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

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Abstract

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”) and (2) price search across stores (“spatial”). Yet, the extant literature has considered only the spatial dimension of price search. We introduce the notion that consumer price search/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) How efficient are the households following different search patterns in taking advantage of price variations in the market? (3) What is the impact of price search on store profits?

We find that the spatial configuration of store and household locations serves to predict a household’s price search pattern (temporal, spatial, both or neither). Interestingly, we find that pure temporal search by a store loyal household yields as much savings as pure spatial search by a cross-store cherry picker, who does not search temporally. We also find that the adverse impact of cherry picking on profits is not as high as has been generally believed. A unique data collection approach enables us to compare and contrast findings about price search from surveys and revealed purchase data.
1. Introduction

Due to the use of promotional pricing by supermarkets, 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 savings over a household’s entire basket can be potentially large enough to be cost-effective. Due to the repeat and frequent nature of grocery purchases, the total potential savings for consumers on groceries by cherry picking through diligent price search across time (“temporal”) and across stores (“spatial”) can be very significant.\(^1\)

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 weak or non-existent store-traffic effects of promotions or pricing 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 1999). Consumer surveys corroborate this in that they find that the proportion of consumers who shop at multiple stores on a regular basis is 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/delay) and purchase quantities (stockpiling) within a store in response to price promotions. A consumer may also delay purchases in order to wait for better deals (e.g., Hendel and Nevo 2005). 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

\(^1\) The Food Marketing Institute (2004) reports that average grocery spending per week for a household is about $90.
goods, Conlisk and Gerstner (1984) discuss how firms can use price promotions to discriminate among consumers who can shift purchases over time and those that cannot. We refer to this as the “temporal” dimension of price search. Inter-temporal price search is manifested in household choice data as changes in purchase timing (acceleration/delay) and quantities (stockpiling on deals; reduced purchase quantities at high prices). Price promotions can help a retailer obtain a higher wallet share from even its price sensitive shoppers who for a variety of non-price related reasons (e.g., location, preference for offered assortment etc.) have a preference to shop at their stores. At the same time, the store can charge higher prices 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 sensitive 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 one’s price sensitive and insensitive customers), a store manager needs to understand the price search behavior of not only cross-store shoppers, but also that 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 cross-store price search in the extant literature to include temporal price search by characterizing price search in grocery shopping along 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? What variables serve to predict one of the four price search patterns for a household? We generate our hypotheses about the predictors of price search patterns based on 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 time opportunity cost of search would 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 models) routinely assume geography to be the underlying source of differentiation between stores. Many store choice models using revealed preference data treat this as a form of unobserved heterogeneity. Others using 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 household and distance between households and the warehouse store in estimate 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, 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 to generate a rich set of location based hypotheses about search behavior along the two dimensions of price search. Indeed 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 perfectly cherry picking through both inter-temporal and cross-store price search. 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 gives more returns to price search: pure temporal search by store loyal households or pure spatial search by store switchers? How much does one gain by doing both temporal and spatial search?
This research question is also important from a methodology perspective. Extant research on price search exclusively uses either survey data or revealed purchase data. Examples of survey based papers are Urbany et al. (1996) and Putrevu and Ratchford (1997). They 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 provides 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 gives insights about revenues and profits, but not about the motivation behind search.

An open question is whether the two types of research are likely to lead to similar conclusions i.e., Are self-reported measures of search by consumers consistent with their actual behavior? Putrevu and Ratchford 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 Lockman 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.”

To this end, we collect survey data from households for whom we also have access to their actual purchasing behavior. This is a particularly difficult task, because widely available panel data tends to be historic, preventing us from conducting surveys of these households. We obtain a retailer’s cooperation in obtaining a “live” household panel for which we obtain access to their purchase transactions in real time. Therefore we were able to survey these households and track their purchases over time. We use the “live” data on a household’s purchases at the focal retailer to obtain prices for the same products at the competing retailer over multiple weeks. By comparing prices across the two stores over multiple weeks, we 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 staggered three-week time windows (i.e., over 25,000 observations) from the competing retailer. We provide more details about the
data collection in Section 3. This labor-intensive data collection helps us to compare and contrast findings using stated search and revealed purchase data for the first time in the literature.

