

**The Temporal and Spatial Dimensions of Price Search:  
Insights from Matching Household Survey and Purchase Data\***

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## **The Temporal and Spatial Dimensions of Price Search: Insights from Matching Household Survey and Purchase Data**

### **Abstract**

Price promotions are pervasive in grocery markets. A household can respond to price promotions by effective cherry picking through (1) spatial price search across stores and (2) temporal price search across time. But extant research has only analyzed these two dimensions of price search separately; therefore they under-estimate both the consumer response to price promotions and the impact of promotions on retail profit. In this paper, we therefore introduce an integrated analysis of spatial and temporal price search. We seek answers to three questions: First, what are the predictors of household decisions to perform either spatial or temporal price search, both or neither? Second, how effective are the temporal, spatial and spatio-temporal price search strategies in obtaining lower prices? Finally, what is the impact of alternative price search strategies on retailer profit? We use a unique data collection approach that combines household surveys with observed purchase data to address these questions. Our key results are: Geography (the spatial configuration of store and household locations) and opportunity costs are useful predictors of a household's price search pattern. Households that claim to search spatio-temporally avail about  $\frac{3}{4}$  of the available savings on average; even those that claim not to systematically search on either dimension avail about  $\frac{1}{2}$  of the available savings. Households that search only temporally save about the same as ones that search only spatially. The negative effect of cherry picking on retailer profits is not as high as is generally believed.

## **The Temporal and Spatial Dimensions of Price Search: Insights from Matching Household Survey and Purchase Data**

Weekly price promotions are a pervasive feature of grocery retailing. A.T. Kearney (2005) estimates that retailers spend from 5 to 10% of their gross revenues in a category on promotions. A.C. Nielsen (2006) estimates that U.S. retailers spent 26.7 billion dollars on promotions in 2005 and promotional sales accounted for roughly 41.5 % of total supermarket sales. Given such widespread use and the magnitude of the dollars spent, retail managers and academic researchers have a great interest in understanding how consumers react to retail price promotions and how it affects retailer profitability.

The theoretical literature offers two main rationales on why supermarkets offer promotions that are both based on heterogeneity in household price search behavior. The first explanation based on Varian (1980) relies on household heterogeneity in *spatial* price search across stores. Some consumers search a lot across stores, while others are loyal to their preferred store and do not search. Temporal price promotions arise in equilibrium as a means by which competing retailers offer low prices periodically to attract price sensitive consumers who search across stores, while charging high prices on average from the high search cost consumers who do not search across stores.

The second explanation based on Conlisk, Gerstner and Sobel (1984) and Sobel (1984) relies on household heterogeneity in willingness to search for low prices across time within a store; i.e., it relies on heterogeneity in *temporal* price search. Consumers with low willingness to pay shift their purchases to promotional periods when prices fall below their reservation prices (i.e., they are willing to search for low prices over time), while consumers with high willingness to pay purchase at regular prices. Conlisk et al. (1984) and Sobel (1984) model durable goods; in the context of frequently purchased nondurable goods, low willingness to pay customers who wait for the promotion, will also stockpile to cover their needs during the non-promotion periods, thus obtaining a low average price for the product (e.g., Mace and Neslin 2004; Neslin, Henderson and Quelch 1985; Jacobson and Obermiller 1990). Promotions serve as a price discrimination mechanism where high willingness to pay customers who do not search across time pay high prices on average, while low willingness to pay consumers who search across time pay low average prices.

To evaluate the profitability of price promotions, a retailer needs to understand how households cherry pick in response to price promotions by price search along both the spatial and temporal dimensions. But extant empirical research on price search treats these two dimensions of price search separately. Newman (1977) and Beatty and Smith (1987) provide an extensive review of the literature on spatial price search for durable goods. In recent years, several papers have also focused on understanding spatial price search in grocery markets using either actual purchase or survey data (e.g., Carlson and Gieseke 1983; Putrevu and Ratchford 1997; Fox and Hoch 2005). A parallel empirical literature has focused on the temporal dimension of price search. This literature investigates consumer response to promotions through stockpiling, purchase acceleration and purchase delays (e.g., Neslin, Henderson and Quelch 1985, Mela, Jedidi and Bowman 1998). Here consumers get low average prices for goods consumed over time merely by shifting their purchase timing or quantities, without doing cross-store shopping.

To our knowledge, there has been no empirical research on price search that investigates household price search jointly along the spatial and temporal dimensions. Yet, by accounting for only one of the dimensions of price search, we are likely to grossly underestimate the market's response to price promotions and consequently its impact on retailer profitability. Given the large body of research on consumer response to price promotions, we believe this is a significant void in the existing literature. We therefore introduce an integrated analysis of spatial and temporal price search in response to price promotions and the impact of such search on retailer profitability.

### *Research Questions*

In this paper, we seek to understand the heterogeneity in household's price search behavior in response to retail price promotions in order to evaluate the impact of the promotions on retail profitability. Our analysis seeks to answer three inter-related research questions. In order to understand the price search behavior of consumers, we need to describe and predict the characteristics of the different search segments so that the retailer can effectively use price search as a basis for segmentation. This leads to our first research question: What are the predictors of different types of consumer price search strategies? We use an economic model of price search, where households trade 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),

to generate predictors of search segment membership. We also use a number of household characteristics and attitudes (e.g., opportunity cost, search skill, shopping mavenism) variables as predictors. We then empirically test whether these variables are effective in predicting price search patterns.

Of particular interest as a predictor of price search strategy is geographic location, because this is an easy variable to use for targeted promotions. Theoretical models (e.g., Hotelling models) routinely use geographic locations to model search across stores, but there is limited empirical work on the role of geography to explain price search in grocery markets. 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 household and distance between households and the warehouse store in estimating store price elasticities, but do not consider distance between stores on the price elasticity. 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. Structural econometric models of price search (e.g., Thomadsen 2005; Chan et al. 2005) infer travel cost for consumers between stores by *assuming* that observed prices among competing stores are in equilibrium. They assume only spatial price search. To the best of our knowledge, the role of geography in household price search behavior along the temporal dimension has never been investigated.

The second question addresses the issue of the level of savings consumers obtain through search in grocery markets. Specifically, to what extent do households who follow different price search strategies (temporal, spatial, spatio-temporal) pay lower prices relative to households who do not search along either dimension? Are there differences in realized savings by searching along either the temporal or spatial dimension or along both dimensions? If indeed there are differences in savings realized by households following different price search strategies, then price search is potentially a useful segmentation variable. This leads us to our third research question. How do household price search patterns relate to retailer profits? Which of these search segments are most profitable? Which segment provides the greatest profit margins? Are there segments of consumers that contribute disproportionately to losses from promotions? Currently there is only speculation that cherry picking behavior by price sensitive shoppers adversely

impacts retail profitability (e.g., Dreze 1999; McWilliams 2004; Mogelonsky 1994). However, there is no systematic empirical evidence on this issue (Fox and Hoch 2005).

