pointed out that although market mavenism can explain stated price search patterns (consistent with Urbany, Dickson, and Kalapurakal 1996), its ability to explain observed price search efficiency after controlling for location variables and opportunity costs is insignificant. Since mavens will engage in search even if there are no financial returns, we can see why geographic location and opportunity cost explain price search efficiency better than stated price search patterns. Similarly, perceived search skills can explain the choice of search pattern, but do not explain price search efficiency.

A possible reason why market mavenism and perceived search skills do not explain price search efficiency beyond the location and opportunity cost variables is that market mavenism and perceived search skills might be correlated with distance or opportunity cost. That is, people may not perceive themselves to be mavens or as having high search skills if the stores are far away or far apart or they have high opportunity cost. However, when we conducted a hypothesis test of differences between the groups, we found no evidence of such an endogenous relationship between these sets of variables ($p > .1$).

It appears, then, that survey data help explain why people adopt search patterns that may not appear optimal given observed locations and opportunity costs (e.g., mavens enjoy shopping and are unconcerned about whether or not it saves them money). On the other hand, behavioral data shows that people who enjoy shopping and shop often do not necessarily get better prices. Thus, while both types of data give broadly similar insights about price search, they also serve complementary purposes: survey data give better insight into observed price search behavior, while objective data give greater insight into market outcomes from price search.

Impact of price search patterns on retailer profits

How do price search patterns affect retailer profits? We used data from the 255 surveyed households' actual shopping trips at Chain A in 2002 to compute average profit margins and weekly profits for the stores participating in our study. By using data over the whole year (rather than only during the study period), we obtain more accurate and stable measures of profits.

Averages. The top panel of Table 7 reports the averages for margins and weekly profits per household, broken down by stated price search patterns as well as by observed household-store spatial patterns. In addition, we also report some descriptive statistics such as trip frequency, basket sizes, and the self-reported wallet shares for the cooperating store.

The averages across different price search patterns are consistent with our hypotheses. For instance, the average profit margin per household is the highest for the incidental cherry pickers and the lowest for the spatio-temporal cherry pickers, with a difference in profit margins of about 20%. Consistent with our estimates of price search efficiency, we find that households who are store loyal but do temporal price searches and households that do spatial price searches provide intermediate profit margins. But as noted earlier, the temporal shopper is more valuable to the store in terms of aggregate profits. Our results should also reassure retailers because even the temporal cherry pickers make a positive average contribution to the bottom line.

In terms of total weekly profits, the temporal segment provides the greatest average profits, even greater (by about 15%) than the incidental price search segment. Though the temporal segment has lower margins than incidental price search segment, the average share of wallet that they devote to Chain A is 67%, compared with the 60% wallet share for households who do incidental price search. This explains why households in the temporal segment provide greater average profits than households in the incidental price search segment even though they have lower profit margins.

The averages in Table 7 are also consistent with our expectations for the household-store spatial patterns. For example, the profit margins are greatest for LLL households and lowest for SSS households, although SSS households visit the store most often and LLL households visit least often. As expected, LLL households had the biggest baskets and SSS households had the smallest baskets. Most interestingly, the aggregate weekly profits are greatest for the LLL households and the LSL households. In other words, the greatest aggregate profits are obtained from households when the two competing stores are farther apart and cross-store shopping is least likely.

To find out if the differences in averages of margins and weekly profits across the different segments were statistically significant, we performed regressions with different store performance measures as dependent variables and the stated cherry-picking patterns and spatial pattern as explanatory variables. We also included a few additional control variables. The