Our third and final 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 datasets have no information on profit margins.\(^2\) Further, most scanner datasets 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 cherry picking behavior by price sensitive grocery shoppers can adversely impact retail profitability significantly (e.g., Dreze 1999; Mogelonsky 1994), but there is no empirical evidence. We address this question using a unique dataset that has information on both profit margins and all purchases (over a one year period) of households at the cooperating retailer.

In summary, our study is unique in the price search literature for its investigation of households’ revealed price search efficiency by explicitly taking into account their effectiveness in taking advantage of both temporal and spatial price variations in the market. It helps to answer three substantive research questions and one methodological research question. The substantive questions are: (1) What variables determine a household’s price search on the temporal and spatial dimensions? (2) How efficient are the households following different search patterns in taking advantage of price variations in the market? (3) What is the impact of price search on store profits? We also address the methodological research question of whether findings from survey based research are comparable to results from objective revealed purchase data.

The rest of the paper is organized as follows: Section 2 discusses the conceptual framework and the hypotheses that we seek to test. Section 3 discusses the data collection strategy and Section 4 presents the results of the empirical analysis. Section 5 concludes with the implications of our findings and future research directions.

2. Conceptual Framework and Research Hypotheses

2.1 Types of Price Search Patterns

Consider a duopoly grocery retail market where price variations occur both temporally (across weeks, since cycle time for price changes is weekly) within a store and across stores. The

\(^2\) The University of Chicago’s Dominick’s database has profit margins, but the data is not at the household level.
The duopoly assumption is reasonable and consistent with reality in many US 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. For purposes of exposition, we split consumers into high or low types along the temporal and spatial price search dimensions. This leads to four types of 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 because these products happen to be available on sale at their preferred store when they wanted to purchase them. We label this search pattern as “incidental price search.”

A second type of shopper tends to be loyal to their preferred store and therefore do not take advantage of spatial price variations across stores. They shift purchases over time to avail themselves of promotions at their preferred store. We label this search pattern as “store-loyal inter-temporal price search.”

A third type of shopper takes trips across stores to pick the best contemporaneous prices (on any given shopping trip) across stores to take advantage of cross-store spatial price differences. This segment is the focus of the study by Hoch and Fox (2005). This segment 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 pattern as “trip-specific cross-store 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 as “cross-store inter-temporal price search”.

2.2 What variables characterize a household’s price search pattern?

We start with the premise that consumers choose that 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**

**Price Dispersion**

A common measure of price dispersion in a market is “Information Value,” which is the range of prices in a market. It is called “Information value” because it is the maximum possible savings (and therefore potential benefit) from price search for a consumer given perfect price information (Baye et al. 2003). Several papers have quantified the benefits of price search (information value) in durable goods markets (e.g., Brynjolfsson and Smith 2000; Clemons et al. 2002; Ratchford et al. 2003), but the benefits from price search in grocery markets have been a source of debate given the low prices of grocery products (Urbany et al. 2000).

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 cross-store, inter-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:

\[
\text{Information Value}_i = \sum_{j}^{n_i} BV_{ij}^{\text{max}} - \sum_{j}^{n_i} BV_{ij}^{\text{min}},
\]

where

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

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

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

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3 Fox and Hoch (2005) report the average savings obtained by shoppers through within-trip cross-store cherry picking within a trip 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.
Since it would be insightful to also identify the potential benefits from other types of price search patterns, we quantify the information values from store-loyal inter-temporal price search and within-trip cross-store price search by measuring the price dispersion purely along the temporal and spatial dimensions respectively. Thus, for the store-loyal inter-temporal search, $BV_{ij}^{\text{max}}$ and $BV_{ij}^{\text{min}}$ are based on basket values only across time within the store, while for within-trip cross-store search, the basket values are computed only across stores on the week of the trip.

Clearly the greatest potential benefit will be from cross-store inter-temporal price search. It is not a priori clear (without looking at the relative level of price variation within and across stores) whether trip-specific cross-store price search or store-specific inter-temporal price search leads to greater savings. Therefore it is of empirical interest as to whether there is greater potential benefit from temporal or spatial search.

**Personal Characteristics**

Some consumers may derive utility from price search. 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 associated with cross-store inter-temporal price search.

**Costs of Cherry Picking**

**Store and Household Location**

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 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.

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 locations and the distances between the two closest stores for that consumer 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). 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 explain our rationale behind how the spatial configurations of the household and stores affect their choice of price search patterns. The pictorial descriptions below can be helpful in understanding the logic of the hypotheses.