### *Data Challenges*

Answering the above research questions pose several major data challenges. Standard approaches using only surveys of *stated* household purchase behavior (e.g., Putrevu and Ratchford 1997; Urbany, Dickson and Kalapurakal 1996; Urbany, Dickson and Sawyer 2000), or only field or scanner data on *observed* household purchase behavior (e.g., Carlson and Gieseke 1983; Mela, Jedidi and Bowman 1998; Mace and Neslin 2004; Neslin, Henderson and Quelch 1985) cannot fully answer these research questions.

Surveys of price search behavior typically survey households on general aspects of price search behavior and attitudes towards price search, but are not explicitly linked to actual purchases at the store. Therefore we cannot measure the households' actual price search effectiveness or its impact on retailer profits using such data. On the other hand, scanner data sets also have several limitations. First, they do not have attitudinal data on price search (e.g., shopping mavenism). Second, typical scanner data sets obtained from firms such as Nielsen and IRI are only for a small number of product categories. Even the Stanford basket database does not cover categories like fresh produce and meat,<sup>1</sup> making an accurate characterization of consumer savings and the effect of price search on retailer profitability impossible. Since it is well-known that retailers feature loss-leaders to get consumers into the store who then buy other products at regular prices, retailer profitability measures of price promotions would be biased if we do not observe the complete basket of items bought by a household. Finally, scanner datasets have information about consumer choices and retail prices, but not on retail margins. The only widely available dataset with retail margins is the Dominicks Finer Foods dataset, but these data are not available at the household level.

To overcome these limitations, we undertake a primary data collection strategy that matches observational field and scanner data with survey data of the corresponding households to capture all the information required for our analyses. First, we enlisted the cooperation of one

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<sup>1</sup> Fresh produce and meat are both a significant component of a household's spending and more profitable to the retailer. In our data, they account for 26% of shopping expenditures and their retail margins are 53% higher than

retail chain in a market which is essentially a duopoly. The chain provided us information on the entire basket of purchases by a “live” panel of households and the chain’s profit margins on these items. However we needed two additional pieces of data. First, to measure the savings from spatial price search and price search effectiveness, it is also critical that we have information about the prices at the competing retailer. Second, we need survey data on household attitudes to shopping and shopping patterns. For this, we developed the following novel but labor-intensive primary data collection strategy.

We started by surveying a “live” panel of households who shopped at the cooperating retailer on their stated price search behavior as well as other shopping and attitudinal characteristics. We then tracked each of these household’s purchases over multiple shopping trips at the focal retailer over a time period of roughly a month. Using the “live” data on purchases by the household panel at the focal retailer, we then manually collected prices for the same products at the competing retailer for that week and two subsequent weeks after each of their tracked purchases at the focal retailer. In all, through direct field observations, we obtained prices on about 8,500 distinct product items over staggered three-week time windows (i.e., over 25,000 observations) from the competing retailer. By comparing prices across the two competing retailers over multiple weeks, we are able to make inferences about the gains from spatial and temporal price search as well as household price search effectiveness. We provide additional details about the data collection process later in the “Data” section.

## Conceptual Framework

### *Types of Price Search Strategies*

Consider a duopoly retail market for groceries where price variations occur temporally (across weeks, since cycle time for price changes is weekly) within a store and spatially across stores. The duopoly assumption is reasonable and consistent with reality in many US markets (Fox and Semple 2002) including the market we study.<sup>2</sup> Consumers can therefore benefit from both temporal and spatial price search. For purposes of exposition, we split consumers into high

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other categories. These categories are also frequently promoted, suggesting that a complete picture of price search and its impact on retailer profits can be obtained only if we include these categories.

<sup>2</sup> Grocery purchases through other retail formats have increased channel blurring (Inman, Shankar and Ferraro 2004). We abstract away from this issue and focus only on the supermarket format.

or low types along the temporal and spatial price search dimensions. This leads to the four types of price search strategies among grocery shoppers (see Figure 1 below).

[Figure 1 about here]

Some shoppers do not search actively either across stores or across-time. But they can still get low prices on promoted products because these products happen to be available on sale at their preferred store when they wanted to purchase them. We label this search strategy as “*incidental price search*.”

A second segment of shoppers tends to be mostly loyal to her preferred store and therefore do not take advantage of price variations across stores. This segment shifts purchases over time to avail themselves of promotions at their preferred store. We label this search strategy as “*temporal price search*.”

A third segment of shoppers takes trips across stores to pick the best contemporaneous prices (on any given shopping trip) to mostly take advantage of cross-store spatial price differences. This shopper is the focus of the cherry picking study by Hoch and Fox (2005). This shopper may have less store loyalty than the previous two segments; though it is quite possible they could buy most of their (non-deal) purchases at a preferred store and buy only low-priced items at other competing stores. We label this search strategy as “*spatial price search*”.

The fourth segment of shoppers takes advantage of both spatial and temporal price variations by making regular weekly shopping trips to both stores. These shoppers actively 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 strategy as “*spatio-temporal price search*”.

### ***What are the Predictors of a Household’s Price Search Strategy?***

We use a cost-benefit framework on the premise that consumers choose that search strategy which maximizes potential savings for the household, net of their costs (e.g., Urbany, Dickson and Kalapurakal 1996; Putrevu and Ratchford 1997). 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 U.S.,  $S$  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. We also consider certain stated personality characteristics and attitudes that may affect search behavior.

### *Geography*

We denote a consumer's geographic locations and the distances between the two closest competing stores for that consumer using the 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), though we will consider both a dichotomous and continuous variable specification for distance in our empirical analysis. We represent the relevant distances using a three dimensional vector  $D_{12}D_1D_2$ , i.e., if there is a segment with  $D_{12}=L, D_1=S, D_2=L$ , we will refer to that segment as LSL segment. We now explain our rationale behind how the spatial configurations of household and stores affect their choice of price search patterns. The pictorial descriptions below in Table 1 under the column "Most Likely Consumer-Store Spatial Pattern" can be helpful in understanding the logic of our expectations.

[Table 1 about here]

Our expectation about the effect of spatial configuration on search behavior is based on the following basic argument. When stores are close to each other i.e.,  $D_{12} = S$ , consumers will engage in greater spatial search; conversely, when stores are far away from each other i.e.,  $D_{12} = L$ , consumers will engage in limited spatial search. Similarly when the distance between a store and the consumer is small, i.e., when  $D_1 = S$  or  $D_2 = S$ , the consumer will visit the corresponding store more often, i.e., will engage in more temporal search at the store that is close to home; conversely, when  $D_1 = L$  or  $D_2 = L$ , the consumer will visit the corresponding store less frequently, i.e., will engage in less temporal search at the store that is far away from the home. Given these expectations, we now make specific predictions about the type of search pattern to be adopted by households with different types of store-household spatial configurations.