Table 7
Averages of Retailer Performance Measures at the Cooperating Chain

Performance-related Measures at the Cooperating Retail Chain	For All Shoppers	By Stated Cherry-picking Behavioral Pattern: Spatio-temporal	Temporal	Spatial	Incidental	By Observed Household-Store Spatial Pattern: SSS	LSL	SLL	LLL
Surveyed sample (*N* = 255)									
Average profit margin[1,2]	.23	.21	.22	.23	.26	.19	.24	.24	.33
Average trip frequency[1]	.94	1.18	1.12	.74	.66	1.21	1.02	.77	.48
Wallet share[1,3]	.61	.62	.67	.56	.60	.63	.70	.62	.53
Average trip basket size[1]	$35.43	$25.30	$33.28	$30.65	$51.22	$25.78	$33.91	$35.38	$67.96
Average weekly profit[1,2]	$7.20	$6.83	$8.67	$5.85	$7.47	$6.57	$8.78	$6.45	$9.06
All loyalty card-holding households at two Chain A stores (*N* = 21,963)		Not Applicable							
Average profit margin[1,2]	.25					.21	.26	.25	.32
Average trip frequency[1]	.72					1.04	.76	.60	.45
Average trip basket size[1]	$33.34					$25.26	$30.73	$35.25	$44.34
Average weekly profit[1,2]	$5.58					$5.21	$5.93	$5.42	$5.99

[1]Based on actual purchase scanner data over one year (2002). [2]Scaled for confidentiality reasons. [3]Based on self-reported data from survey (2003).

results for the surveyed sample of 255 households are shown in Tables 8.[18] As reflected in our analysis of means in Table 7, the regression results show the relative differences are consistent with our hypotheses and are also statistically significant.

Extreme cherry picking: Do certain households provide negative net margins?

As promotions have increased in grocery retailing, there has been concern in the academic and trade literature (e.g., Mogelonsky 1994; Drèze 1999) about their negative impact on profits. Our analysis above shows that all the price search segments are profitable on average. Nevertheless, there could be some shoppers who are extreme cherry pickers and therefore buy only deeply discounted (loss leader) items at a store, while they shop at their primary store for the rest of their weekly groceries. If the proportion of extreme cherry-picking households is large, loss leader pricing to increase store traffic may be highly unprofitable, and retailers may need strategies to discourage such customers. (Drèze 1999; Levy and Weitz 2004). We therefore decided to quantify the proportion of extreme cherry-picking households in our study.

To perform a robust analysis of extreme cherry-picking households, it was necessary to use a larger sample than the 255 we used in the previous analysis. We therefore turned to a database of all loyalty-card holder households at two Chain A stores (one with a competing store very close; the other with a competing store much further away—they are also two of the four stores used in our study) for whom we had nine-digit zip code data. These 21,963 households accounted for over 75% of total sales in 2002 in each of the stores. We also inferred whether these households use Chain A as their primary grocery store.[19] For comparison with our in-sample house-

Table 8
Retailer Profit Analysis

Explanatory Variable	Model 1 DV: Average Profit Margin	 DV: Average Weekly Profit	Model 2 DV: Average Profit Margin	 DV: Average Weekly Profit
Stated cherry-picking behavioral pattern				
Spatio-temporal	−.060*** (.013)	−2.186** (1.030)		
Temporal	−.045*** (.016)	1.487 (1.217)		
Spatial	−.031** (.016)	−1.996* (1.235)		
Incidental (base category)				
Consumer-store spatial patterns				
SSS			−.151*** (.019)	−5.731*** (1.637)
LSL/LLS			−.095*** (.019)	−1.859 (1.639)
SLL			−.098*** (.018)	−4.199*** (1.612)
LLL (base category)				
Primary shopper with respect to focal store	.044*** (.014)	5.981*** (1.083)	.063*** (.015)	6.662*** (1.315)
Household size	.002 (.004)	3.190*** (.311)	.009** (.004)	3.583*** (.334)
Unit opportunity cost of time			.000 (.000)	.003 (.021)
Market mavenism			−.008 (.005)	−.153 (.461)
Perceived search skills			−.023*** (.008)	−1.360* (.729)
Intercept	.219*** (.022)	−8.665*** (1.757)	.350*** (.036)	−2.469 (3.180)
R^2	.09	.31	.30	.35
N	254	254	228	228

*$p < .1$; **$p < .05$; ***$p < .01$

holds, we report the same measures as for the in-sample households (except the self-reported wallet share measures) in the bottom panel of Table 7.