[Table 1 about here]

Households of type LLL, who are far away from either store and also face large inter-store distances, are most likely to adopt incidental price search because they can’t visit either store often to take advantage of inter-temporal price variations and also find it costly to perform cross-store 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 store-loyal inter-temporal price search at their closest store because they can visit it more often. But they do not perform much cross-store 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, trip-specific cross-store price search is very likely. 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 hypothesis as part of a broader set of hypotheses.

Finally, we expect that households of the SSS type would most likely indulge in cross-store, inter-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.

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\(^4\) We will consider both a dichotomous and continuous variable specification for distance in our empirical analysis.
**Personal Characteristics**

We expect that an increase in *unit opportunity cost of time* for a household *reduces* the likelihood of cross-store inter-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 least likely to do incidental price search and most likely to do cross-store inter-temporal price search.

The above hypotheses are summarized in Table 2 on the left panel under the heading “Determinants of Price Search Patterns.”

**2.3 How Efficient are Households with Different Price Search Patterns?**

We use an objective metric called *price search efficiency* to capture the relative extent of realized savings from price search. The idea behind the construct is similar to that developed in studies for durable goods (e.g., Srinivasan and Ratchford 1993) in that the returns to 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 “*Price Search Efficiency*” (PSE) for a household $i$ based on all the items purchased across multiple shopping trips $n_i$ tracked over about a month:

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

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

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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 insignificant. To conserve space, we omit the discussion of the hypotheses associated with these variables.
For computing $BV_{ij}^{\text{max}}$ and $BV_{ij}^{\text{min}}$, we use both cross-store (across the cooperating and competing chains) and inter-temporal (across monitored weeks) market price dispersion for all the items in the shopping basket for trip $j$ under consideration. Thus, Maximum Potential Savings is computed for each household “as if” they did cross-store inter-temporal price search. This enables us to evaluate the efficiency of all households on a comparable basis. If all of the potential savings is captured, a household’s price search efficiency 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 efficiency is 0%.

2.4. 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 get lower prices on average. The self-declared “cross-store inter-temporal” households should obtain the lowest prices on average (highest price search efficiency) and the self-declared “incidental” price search households should pay the highest prices (lowest price search efficiency) on average. The other two segments should pay the intermediate level of prices. It is of empirical interest as to whether “store-loyal inter-temporal” households or “trip-specific cross-store” households are more efficient and obtain better prices on average.

In Section 2.2, we hypothesized that that households with certain spatial configurations are most likely to pick a cherry picking pattern. Thus if the SSS segment is most likely to use the cross-store inter-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 would have intermediate levels of price search efficiency.

2.5 Impact of Price Search Patterns on Store Profits

We expect profit margins to be greatest for the incidental cherry pickers and lowest for the inter-temporal cross-store cherry pickers. For the other two segments, the profit margins will be intermediate. Whether the focal store-loyal inter-temporal cherry pickers have higher profit margins than the trip based cross-store cherry picker is an empirical question.

The hypotheses of Section 2.4 and 2.5 are summarized in Table 2 on the right panel under the title “The Effect of Cherry Picking Patterns on Price Search Efficiency and Store Profits”.

While we state specific hypotheses about the relative levels of profit margins for the different search patterns, we do not have specific hypothesis about the average profits from households
with the different search patterns. We expect that either the incidental cherry pickers (highest margins) or the store loyal inter-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.

3. Data

3.1 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 chains accounting for more than 85% market share. We obtained the cooperation of one of the retail 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 those stores and 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 hypotheses.

Given our research purposes, we augmented the transactional data of consumers obtained from Chain A 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’s through direct observation.\(^6\)

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 qualify for inclusion in the sample for our study. The qualifying criteria were (1) that the intercepted

\(^6\) We obtain 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 purchase information from Chain B also would have been ideal, we are able to answer our research questions without this. Given our objective of comparing stated price search propensity with observed search propensity, we accepted this tradeoff in data collection.
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. 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 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 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. 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 inter-temporal (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 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

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7 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 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 “lean” capacity to perform the data collection.
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.

As discussed earlier, the directly observed price information from both chains on items in each shopper’s basket helped us develop measures of revealed price search efficiency. The information from the mail-in surveys allows us to compare households’ revealed price search efficiency against their self-stated price search propensity and to construct other attitudinal and personal characteristics measures. This serves to assess the comparability/validity of two alternative methods (observation versus surveys) to collect information about price search.