Households of type LLL, who are far away from either store and also face large inter-store distances, are not likely to search much either spatially or temporally and are therefore most likely to adopt incidental price search.

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

Households of the SLL type, who are far away from either store, but for whom stores themselves are close by, are most likely to use 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 store and shorter inter-store distances lead to greater cherry picking behavior. Our study nests this prediction as part of a broader set of expectations.

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 small inter-store distances.

We can also cross-validate the expectations about geography and price search by testing the price search effectiveness for the different geographic segments. Since the SSS segment searches both temporally and spatially, it should also have the greatest price search effectiveness. By the same logic, the LLL segment which searches neither temporally or spatially should have the lowest price search effectiveness. The LSL and SLL segments would have intermediate levels of price search effectiveness.

### *Personal Characteristics*

Spatio-temporal price search requires the most effort and time, while incidental price search requires the least effort. We therefore expect that an increase in *unit opportunity cost of time* for a household *reduces* the likelihood of spatio-temporal price search most and *increases* the likelihood of incidental price search most. The net effect on the likelihood of choosing the two other intermediate price search patterns cannot be ordered, but should lie between the two extreme patterns.

Some shoppers may have greater ability to remember prices and organize information and hence have lower cost to take advantage of market price variations through price search.

Such shoppers with greater *price search skills* who are more efficient in their price search are most likely to do least likely to do spatio-temporal price search and least likely to do incidental price search.

Some consumers may derive utility from the price search process itself. For example, *market mavens* are shoppers who obtain “psychosocial” returns from sharing relevant market information with others rather than by the direct economic benefit to themselves. Hence they collect relevant market information with the intent of sharing it with others (Feick and Price 1987; Urbany et al. 1996). Urbany et al. (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 positively associated with spatio-temporal price search.

The above expectations are summarized in Table 1 on the left panel under the heading “Determinants of Price Search Strategies.” We also 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 those turned out to be insignificant. To conserve space, we omit the discussion of the expectations associated with these other variables.

### ***How Effective are the Different Price Search Strategies in Obtaining Low Prices?***

We adapt a construct used by Srinivasan and Ratchford (1993) to measure returns to price search for durable goods to quantify a household’s observed *price search effectiveness* for grocery products. Intuitively, the effectiveness of a household’s price search is the ratio of realized price savings relative to maximum potential savings given the market price dispersions along both spatial and temporal dimensions. We propose the following measure of “*Price Search Effectiveness*” (PSE) for a household  $i$  based on all the items purchased across multiple shopping trips  $n_i$  tracked over about a month:

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

where  $BV_{ij}^{\max} = \sum_{k=1}^{m_j} Q_{ijk} P_{ijk}^{\max} =$  Maximum possible \$ value that could have been paid by household

$i$  for the shopping basket purchased on trip  $j$ , across stores and across time;

$$BV_{ij}^{\min} = \sum_{k=1}^{n_j} Q_{ijk} P_{ijk}^{\min} = \text{Minimum possible \$ value that could have been paid by household } i \text{ for}$$

the shopping basket purchased on trip  $j$ , across stores and across time;

and  $BV_{ij}^*$  is the actual \$ value that was paid by household  $i$  for the shopping basket purchased on trip  $j$ .

In the above formulation,  $Q_{ijk}$  is the purchased quantity for item  $k$ ,  $P_{ijk}^{\max}$  is the maximum market price for item  $k$  across stores and time,  $P_{ijk}^{\min}$  is the minimum market price for item  $k$  across stores and time. Since  $BV_{ij}^{\max}$  and  $BV_{ij}^{\min}$  include both spatial and temporal market price dispersion for all the items in the shopping basket for trip  $j$  under consideration, the *Maximum Potential Savings* is computed for each household “as if” they did perfect spatio-temporal price search. This enables us to evaluate the effectiveness of all households on a comparable basis. If all of the potential savings is captured, a household’s price search effectiveness is 100%. On the other hand, if every item was purchased at the highest price and thus no savings is captured by the household, the household’s price search effectiveness is 0%.

If households’ stated search patterns are consistent with observed behavior, then households who claim to search more get lower prices on average. The self-declared “*spatio-temporal*” households should obtain the lowest prices on average (highest price search effectiveness) and the self-declared “*incidental*” price search households should pay the highest prices (lowest price search effectiveness) on average. The other two segments should pay the intermediate level of prices. It is of empirical interest as to whether “*spatial*” households or “*temporal*” households are more effective in obtaining better prices on average. These expectations are summarized in Table 1 under the Column “Observed Price Search Effectiveness.”

### ***How do Price Search Strategies Affect Retailer Profits?***

Our expectation is that profit margins will be greatest from households that do the least search; and lowest from those households that do the most search. Therefore we expect profit margins to be the greatest for the incidental cherry pickers and lowest for the spatio-temporal cherry pickers. For the other two segments, the profit margins will be intermediate. Whether the

temporal cherry pickers have higher profit margins than the spatial cherry picker is an empirical question. These expectations are summarized in Table 1 under the column “Profit Margin.”

While we state specific expectations about the relative levels of profit margins for the different search strategies, we do not have specific expectations 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 be the most profitable in terms of aggregate profits. But the specific ordering of these two segments is an empirical question.

## Data

### *Data Collection Strategy*

The data is from four suburban areas of a mid-size city in the northeastern U.S. in 2003-2004. Each area is effectively a duopoly with two regional competing grocery chains accounting for more than 85% market share. We obtained the cooperation of one of the grocery chains, who provided us “live” access to customer transactions data at its stores on a daily basis. We label this cooperating chain as “Chain A” and the other chain as “Chain B.”

We selected a group of *four* stores of Chain A paying special attention to the relative geographic distance between each of those stores and the corresponding nearest stores from Chain B. Specifically, we chose *two* Chain A stores that had competing Chain B stores within half a mile and another *two* Chain A stores that had competing Chain B stores more than two miles away. This ensured that there was significant variation in inter-store distances in the data to test our expectations and the distances are reasonably consistent with the average inter-store distance of 1.43 miles and standard deviation for this suburban market. We also had geo-coding information for all the loyalty card customers of Chain A, which was used to compute consumer-store distances.

As stated in the introduction, we augmented the transactional data of consumers obtained from Chain A to help answer our research questions in two ways: (1) We surveyed these consumers about their search behavior and other relevant attitudes towards grocery shopping. (2) We collected the corresponding prices for the products purchased in Chain A in any given week at Chain B through direct observation by visiting Chain B.