The larger sample is virtually identical to the surveyed sample in terms of relative magnitudes of average profit margins, trip frequency, and basket size for the different segments. For weekly profits, though the relative magnitudes across the groups are the same, the larger sample has lower total profits, especially for the LSL and the LLL households. This suggests that our surveyed sample systematically oversampled households who spent more at Chain A. But, since the profit margins are virtually identical, there is little reason to suspect bias in the price search efficiency regressions reported earlier. In terms of extreme cherry picking, only 1.2% of the 21,963 households (i.e., 255 out of 21,963 households) contributed a net negative profit to the store over the one-year period. As expected, the extreme cherry pickers were all secondary shoppers at Chain A.[20]

What are the characteristics of these extreme cherry pickers? Their average trip basket size is only \$13.60 (as opposed to \$33.34 for all households). Also, a trip-level analysis of these extreme cherry pickers indicates that about 27% (70) of these 255 households engaged in at least one almost exclusive “loss leader trip” during 2002. We considered a trip to be a loss leader trip if at least 90% of the items purchased were loss leader items and there were at least four such items in the basket. Finally, the spatial pattern distribution for these 255 households is consistent with our expectations. Most of the extreme cherry-picking households belonged to the SSS location pattern (44%). This was followed by the SLL (38%) and the LSL (18%).

What impact does this group of extreme cherry pickers (who are all secondary shoppers) have on the chain's overall profits? The net loss from these households is about .2% of the total aggregate positive profit to Chain A from the rest of their customers, about .8% of profits from customers belonging to the SSS location pattern (the ones most likely to do spatio-temporal shopping), and about 1.2% of profits from all secondary shoppers. We therefore conclude that extreme cherry pickers have little impact on overall retailer profitability.

Insights and Implications

Our findings have some interesting implications for managers and researchers. First, it appears that store-household spatial patterns have a significant impact both on households' stated price search patterns and their observed price search efficiency. In particular, distances between competitive stores and distance between stores and households interact in determining price search patterns. Not only do households choose the price search pattern (stated pattern) that maximizes their savings opportunities (given their cost of price search), they are also effective in taking advantage of these savings opportunities (as measured by objective price search efficiency).

Additionally, location and opportunity cost matter more than individual-specific traits such as perceived search skills and shopping mavenism in determining price search behavior. This has important implications for theoretical and empirical research. The results suggest that Hotelling-type models (widely used in theoretical research and structural econometric models of location) do capture the most important factors affecting consumer search. Many empirical models of store choice treat household locations as unobserved heterogeneity; our analysis highlights the fact that geographic location should be an important variable in explaining store choice. Second, the savings obtained from the spatial and temporal components of price search are insightful. On average, 54% of the potentially available savings can be obtained by sheer chance by an incidental cherry picker, while the most price-sensitive shoppers, shopping across both stores and time, only obtain 76% of the potentially available savings. This has interesting implications for evaluating the benefits of a promotion. A full-fledged structural model would be needed to evaluate the tradeoffs in a shift in promotion policy, but it is illuminating that an incidental cherry picker (who is not price sensitive) can take substantial advantage of a promotion by sheer chance.

Contrary to the conventional wisdom that people who shop across stores obtain greater savings, we find that households that engage in spatial search across stores do marginally worse (earning 66% of potential savings) than store-loyal households that search temporally across time (which earn 68% of potential savings).

Third, though incidental price searchers are the most profitable customers in terms of profit margins per dollar sold, temporal price searchers are the most profitable in terms of aggregate profits. The store loyals compensate for their lower margins with a much greater wallet share than the incidental cherry pickers. This suggests that price promotions serve an important defensive role in retaining store-loyal households (as theorized by Little and Shapiro 1980). If a retailer does not price promote, it is possible that many of the store-loyal households that engage in temporal price search may shift to a competing store to take advantage of spatial price promotions. Our results on information values showing that temporal variation is greater than spatial variation suggests that firms indeed take the defensive role of price promotions very seriously.