Finally, in order to address the question of the impact of price search on chain’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.

3.2 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). Existing studies of consumer’s price search propensity focus on spatial price search. However, we use two constructs to distinguish between consumers’ stated 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’ temporal and spatial price search propensity measures to
classify consumers into high and low types along each dimension.\textsuperscript{8} 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.

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 ($D_{12}$). Rather than directly include distance variables in the regressions, we found that analysis based on a binary classification of distances into “small” and “large” fits the data better.\textsuperscript{9} 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. We found that the results are robust to changes in the split threshold (e.g., 2 miles).

4. Empirical Analyses and Results

\textbf{4.1 Are there potential benefits from price search?}

We report the information value (i.e., maximum potential savings) from the different price search patterns based on the 710 tracked shopping baskets in our data in Table 3. To gain

\textsuperscript{8} A median split of consumers along the temporal and spatial dimensions based on the sum of the corresponding price search propensity scales yields similar results as we report in the paper.

\textsuperscript{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.
insights about the role of basket size on potential benefits from search, we also report these values grouped by basket sizes.

[Table 3 about here]

As expected, we find that the average information value is greater for larger baskets across the four different search patterns. In fact the information value is convex in basket size, i.e., the savings from larger baskets are more than proportionately greater than for smaller baskets. On basket values greater than $90, with cross-store 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 cross-store inter-temporal price search. Interestingly, the average potential savings of $8.49 from price search on purely the temporal dimension (store-specific inter-temporal) is greater than $7.20 savings from search on purely the spatial dimension (cross-store within-trip). This is an interesting and somewhat surprising empirical insight, in that there is greater potential for savings by being loyal to a store and cherry picking temporally, rather than by shopping across stores each week, without cherry picking temporally.

4.2 What variables characterize a household’s price search pattern?

To see how the distribution of price search patterns change as a function of competitive store proximity, we report the percentage of households who adopt the four price search patterns in Table 4a. For the two stores far away from each other (greater than 2 miles), only 3% of the sample do pure-within trip cross-store cherry picking. 20% of the sample do cross-store inter-temporal price search. In contrast, when stores are close to each other, 21% do within trip-cross store price search and 46% do cross-store inter-temporal price search. The percentage of households who do store-specific temporal price search is 40% when stores are far apart, but fall to 11% when the stores are close by.\textsuperscript{10}

\textsuperscript{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 2 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

16
The percentage of households with the different spatial locations for stores far away (> 2 miles) from each other are: SSS (48%), SLL (47%), LSL (27%), LLL (10%). In contrast, the percentage of households with the different spatial locations for stores adjacent to each other (<0.3 miles) are: SSS (0%), SLL (0%), LSL (23%), LLL (67%).

We explain the household’s choice of price search pattern using a multinomial logit model. 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.” The results are reported in Table 5.

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 cross-store inter-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. First, we interpret the spatial configuration estimates across columns. The coefficient of LSL/LLS is highest (2.59) for store-specific inter-temporal price search (relative to the other price search patterns), supporting the hypothesis that households that are close to one of the stores, but have large inter-store distance are most likely to be loyal to one of the stores and most likely to do store specific inter-temporal price search. The coefficient of SLL is highest (2.55) for within-trip cross-store price search as expected. The coefficient of LLL is highest (5.52) for incidental price search as hypothesized.

Next, we interpret the spatial configuration estimates within each column. Within the incidental price search column, LLL has the highest coefficient of 5.52 (relative to the other observations) is 3.5 miles. The 75th percentile distance between competing stores is 4.3 miles. Indeed the average distance between stores are higher, and thus explains our above average proportion of cross-store shopping.

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

Since SSS is treated as the base case in Table 5, we are unable to check our hypothesis of whether SSS households prefer cross-store inter-temporal cherry picking. We therefore estimated the model with LLL as the base case. Indeed SSS has significantly negative coefficients for the three price search patterns relative to the base case of cross-store inter-temporal price search, supporting our hypothesis.
location variables) as predicted. Interestingly, both LSL/LLS and LLL have the highest coefficients (2.59) for store loyal inter-temporal search, i.e., distances between stores reduce cross-store shopping. But as we stated earlier, LSL/LLS households prefer store-loyal inter-temporal price search while LLL households prefer incidental price search most. Finally trip-specific cross-store 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 cross-store inter-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 (0.24) relative to the cross-store inter-temporal price search. The marginal effect of opportunity cost on the probability of both store-specific inter-temporal price search (0.14) and cross-store within-trip price search (0.16) is not significantly different, though we expected the effect to be greater for cross-store within trip 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 cross-store price search and less store-specific inter-temporal (-0.89) 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 cross-store within trip price search most and are least likely to do incidental price search (-0.7), 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 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 observed price search patterns, location and opportunity costs are the most important variables in explained observed price search patterns.