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 qualify 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/her household and (2) should have a “loyalty” card from Chain A. The second criterion ensured that we had identifier information (loyalty card number) to scan the transaction database of Chain A for shopping visits by the respondent. Since over 95% of shoppers had a loyalty card, this was not very restrictive. If the intercepted shoppers met the qualifying criteria, the interviewer collected the following information about them: (1) loyalty card number (2) which store they considered their 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 with a request to return the finished questionnaires in pre-paid return envelopes. If the responses were not returned within a month, we sent a reminder. We obtained responses from 255 shoppers at 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 data base 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 shopping basket of the respondent over that week and the two following weeks at Chain A from the transaction database of Chain A. We obtained the *contemporaneous* price data from Chain B for all products in that household’s basket by visiting the competing Chain B store for that week and the following two weeks.<sup>3</sup> This systematic (and labor-intensive) data collection approach ensured that we collected complete information on actual prices paid by a consumer as well as the temporal (over three weeks) and

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<sup>3</sup> We restricted data collection to baskets of 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 inter-temporal price data for households that we began tracking in the previous 2 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 “lean” capacity to perform the data collection.

spatial (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 performed the same process of obtaining price information for purchased items in their baskets for multiple trips. For most households we obtained information for 3 trips. For a few households, we were able to obtain only data on 2 trips within the data collection period. Overall, we collected price data on about 8,500 distinct items over 710 shopping trips for the 255 households who responded to our survey. Considering 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 6 months in 2003 and 2004. Note that if a household did not use a loyalty card, it would not be found in our data. About 87%-90% of the ACV in the selected four stores in Chain A is accounted for by loyalty cards. However, since a household may not use a loyalty card when it does not avail of price promotions, our data may marginally over-estimate price search effectiveness and underestimate retailer profit margins.

Finally, in order to address the question of the impact of price search on the retailer's profits, we obtain information about profits and profit margins of the 255 sample households with respect to Chain A 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 customer profitability due to cherry picking.

### ***The Measures***

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

We draw on Feick and Price (1987) and Urbany et al. (1996) to construct the "market mavenism" measure. The "perceived search skills" construct is based on Putrevu and Ratchford

(1997) and Urbany et al. (1996). While existing studies of consumers' stated price search propensity focus only on spatial price search, we distinguish between consumers temporal and spatial price search propensities. We draw on existing research for the five items used in the spatial price search propensity scale. We developed the five items used in the temporal price search propensity scale.

We perform a two segment cluster analysis (using Ward's method with squared Euclidean distances) of consumers' stated temporal and spatial price search propensity measures to classify consumers into high and low types along each dimension. The average score on the temporal price search propensity for the high and low segments were 3.6 (s.e. = 0.039) and 2.1 (s.e. = 0.054) on a 5 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 the spatial price search propensity is 4.01 (s.e. = 0.038) and 2.32 (s.e. = 0.064) indicating a high degree of discrimination between the high and low types on the spatial dimension as well. We also tested for the robustness of our results using a median split of consumers along the temporal and spatial dimensions based on the sum of the corresponding price search propensity scale items. The results are similar with such a split.

The observed price search effectiveness of each household was computed across multiple shopping trips (2-3 trips) at Chain A. It takes into account both the cross-store (across Chain A and Chain B) and inter-temporal (over 3 weeks since the week of purchase) price dispersion in the market for all the items purchased in a trip. As these tracked trips for each household are spread typically over a month, the measure can be interpreted as the observed price search effectiveness of the household over a basket of monthly purchases at Chain A.

As Putrevu and Ratchford (1997) point out in their study, it is very difficult to develop a multi-item scale for the unit opportunity cost measure exhibiting high scale reliability. At the same time, using the respondent's actual wage rate as a measure requires us to impute a wage rate for those who do not work. We follow 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 represent spatial pattern with three variables: distance of household to closest Chain A store ( $D_1$ ) and Chain B store ( $D_2$ ) and distance between the two stores ( $D_{12}$ ). Shopping trips involve fixed costs of travel to the stores and the actual time cost of 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. Hence we expect that the effect of distance on number of trips taken to have threshold effects. Therefore a binary categorization of distances seemed conceptually appropriate. We use the research design driven natural break to classify stores close to each other ( $D_{12} < 0.3$ ) miles as “small” and stores far away from each other ( $D_{12} > 2$ ) miles as “large”. For distance between the household and the store, we report results using a median split (1.8 miles) to classify distances as large or small. Our results are robust to changes in the split threshold over a wide range (1.4-2.2 miles) around the median value. We also test for whether threshold effects exist by directly including distance variables into the regression.

## Results

### *What are the Predictors of a Household’s Price Search Strategy?*

We first report a cross-tabulation of stated price search patterns against the geographic configuration of the household and stores in Table 2. For spatio-temporal, spatial and temporal price search, the diagonal elements of the table have the highest frequency corresponding to each column, suggesting support for our expectations on the role of geography described earlier. For instance the SSS configuration is most common among spatio-temporal price search households, the SLL configuration is most common among spatial price search households and the LSL configuration is most common among temporal price search households. The incidental price search households are evenly distributed across the different types of location configurations suggesting that opportunity cost should have an additional role besides geography in explaining the price search patterns. However it should be noted that LLL households almost always choose incidental price search, consistent with our expectations.

[Table 2 about here]

The results of the multinomial logit regression model are reported in Table 3. The main explanatory variables are the cost of search variables: (1) the location configuration of the households and stores and (2) unit opportunity costs. Besides we use individual specific variables

such as perceived search skills, and shopping-related personality traits such as the self-perception of being a “market maven.”

[Table 3 about here]

The multinomial logit regression results are reported in three columns- one for each price search pattern, i.e., each variable of interest has different effects on the likelihood that a certain price search pattern is chosen. We have only three columns because we treat incidental 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 expectations about the role of location configuration on price search patterns are supported by the data. First, we interpret the spatial configuration estimates across columns. The coefficient of SLL is highest (2.07) for spatial price search as expected; i.e., households which are far away from both stores, but the stores themselves are close to each other are more likely to do spatial price search. The coefficient for LSL/LLS is significantly negative for spatial and spatio-temporal price search, suggesting that when stores are far apart households are less likely to spatial search. However the positive coefficient (correct sign) for temporal search is not significantly different from the base “incidental” price search case. The coefficient of LLL is significantly negative with respect for spatial, temporal and spatio-temporal price search as expected, suggesting that incidental price search is the most likely search pattern for the LLL household. Since SSS is treated as the base case in Table 3, we are unable to check whether SSS households prefer spatio-temporal cherry picking. We therefore estimated the model with LLL as the base case. Indeed SSS has significantly positive coefficients for the three price search patterns relative to the base case of incidental price search, supporting our expectation.<sup>4</sup>

Opportunity cost is significant and negative as expected for all price search patterns, suggesting that an increase in opportunity cost decreases the likelihood of all three types of price search relative to incidental price search. An increase in opportunity cost has the greatest impact in reducing the likelihood of using spatio-temporal price search (-0.24) relative to incidental price search. The marginal effect of opportunity cost on temporal price search (-0.10) and spatial

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<sup>4</sup> A challenge with using LLL as the base case in the regression is that almost all LLL households do incidental price search; therefore the predictor matrix becomes close to a singular matrix, leading to high standard errors on some of the coefficients.

price search (-0.08) is not significantly different, though we expected the effect to be greater for spatial price search since that requires 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 that they are more skillful tend to do more spatial (2.11) and spatio-temporal price search (2.08) relative to temporal (1.19) or incidental price search (base case). 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 have a positive coefficient for spatial, temporal and spatio-temporal search as expected, 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 3 is 0.45. With the location variables removed, the  $U^2$  drops to 0.33. With location and opportunity cost removed, the  $U^2$  with the perceived price search skills and mavenism drops to 0.09. Thus while attitudinal variables do help to explain stated price search patterns, location and opportunity costs are the most important variables in explaining observed price search effectiveness and promotional responsiveness. This is particularly useful for retailers because they can implement targeted promotions using household geographic location and opportunity cost-- information that is readily available to retailers from syndicated sources.