Households from even the most search-intensive segment (spatio-temporal) provide an average margin and total weekly profits that are only about 20% and 10% below those who do not search actively. Further, the common concern that there is likely to be a large group of extreme cherry pickers who purchase only loss leader items and therefore can have a substantial negative impact on profits is overblown. Only about 1.2% of the households in our study made a net negative contribution, and those net losses were around .2% of all profits from the profitable households. In short, there are very few households who only take advantage of loss leader items and buy nothing else at a store. Their collective impact on retailer profits is very minimal.

Limitations and Suggestions for Future Research

This study is constrained by certain limitations that suggest interesting possibilities for future research. First, this study focused on four sets of competitive stores within one suburban market. Clearly, it would make sense to investigate markets with different characteristics and see how those affect price search efficiency. Second, we have focused on price search efficiency across the entire basket of purchases made by households. While this does make sense as a first step, a deeper investigation of how price search efficiency varies across categories (e.g., stockpilable versus non-stockpilable; regularly versus irregularly purchased categories; impulse versus planned purchases, etc.) could offer marketing managers additional insights. Examples of studies on category characteristics are Narasimhan, Neslin, and Sen (1996) and Bell, Chiang, and Padmanabhan (1999). Also, it would make sense to study how price search efficiency is affected by the use of marketing mix variables such as features and displays. One may expect features to affect spatial efficiency more, while displays may affect temporal efficiency more. Overall, there is an opportunity to understand how price search efficiency varies as a function of market characteristics, category characteristics, and marketing mix variables.

In this study we focus on two dimensions of cherry picking: spatial (the "where" dimension) and temporal (the "when" dimension). A third way in which consumers can get lower prices for their groceries is through brand switching (the "what" dimension). Taking this third dimension into account could mean higher potential information values and greater opportunities for savings. But incorporating the brand-switching dimension of price search into estimates of price search efficiency is difficult because it requires extensive purchase histories from consumers or subjective judgments on the part of researchers to identify household-level substitute brands and consideration sets in each product category.

A systematic study of the effect of brand switching on price search efficiency was beyond the scope of this study and should be addressed in future research. Nevertheless, to gauge the robustness of our results, we compared price search efficiency in non-branded product categories (e.g., fresh meat, seafood, fruits, vegetables, and baked goods), where the brand-switching dimension is irrelevant, with price search efficiency in branded categories. As expected, the estimated price search efficiency is marginally higher for nonbranded product categories because there is no downward bias due to omission of brand switching. But the ordering of the segments based on stated cherry-picking patterns and spatial locations is identical to the results reported.

There is a long research tradition focusing on inferring consumer preferences and sensitivity to prices and other marketing mix variables using consumers' observed choice behavior. These analyses are typically for a single category. Recently, however, there has been a trend to study choices across categories (e.g., Manchanda, Ansari, and Gupta 1999; Chib, Seetharaman, and Strijnev 2002). In terms of store choice, a few papers model consumer store choice with data from a single category (e.g., Bucklin and Lattin 1992; Venkataraman 2004). Bell and Lattin (1998) model consumer choice between EDLP and High-Low store formats at the basket level rather than for a single category on the grounds that the consumer chooses a store based on the total cost of shopping for their entire basket. Their analysis accounts for crosssectional cherry picking across stores, but does not model temporal cherry picking. A model incorporating temporal cherry picking needs to extend the current literature on dynamic structural models of consumer choice (e.g., Sun, Neslin, and Srinivasan 2003) both in terms of estimation methodology and modeling.

We believe that the insights gained from our descriptive analysis of cherry-picking patterns across stores at the basket level should be useful in developing a structural model of store competition that accounts for the fact that consumers choose stores on the basis of their baskets of purchases and can choose from either temporal or spatial cherry-picking patterns. Further, with the increasing variety of retail formats available (e.g., mass merchandisers, supermarkets, wholesale clubs) for grocery purchases, there has been an interest in how consumers choose across retail formats depending on their locations and needs (e.g., Fox, Montgomery, and Lodish 2004). We hope our paper serves as a starting point for this interesting stream of research. ■

Appendix

List of Items for Various Multi-item Scale Constructs Used in the Empirical Analyses

All items were responses from mail surveys and were evaluated on a 5-point scale anchored by "strongly agree" and "strongly disagree."