4.3 How Efficient are Households with Different Price Search Patterns?
To address the question about actual savings from price search, we compute the observed price search efficiency of each household across multiple shopping trips (2-3 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 regress observed price search efficiency 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 efficiency, but is still able to obtain 54% (the intercept) of the maximum potential savings. Interestingly, while the store specific inter-temporal cherry picker saves as much as 68% (intercept + store-specific inter-temporal) of potential savings, the trip-specific cross-store cherry picker saves only 66% (intercept + trip-specific cross-store) of potential savings. However, households who do cross-store and inter-temporal cherry picking are able to obtain as much 76% (intercept + cross-store inter-temporal) of the maximum potential savings.\(^{13}\) Thus, cross-store inter-temporal cherry pickers have 22 percentage points greater price search efficiency with respect to incidental cherry pickers; the corresponding differences with respect to pure (i.e., only within-trip) cross-store cherry pickers and pure (i.e., store-loyal) inter-temporal cherry pickers are 14% and 13% respectively.\(^{14}\)

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

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\(^{13}\) 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.

\(^{14}\) A potential concern in interpreting relative savings from alternative price search patterns is that we use “prospective” inter-temporal time windows (i.e., purchase week + next 2 weeks) to account for intertemporal search. Could results differ if we used both “prospective” and “retrospective” (i.e., purchase week +/- 2 weeks) time windows? But it is impossible to know the prices for the products purchased by the household at Chain B in weeks before our survey began. 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 analysis of price search efficiency only along the inter-temporal dimension within Chain A, where we have retrospective data. The average store-specific (Chain A) inter-temporal efficiency for sample households using the 3-weeks and 5 week time window is...
advantage of price specials at their loyal store. At the same time, those who also engage in cross-
store cherry picking increase their potential savings by an additional 8% of the average max-
imum 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. Thus a price promotion is used
by not merely by the price sensitive shopper who searches for low prices, but also those who are
price insensitive.

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 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 (has
the highest estimated coefficient of 0.327) and the LLL households have the lowest price search
efficiency (all estimated price coefficients are positive, when LLL is the base case). Inter-
estingly, we find that these underlying location variables have greater explanatory power
than the stated price search patterns themselves. 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 captures 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.

Unfortunately, much of recent research on store choice using purely observed scanner
data on household choice 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.,

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15 From Table 5, we see that stated price search patterns already account for 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 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
more noisy 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.
Bucklin and Lattin 1992). It is therefore not surprising that these papers are unable to explain store choice effectively. These insights suggest that extant theoretical research on retailer choice using Hotelling models that usually model store and consumer locations and consumer opportunity costs have incorporated the most important tradeoffs in their research. It also suggests that the omission of location information in many empirical models of store choice (which treat locations as a source of unobserved heterogeneity) is a serious limitation.

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 that the effect of distance on number of trips taken to have threshold effects. Therefore a binary categorization of distances seemed conceptually appropriate. However, it is critical to check if the fit can be improved by using distance variables directly. Such a model using distances as continuous variable is estimated in Model 3. As expected we find that distances between the household and primary store and distance between primary and secondary store are negative, demonstrating that greater distances to the store and between stores reduce the price search efficiency 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.

In all three models, we do not find the average trip basket size to be significant. In retrospect, this is not surprising because we have already shown in Table 2 that as basket values increase the potential benefits increase; hence even though observed price search efficiency does not change with basket size, the total savings obtained increases as basket size increases.

Unlike Fox and Hoch (2005), who demonstrate that households shop across stores more often when they have larger baskets to purchase, we do not test the endogeneity of trip size. This is because we do not have data on whether consumers actually shopped at multiple stores. Also, our focus in this paper is to measure average objective price search efficiency of a household. By using data over multiple trips extending over about a month, we capture the price search efficiency and profitability of the households over their monthly basket of purchases. This information will enable firms to target cross-store cherry picking households differentially compared to households that do inter-temporal cherry picking.
4.4. Are Stated Search Patterns Consistent with Observed Behavior?