### ***How Effective are the Different Price Search Strategies in Obtaining Low Prices?***

We next regress observed price search effectiveness against the stated price search patterns of households. We include 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 4.

[Table 4 about here]

As expected, the incidental cherry picker has the lowest price search effectiveness, but is still 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 who do spatio-temporal cherry picking are able to obtain as much as 76% (intercept

+ spatio-temporal) of the maximum potential savings.<sup>5</sup> Thus, spatio-temporal cherry pickers have 22 percentage points greater price search effectiveness relative to incidental cherry pickers; the corresponding differences with respect to pure spatial cherry pickers and pure temporal cherry pickers are 14% and 13% respectively.<sup>6</sup>

Our results suggest that conscientious shoppers who shop at only one store but shift their purchase timing to take advantage of price specials at their loyal store can still obtain a significant fraction of the maximum potential savings. Those who additionally engage in spatial cherry picking (i.e., spatio-temporal) increase their realized savings by an additional 8% of the maximum potential savings. Perhaps, the most intriguing finding is that about 54% of the maximum possible savings are obtained by “incidental search” households who do not search for low prices at all. In other words, even a household which is not *actively* seeking price promotion deals, typically ends up capturing about half of the potential savings created by market promotions. Note that even if the household claims to not actively seek price promotions, it can purchase accelerate or stockpile when it sees a promotion.

In Model 2, rather than using stated price search patterns as explanatory variables, we use the underlying “drivers” – location, opportunity cost and attitudinal variables that we had identified earlier (see Table 1) to explain price search effectiveness. The results are consistent with our expectations. We find that SSS households have the greatest price search effectiveness (has the highest estimated coefficient of 0.327) and the LLL households have the lowest price search effectiveness (all estimated price coefficients are positive, when LLL is the base case).

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<sup>5</sup> The coefficient 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.

<sup>6</sup> As noted earlier, these relative price search effectiveness results across alternative price search patterns are based on our use of “prospective” time windows (i.e., purchase week + next 2 weeks) to account for temporal search. Could results differ if we used both “prospective” and “retrospective” (i.e., purchase week +/- 2 weeks) time windows? But it was impossible for us to make “retrospective” field observations of competing prices at Chain B in weeks before the specific product items are purchased by a household at Chain A. However, conceptually, the use of only prospective windows should not have any systematic effects on our results because consumer inventory for the product during the survey week will be randomly distributed across both consumers and purchased categories. We verify this by restricting our analysis of price search effectiveness only along the temporal dimension within Chain A, where we have retrospective data. For our sample households, the correlation of such price search effectiveness values between the 3-weeks and 5 week time windows is 0.99 and the averages are virtually identical (0.728 vs, 0.726). Therefore the use of only prospective time windows in the analysis is unlikely to have much impact on the conclusions drawn.

Interestingly, we find that these underlying location variables have greater explanatory power than the stated price search patterns themselves.<sup>7</sup> The  $R^2$  of the model increases from 16.4% to 26% when the underlying determinant variables of location 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 observed price search effectiveness. Of the 24.9%  $R^2$ , 17.7% comes from the location variables and 7.2% comes from unit opportunity cost of time.<sup>8</sup> This is an encouraging result because it suggests that geography and opportunity cost, information on which are easily available to retailers, are the most useful predictors of how effective consumers are in taking advantage of price promotions. We further validate this later by using these variables to predict consumers' stated price search patterns.

Unfortunately, much of recent research on households' store choice using scanner data treats location and attitude/motivation variables as unobserved heterogeneity (e.g., Bucklin and Lattin 1992, Popkowski Leszczyc, Sinha and Timmermans 2000) and focus 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. Thus the omission of location information in empirical models of store choice (which treat locations as a source of unobserved heterogeneity) is a serious limitation. Our results also suggest that the extant theoretical research on retailer choice models that uses store and consumer locations and consumer opportunity costs within Hotelling framework (e.g., Thomadsen 2005; Chan, Seetharaman and Padmanabhan 2005) does in fact incorporate the empirically most important tradeoffs in their models.

In Model 3, we report the results using distances directly in the model rather than as binary variables. As expected, we find that the distances between a household and its focal store and the distance between the focal and the competing stores have negative impact, demonstrating that greater distances to the focal store and between the competing stores reduce the observed

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<sup>7</sup> As stated price search patterns already account for opportunity cost, it is not surprising that opportunity cost is not significant in Model 1, if it were included. Hence we do not include opportunity cost in Model 1.

<sup>8</sup> We checked if including self-reported household income rather than unit opportunity cost of time improves the fit. Household's incomes have a correlation of 0.75 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 noisier proxy for opportunity cost of time. However, the correlation of 0.75 also suggests that wage rates are a reasonably proxy when opportunity cost data is unavailable. We thank a reviewer for suggesting this check.

price search effectiveness of the household. 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 the Model 2 with discretized distances has greater explanatory power, suggesting evidence for threshold effects of distance in the decision to go shopping.

In all three models, we do not find the average trip basket size to be significant. In retrospect, this is not surprising because as basket values increase the potential benefits increase; hence even though observed price search effectiveness does not change with basket size, the total savings obtained increases as basket size increases. This argument is validated later in Table 3.

We note here a difference in our study with respect to Fox and Hoch (2005). Unlike Fox and Hoch who demonstrate that households shop across stores on a single day more often when they have larger baskets to purchase, we do not test the endogeneity of trip size. First, we do not have data on whether consumers actually shopped at multiple stores on a single day to test this. Second, this is reasonable given our research focus of segmenting households based on their overall price search behavior, rather than segmenting the trips themselves. We measure average price search effectiveness of a household not over a given trip (as in Fox and Hoch), but over all trips in a given month.