1. Temporal Cherry-Picking Propensity (five items; Cronbach's alpha = .82)
I usually plan the timing of my shopping trip to a particular grocery store so as to get the best price deals offered at that store.[1]

There are times when I delay my shopping trip to wait for a better price deal.[1]

Although planned before making a shopping trip, I often do not buy some items if I think they will be on better deal shortly.[1]

I keep track of price specials offered for the grocery products at the stores I regularly buy from.[1]

To get the best price deals for my groceries, I often buy the items I need over two or three trips.[1]

2. Spatial Cherry-Picking Propensity (five items; Cronbach's alpha = .89)
I often compare the prices of two or more grocery stores.[2]

I decide each week where to shop for my groceries based upon store ads/flyers.[2]

I regularly shop the price specials at one store and then the price specials at another store.[2]

Before going grocery shopping, I check the newspaper for advertisements by various supermarkets.[3]

To get the best price deals for my groceries, I often shop at two or three different stores.[3]

3. Market Mavenism (four items; Cronbach's alpha = .89)
I like it when people ask me for information about products, places to shop, or sales.[2,4]

I like it when someone asks me where to get the best buy on several types of products.[2,4]

I know a lot of different products, stores, and sales, and I like sharing this information.[2,4]

I think of myself as a good source of information for other people when it comes to new products or sales.[2,4]

4. Perceived Search Skills (eight items; Cronbach's alpha = .71)
I know what products I am going to buy before going to the supermarket.[3]

I am a well-organized grocery shopper.[3]

Before going to the supermarket, I plan my purchases based on the specials available that week.[3]

I can easily tell if a sale/special price is a good deal.[3]

It is very difficult to compare the prices of grocery stores (reverse coded).[2]

It is very difficult to compare the quality of meat and produce between grocery stores (reverse coded).[2]

I prepare a shopping list before going grocery shopping.[3]
I presort my coupons before going grocery shopping.[3]

[1] New item developed in this study.
[2] From Urbany, Dickson, and Kalapurakal (1996).
[3] From Putrevu and Ratchford (1997).
[4] From Feick and Price (1987).

Notes

1. The Food Marketing Institute (2004) reports that average grocery spending per week for a household is about $90.

2. The University of Chicago's database for the Dominick's grocery chain has profit margins, but the data are not at the household level.

3. Fox and Hoch (2005) report that the average savings shoppers enjoy as a result of spatial cherry picking is about $15. They conclude that consumers with a median opportunity cost of time can have a net gain from cross-store within-trip price search. But there are no empirical insights on savings from temporal price search.

4. We will consider both a dichotomous and a continuous variable specification for distance in our empirical analysis.

5. We included a number of other demographic variables such as age of head of household, sex of primary shopper, household size, etc., in our empirical analysis, but these turned out to be insignificant. To conserve space, we omit discussion of the hypotheses associated with these variables.

6. We obtained Chain B's prices for products bought at Chain A through visits to Chain B, but it was not possible to observe the purchases of the consumers at Chain B's stores. While having purchase information from Chain B would have been ideal, we are able to answer our research questions without it. Given our objective of comparing stated price search propensity with observed search propensity, we accepted this tradeoff in data collection.

7. We restricted data collection to baskets from only about 10 households in any given week to make the manual data collection practical. Even with about 10 households added in a given week, we had to collect about 600-700 prices in any given week because we also needed to collect temporal price data for households that we began tracking in previous weeks. When we received more than 10 survey responses in a given week, we delayed data collection related to baskets of the excess households until we had a manageable list of prices (less than 700) to collect on any given week.

8. A median split of consumers along the temporal and spatial dimensions based on the sum of the corresponding price search propensity scales yields results that are similar to those we report in the paper.

9. The comparisons are reported in Table 6. The binary variables work better probably because of the threshold effects of distance in the decision to go shopping. With short distances, the time for shopping dominates travel time; hence store-household distance may have limited impact on household decisions to make a trip. As the household-store distance increases, households may decide to reduce household trips and consolidate their purchases.

10. The percentage of cross-store shoppers in our sample appears to be large, relative to the 10-15% reported in past research (e.g., Urbany, Dickson, and Key 1991; Slade 1995) even in the case of the two stores whose competitors are more than 2 miles apart (actual distances are 2.05 miles and 2.7 miles). This could be because mean distances between stores are greater than 2.5 miles. The average distance between a store and its closest competitor across all 158 stores of the cooperating chain is 4.7 miles. The trimmed mean (excluding the top and bottom 5% of observations) is 3.5 miles. The 75th percentile distance between competing stores is 4.3 miles. The fact that the average distance between competing stores is higher than the 75th percentile distance between competing stores may explain our above-average proportion of cross-store shopping.

11. We exclude 18 observations that had unusual spatial configurations (e.g., SLS, SSL etc.) that were not of interest.

12. Since SSS is treated as the base case in Table 5, we are unable to check our hypothesis that SSS households prefer spatio-temporal cherry picking. To see if that hypothesis was supported, we estimated the model with LLL as the base case, and indeed, SSS has significantly negative coefficients for the three price search patterns relative to the base case of spatio-temporal price search.

13. The coefficients for primary shopper and average number of items are insignificant and do not have any impact on the savings percentage reported when they are omitted from the regression.

14. A potential concern in interpreting relative savings from alternative price search patterns is that we use prospective temporal time windows (i.e., purchase week + next two weeks) to account for temporal search. Could results differ if we used both prospective and retrospective (i.e., purchase week +/− two weeks) time windows? But it is impossible to know the prices for the products purchased by the household at Chain B in the weeks before our survey began. Conceptually, the use of only prospective windows should not have any systematic effects on our results because the consumer inventory for the products during the survey week will be randomly distributed across both consumers and purchased categories. We verified this by restricting analysis of price search efficiency only along the temporal dimension within Chain A, where we had retrospective data. The average store-specific (Chain A) temporal efficiency for sample households using the three-week and five-week time window is virtually identical (.728 as opposed to .726), and the correlation between the two measures is .99. Therefore, using solely prospective time windows in the analysis should have no impact on the conclusions drawn.

15. From Table 5, we see that stated price search patterns already take into account the opportunity cost. Hence it is not surprising that when opportunity costs are included in Model 1 along with stated price search patterns, they are insignificant.

16. We checked if including self-reported household income rather than unit opportunity cost of time improved the fit. Household incomes has a correlation of .75 with

this opportunity cost measure. But with household income as a proxy for opportunity cost, the explanatory power drops to about 4.6%, suggesting that the income measure is a more noisy proxy for opportunity cost of time. However, the correlation of .75 also suggests that wage rates are a reasonably proxy when opportunity cost data are unavailable. We thank a reviewer for suggesting this check.

17. Opportunity cost is obtained through the survey in our study. When we use self-reported household income instead of opportunity cost, the regression still explains 22.3% of the variance in price search efficiency.

18. The results for the more comprehensive sample are similar and available from the authors. Due to the larger sample sizes, the estimates have much lower standard errors.

19. We considered Chain A to be the primary (secondary) grocery store for a household if the actual annual grocery spending of that household at Chain A in 2002 was at least 70% (less than 30%) of the average annual grocery spending for households residing in the same U.S. "Census Block Group" (CBG) as the given household. The CBG-level grocery spending data are available from syndicated data services. The classification results using this criteria for our sample 255 households had a correlation of .87 with classification results based on consumers' self-reports in our survey.

20. We found that only 1.7% of in-sample households (i.e., 4 out of 255) contributed a net negative margin during 2002. Chain A was the secondary grocery store for those households.

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