Thus far, we have focused on the differences in observed price search effectiveness for the different price search patterns. Another interesting question is what is the range of observed price variation in the market in the spatial dimension, temporal dimension and spatio-temporal dimensions? The average range of price variation has a natural interpretation: it can be interpreted as the “Information Value” of search along that dimension, because that is the maximum potential savings that households can typically obtain by searching along that dimension (Baye, Morgan and Scholten 2003). We report the information value (i.e., the average of maximum potential savings) along the spatial, temporal and spatio-temporal dimensions based on the 710 tracked shopping baskets in our data in Table 5. To gain insights about the role of basket size on potential benefits from search, we also report these values grouped by basket sizes. Note that we do not report information values for incidental price search, because any savings obtained is not from “active” search.

[Table 5 about here]

As expected, we find that the information value is greater for larger baskets across the three different search patterns that consumers can actively engage in. In fact the information value is convex in basket size, i.e., savings from large baskets are more than proportionately greater compared to small baskets. On basket values greater than \$90, along the spatio-temporal dimension, 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 information value is greatest along the spatio-temporal dimension across all basket sizes (\$11.99). Interestingly, the information value of \$8.49 from price search on purely the temporal dimension is greater than \$7.20 savings from search on purely the spatial dimension. While we recognize that this result should be tested for generalizability across other retailers and in other competitive environments, it is an interesting and surprising empirical finding that potential for savings is greater from temporal search compared to spatial search in this market.

### ***How do Price Search Strategies Affect Retailer Profits?***

How do price search patterns affect retailer profits? We use data on actual shopping trips at Chain A by the 255 surveyed households over 52 weeks in the year 2002 to compute average profit margins and weekly profits to the store. By using data over the whole year (rather than during the study period), we obtain more robust measures of profits.

The top panel of Table 6 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 at Chain A.

The averages across different price search patterns are consistent with our expectations. 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 effectiveness, we find that households who do temporal or spatial price search provide intermediate profit margins. Our results are also reassuring to retailers in the sense that even the most price search intensive spatio-temporal segment brings 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 store loyal temporal segment has lower margins than incidental segment, their average wallet is 67%, compared to the 60% wallet share of households who do incidental price search. This explains why we have greater average profits from households in the temporal segment even though they have lower profit margins.

The averages in Table 6 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. In contrast, 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.<sup>9</sup>

[Table 6 about here]

To check whether the above differences in averages of margins and weekly profits across the different segments statistically significant, we performed regressions with different store performance measures as dependent variables and the stated cherry picking patterns/spatial pattern as explanatory variables. We also included additional control variables (e.g., household size). As reflected in our analysis of means in Table 6, the regression results show that the relative differences are not only consistent with our expectations, but they are also statistically significant.

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

Our analysis above shows that all of the price search segments are profitable on average. With the increased use of loss-leaders in grocery retailing, one concern in the academic and trade literature (e.g. Dreze 1999; McWilliams 2004; Mogelonsky 1994) is that there are some

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<sup>9</sup> The average weekly basket size taking into account the purchases at Chain A and the stated share of Chain A is \$62.48 (about \$65 including taxes on non-food items). This estimate is at the low end of published estimates of

“extreme” cherry pickers – the so called “devils” customer group – who mostly buy only loss-leader items, thus in fact yielding negative gross margins for the retailer. If the proportion of such cherry picking households is indeed large, loss leader pricing to increase store traffic may be very unprofitable and one may need strategies to discourage such households. (Dreze 1999, Levy and Weitz 2004). We therefore seek to quantify the size of the extreme cherry picking segment and the extent of losses due to them.

For a robust analysis of extreme cherry picking households, we needed a larger sample than the 255 we used in the previous analysis. We therefore use a database with *all* loyalty-card holder households at 2 stores (one with competitive store very close; the other with competitive store much further away – they are also 2 of the 4 stores used in our actual sample study) of Chain A for whom we have their 9 digit zip code data. These 21,963 households account for over 75% of total sales in 2002 in each of the stores. We also infer whether these households use Chain A as their primary grocery store.<sup>10</sup> For comparison with our in-sample households, we report the same measures as for the in-sample households (except the self-reported wallet share measures) in the bottom panel of Table 6.

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 that our surveyed sample systematically over-sampled households who spent more at Chain A. But, since the profit margins are virtually identical, there is little cause for bias in the price search effectiveness 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) contribute a net negative profit to the store over the one year period. As expected, these are all secondary shoppers with respect to the Chain A. The small number is consistent also in our sample of 255 households. Only 1.7% of in-sample households (i.e., 4 out

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weekly household expenditures. This may be because the stated share of Chain A might have not properly accounted for purchases of non-food products through other channels such as drug-stores, warehouse clubs etc.

<sup>10</sup> Chain A is classified as primary (*secondary*) store for a household if the actual annual grocery spending of that household at Chain A in 2002 is at least 70% (*less than 30%*) of the average annual grocery spending for households residing in the same US “Census Block Group” (CBG) as the given household. The CBG level grocery spending data is available to Chain A from syndicated data services. The classification results using this criteria for our sample 255 households has a correlation of 0.87 with those based on consumers’ self-reports in our survey.

of 255) contributed a net negative margin during 2002; again these four households were also secondary shoppers with respect to Chain A.

What are the characteristics of extreme cherry pickers? Their average trip basket size is only \$13.60 (vs. \$33.34 for all households). Also a trip level analysis of these extreme cherry pickers indicate that about 27% (70) of these 255 households engaged in at least one “exclusive loss leader trip” during 2002. We characterized an “exclusive loss leader trip” as a shopping trip where at least 90% of all the items purchased by the customer on that trip are loss-leader items and there are at least four such items in the basket. Finally, the spatial pattern distribution for these 255 households is consistent with our expectations. In terms of grouping the extreme cherry picking households by location patterns, the largest group belonged to the SSS location pattern (44%). This was followed by the SLL with 38% and LSL with 18%.

What is the impact of this extreme group of cherry pickers (who are all secondary shoppers) on the chain’s overall profits? The net loss from these households are about 0.2% of the total aggregate positive profit to Chain A from the rest of their customers, about 0.8% of profits from customers belonging to the SSS location pattern (the ones most likely to do cross-store inter-temporal shopping) and about 1.2% of profits from the all secondary shoppers. We therefore conclude that extreme cherry pickers have little impact on overall retailer profitability. This is in stark contrast to conventional wisdom that losses produced by these extreme cherry pickers (dubbed as “devils”) wipe out profits generated by the profitable customers (dubbed as “angels”) (McWilliams 2004). However the generalizability of our finding needs to be assessed with future analyses across other market and product contexts.

## Conclusion

This paper introduces an integrated analysis of spatial and temporal price search in response to price promotions and its impact on retailer profitability. Extant research has treated the temporal and spatial dimensions separately and therefore underestimated the impact of retail promotions on household response and retail profitability. Using a novel, but labor intensive data collection approach that combined observational and survey data, we assembled a dataset amenable for such an integrated analysis. The key empirical insights from our analysis are as follows:

- (1) Price search patterns and price search effectiveness are largely driven by geography (store and consumer locations) and opportunity costs. Other individual specific variables have

limited impact. This suggests that a retailer can implement targeted promotions using price search as a segmentation variable because of the easy availability of geography and demographic data.

- (2) Pure temporal and spatial price search households roughly have the same levels of price search effectiveness. Consumers who claim not to search at all (“incidentals”) obtain roughly 50% of the potential savings by being at the right place at the right time. Even the segment that searches most (the spatio-temporal segment) saves only about 75% of the potential savings in the market place.
- (3) The temporal search segment contributes most to the total profits of the retailer, even more than the incidental price searchers, who have greater profit margins. This suggests that periodic price promotions serve an important defensive role in retaining profitable store loyal households (as theorized by Little and Shapiro 1980).
- (4) Contrary to conventional wisdom that extreme cherry pickers have a significant negative impact on retailer profits, we find that the impact of these households on retail profits is minimal.

#### *Limitations and Suggestions for Future Research*

There are certain limitations in this study that suggest interesting possibilities for future research. First, we focused on four sets of competitive stores within one suburban market. Clearly, future research should investigate markets with different characteristics to assess both the generalizability of our specific results and to also investigate how these characteristics affect price search effectiveness. Specifically stores tend to be clustered closer in urban/suburban markets, but tend to be farther apart in rural markets. Hence the proportion of people following different price strategies is likely to be different in such markets, though our inferences of price search effectiveness and retail profit margins for the different search strategies are likely to be more stable.

Second, we focused on price search effectiveness across the entire basket of purchases made by households. While this is a useful first step, a deeper investigation of how price search effectiveness varies across categories (e.g., stockpilable versus non-stockpilable; regularly versus irregularly purchased categories; impulse versus planned purchases etc.) could provide additional

insights to marketing managers. Examples of studies on category characteristics are (Narasimhan, Neslin and Sen 1996, Bell, Chiang and Padmanabhan 1999).

Third, it would be worthwhile to study how price search effectiveness can be 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 effectiveness varies as a function of (1) market characteristics, (2) category characteristics and (3) marketing mix variables.

In this study we investigated the spatial and temporal dimensions of cherry picking. A third dimension in which consumers can choose to get lower prices for their groceries is through brand-switching (the “brand” dimension). Accounting for this third dimension could mean that the opportunity for savings in the market could be greater. But incorporating the brand dimension of price search in estimating price search effectiveness is difficult because it requires extensive purchase histories of consumers or subjective judgments by researchers to identify household level “substitute brands and consideration sets” in each product category. Nevertheless, to gauge the robustness of our results, we compared price search effectiveness in branded categories against non-branded product categories (e.g., fresh meat, seafood, fruits, vegetables and baked goods), where the brand switching dimension is irrelevant. As expected, the estimated price search effectiveness is marginally higher for non-branded product categories (0.67 vs. 0.64) because there is no downward bias from ignoring brand switching. But the ordering of segments based on stated price search patterns and spatial locations are identical to the results reported. However, a systematic study of cherry picking that includes the brand dimension along with the spatial and temporal dimensions should be a focus of future research.

One data limitation of our study is that we only have data on purchases from one chain. It is reasonable to question whether the absence of purchase data from the second chain might bias our estimates of price search effectiveness and retail profits. Fox and Hoch (2005) show that households selectively use secondary stores on cherry picking trips to disproportionately purchase promoted items. In our data, about 20% of shoppers were secondary shoppers at Chain A. Consistent with Fox and Hoch, we do find that secondary shoppers on average have higher price search effectiveness and lower profit margins (0.68, 0.22) relative to primary shoppers (0.67, 0.23). But since our data from Chain A includes both secondary and primary shoppers, our estimates are unlikely to be biased as long as secondary shoppers are correctly represented in our

sample. Future research with larger sample sizes should systematically test for any differences in the temporal and spatial price search behavior of primary and secondary shoppers.

There is a long research tradition on inferring consumer preferences and sensitivity to prices and other marketing mix variables using consumer's observed choice behavior. These analyses are typically for a single category. There has been a recent trend in studying 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 and Kadiyali 2004). Bell and Lattin (1998) model consumer choice between EDLP and High Low Store formats at the basket level rather than a single category on the grounds that consumer decides on store choice based on the total cost of shopping for their entire basket. This analysis accounts for spatial cherry picking, 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.

The insights gained from our descriptive analysis of cherry picking patterns across stores at the basket level should be insightful 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 inter-temporal or cross-store 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., Inman, Shankar and Ferraro 2004, Fox, Montgomery and Lodish 2004). We hope our paper serves as an impetus for launching such an interesting stream of research.

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**Figure 1: Segmentation by Price Search Patterns**

		<b>Temporal Price Search</b>	
		<b>Low</b>	<b>High</b>
<b>Spatial Price Search</b>	<b>Low</b>	Incidental Price Search	Temporal Price Search
	<b>High</b>	Spatial Price Search	Spatio-temporal Price Search

**Table 1: Summary of Expected Relationships and Empirical Results**

Consumers' Stated Price Search Pattern	Determinants of Price Search Patterns				Effect of Search Patterns on Price Search Effectiveness and Profit Margins	
	Most likely consumer-store spatial pattern	Market mavenism	Opportunity cost of time	Perceived search skills	Observed price search effectiveness	Profit Margin
Incidental LLL ✓		Most Negative ✓	Most Positive ✓	Most Negative ✓	Lowest ✓	Highest ✓
Temporal LSL ✓						
Spatial SLL ✓						
Spatio-Temporal SSS ✓		Most Positive ✓	Most Negative ✓	Most Positive ✓	Highest ✓	Lowest ✓

Note: ✓ indicates support for the expectations based on our empirical results at  $p < 0.05$ .

**Table 2: Cross Tabulation:  
Stated Price Search and Household-Store Geographic Configuration**

Household-Store Configuration	Stated Price Search				Total
	Spatio-temporal	Spatial	Temporal	Incidental	
SSS	50	4	6	15	75
SLL	17	35	3	18	73
LSL	13	1	32	17	63
LLL	2	1	1	19	23
Total	82	41	42	69	234

**Table 3: Multinomial Logit Regression: Determinants of Price Search Patterns  
(Incidental Price Search and SSS is Base Case)**

	Spatial	Temporal	Spatio-temporal
	Estimate (Std. Err)	Estimate (Std. Err)	Estimate (Std. Err)
Intercept	-9.25*** (2.35)	-3.16** (1.51)	-3.05* (1.77)
SLL	2.07** (0.81)	-0.19 (0.77)	-0.48 (0.73)
LSL/LLS	-2.51* (1.29)	0.62 (0.62)	-1.97*** (0.70)
LLL	-12.01 (15.68)	-2.93*** (0.84)	-5.52*** (0.97)
Opportunity Cost	-0.08*** (0.03)	-0.10*** (0.02)	-0.24*** (0.03)
Market Mavenism	1.07*** (0.33)	0.54** (0.28)	0.71** (0.29)
Perceived Search Skills	2.11*** (0.58)	1.19*** (0.45)	2.08*** (0.51)

\* p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01

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

**Table 4: Regression results for price search effectiveness across tracked multiple shopping trips**

Explanatory Variable	Dependent Variable: Observed price search effectiveness across multiple shopping trips		
	Model 1	Model 2	Model 3
	Estimate (Std. Err)	Estimate (Std. Err)	Estimate (Std. Err.)
Stated Cherry Picking Behavioral Pattern			
Spatio-temporal	0.221 <sup>***</sup> (0.033)		
Temporal	0.143 <sup>***</sup> (0.039)		
Spatial	0.129 <sup>***</sup> (0.045)		
Incidental (used as “base” category)			
Consumer-Store Spatial Patterns			
SSS		0.327 <sup>***</sup> (0.045)	
LSL/LLS		0.250 <sup>***</sup> (0.046)	
SLL		0.230 <sup>***</sup> (0.045)	
LLL (used as “base” category)			
Distance to the focal store			-0.011 <sup>*</sup> (0.006)
Distance between stores			-0.019 <sup>**</sup> (0.008)
Distance to focal store × Distance between stores			-0.003 <sup>*</sup> (0.002)
Unit opportunity cost of time		-0.003 <sup>***</sup> (0.001)	-0.003 <sup>***</sup> (0.001)
Market mavenism		0.007 (0.015)	0.001 (0.015)
Perceived search skills		0.011 (0.023)	0.031 (0.022)
Primary shopper with respect to focal store	-0.008 (0.045)	-0.086 (0.047)	0.032 (0.045)
Average number of items per tracked shopping trip	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)
Intercept	0.536 <sup>***</sup> (0.051)	0.516 <sup>***</sup> (0.094)	0.654 <sup>***</sup> (0.098)
R <sup>2</sup>	0.164	0.260	0.222
N	228	222	222

\* p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01

Note: We also included various demographic variables (age, sex, income, and household size) in the models, but none of them were significant and therefore not included here in the regressions we report. Also unit opportunity cost of time was not significant when included as a regressor in Model 1.

**Table 5: “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)
<b>Sample average: \$31.22</b>	<b>\$7.20 (5.65)</b>	<b>\$8.49 (6.45)</b>	<b>\$11.99 (9.39)</b>

**Table 6: Averages of Retailer Performance Measures at the Cooperating Chain**

Store Performance Related Measures at the cooperative retail chain	For All Shoppers	By Stated Price Search Pattern				By Observed Household-Store Spatial Configuration			
		Spatio-temporal	Temporal	Spatial	Incidental	SSS	LSL	SLL	LLL
<i>Surveyed Sample</i> (N = 255)									
Avg. profit margin <sup>1,2</sup>	0.23	0.21	0.22	0.23	0.26	0.19	0.24	0.24	0.33
Avg. trip frequency <sup>1</sup>	0.94	1.18	1.12	0.74	0.66	1.21	1.02	0.77	0.48
Wallet share <sup>1,3</sup>	0.61	0.62	0.67	0.56	0.60	0.63	0.70	0.62	0.53
Avg. trip basket size <sup>1</sup>	\$35.43	\$25.30	\$33.28	\$30.65	\$51.22	\$25.78	\$33.91	\$35.38	\$67.96
Avg. weekly profit <sup>1,2</sup>	\$7.20	\$6.83	\$8.67	\$5.85	\$7.47	\$6.57	\$8.78	\$6.45	\$9.06
<i>All Households at two of the stores included in study</i> (N = 21,963)		Not Applicable							
Avg. profit margin <sup>1,2</sup>	0.25					0.21	0.26	0.25	0.32
Avg. trip frequency <sup>1</sup>	0.72					1.04	0.76	0.60	0.45
Avg. trip basket size <sup>1</sup>	\$33.34					\$25.26	\$30.73	\$35.25	\$44.34
Avg. weekly profit <sup>1,2</sup>	\$5.58					\$5.21	\$5.93	\$5.42	\$5.99

<sup>1</sup> Based on actual purchase scanner data over one year (2002).

<sup>2</sup> Scaled for confidentiality reasons.

<sup>3</sup> Based on self-reported data from survey (2003).

## Appendix

### List of items for various multi-item scale constructs used in our 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 Price Search Propensity* (5 items; Cronbach’s alpha=0.82)

- I usually plan the timing of my shopping trip to a particular grocery store in such a way so as to get the best price deals offered at that store.<sup>1</sup>
- There are times when I delay my shopping trip to wait for a better price deal.<sup>1</sup>
- Although planned before making a shopping trip, I often do not buy some items if I think they will be on better deal shortly.<sup>1</sup>
- I keep track of price specials offered for the grocery products at the stores I regularly buy from.<sup>1</sup>
- To get the best price deals for my groceries I often buy the items I need over 2 or 3 trips.<sup>1</sup>

#### 2. *Spatial Price Search Propensity* (5 items; Cronbach’s alpha=0.89)

- I often compare the prices of two or more grocery stores.<sup>2</sup>
- I decide each week where to shop for my groceries based upon store ads/fliers.<sup>2</sup>
- I regularly shop the price specials at one store and then the price specials at another store.<sup>2</sup>
- Before going grocery shopping I check the newspaper for advertisements by various supermarkets.<sup>3</sup>
- To get the best price deals for my groceries I often shop at 2 or 3 different stores.<sup>3</sup>

#### 3. *Market Mavenism* (4 items; Cronbach’s alpha=0.89)

- I like it when people ask me for information about products, places to shop, or sales.<sup>2,4</sup>
- I like it when someone asks me where to get the best buy on several types of products.<sup>2,4</sup>
- I know a lot of different products, stores, and sales and I like sharing this information.<sup>2,4</sup>
- I think of myself as a good source of information for other people when it comes to new products or sales.<sup>2,4</sup>

#### 4. *Perceived Search Skills* (8 items; Cronbach’s alpha=0.71)

- I know what products I am going to buy before going to the supermarket.<sup>3</sup>
- I am a well organized grocery shopper.<sup>3</sup>
- Before going to the supermarket, I plan my purchases based on the specials available that week.<sup>3</sup>
- I can easily tell if a sale/special price is a good deal.<sup>3</sup>
- It is very difficult to compare the prices of grocery stores (reverse coded).<sup>2</sup>
- It is very difficult to compare the quality of meat and produce between grocery stores (reverse coded).<sup>2</sup>
- I prepare a shopping list before going grocery shopping.<sup>3</sup>
- I pre-sort my coupons before going grocery shopping.<sup>3</sup>

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<sup>1</sup>New item developed in this study.

<sup>2</sup>From Urbany et al. (1996).

<sup>3</sup>From Putrevu and Ratchford (1997).

<sup>4</sup>From Feick and Price (1987).