Overall, the results from Model 1 suggest that observed price search efficiency is consistent with the stated price search patterns of households. Therefore, either survey data or objective behavioral data will provide broadly similar insights – thus we shed insight on an unresolved question in the price search literature (Putrevu and Ratchford 1993).

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. 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 in Section 4.2, market mavenism explains stated price search patterns (consistent with Urbany et al. 1996), but it is insignificant in explaining observed price search efficiency after controlling for location variables and opportunity costs. Since mavens will engage in search even if there are no financial returns, we can see why geographic locations and opportunity cost better explain price search efficiency than stated price search patterns. Similarly perceived search skills explain the choice of search pattern, but does 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 these variables might be correlated with distance or opportunity cost, i.e., a person may not perceive oneself to be a maven or have high search skills if the stores are far away or far apart or they have high opportunity cost. A hypothesis test of differences between the groups shows no evidence of such an endogenous relationship between these variables (p >0.1).

Our results thus help us understand the relative usefulness of survey data and behavioral data. The survey data helps us understand why people adopt search patterns that may not appear optimal given observed locations and opportunity costs (e.g., mavens enjoy shopping so much that they don’t care if it saves them money). On the other hand, behavioral data helps us

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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.
understand that just because someone enjoys shopping and shops often, they do not necessarily get better prices.

Overall, we conclude that both types of data give broadly similar insights about price search. But they also serve complementary purposes: survey data gives better insight on observed price search behavior, while objective data gives greater insight on market outcomes from price search.

4.5 Impact of Price Search Behavior on 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 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 cross-store inter-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 inter-temporal shopping and within-trip cross-store shopping provide intermediate profit margins. But as noted earlier, the store loyal inter-temporal shopper is more valuable to the store in terms of aggregate profits. Our results are also reassuring to retailers in the sense that even the most price search intensive segment brings a positive average contribution to the bottom line.

In terms of total weekly profits, the store loyal inter-temporal segment household provides the greatest average profits, even greater (by about 15%) than the incidental price search segment. Though the store loyal inter-temporal segment has lower margins than incidental price search 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 store loyal inter-temporal 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. 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.

[Table 7 about here]

Are the above differences in averages of margins and weekly profits across the different segments statistically significant? To answer this, we perform regressions with different store performance measures as dependent variables and the stated cherry picking patterns/spatial pattern as explanatory variables. We also included a few additional control variables. The results for the surveyed sample of 255 households are shown in Tables 8. As reflected in our analysis of means in Table 7, the regression results show the relative differences are consistent with our hypotheses, but they are also statistically significant as well.

[Table 8 about here]

**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. Dreze 1999; Mogelonsky 1994) about its negative impact on profits. Our analysis above shows that all of the price search segments are profitable on average. Nevertheless, there could be some households 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 grocery shopping. If the proportion of cherry picking households are indeed large, loss leader pricing to increase store traffic may be highly unprofitable and one may need strategies to discourage such customers. (Dreze 1999, Levy and Weitz 2004). We therefore

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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.
quantify the proportion of such “extreme” cherry picking households who disproportionately buy loss-leader products yielding negative net margins for the retailer.

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 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. 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 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 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 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) 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.

What are the characteristics of these 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 almost exclusive “loss leader trip” during 2002. We characterized a “loss leader trip” as a shopping trip where at least 90% of all the items purchased by the customer on that trip are loss-

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19 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.

20 We found that only 1.7% of in-sample households (i.e., 4 out of 255) contributed a net negative margin during 2002. All of these households were also secondary shoppers with respect to Chain A.
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. Most of the extreme cherry picking households 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.

5. Conclusion

Our goal in this paper was to gain insights into how consumers take advantage of price variations in grocery markets through price search. Extant research on price search in grocery markets has focused on cross-store price search. We expand that focus for the first time by systematically investigating a household’s choice of cross-store price search (the spatial or “where” dimension) and inter-temporal price search (the temporal or “when” dimension) in the grocery market. We predicted and tested hypotheses about a household’s price search pattern along the temporal and/or spatial dimensions.

We quantified the extent to which consumers can benefit from search along the temporal and spatial dimension by reporting information values in the market for alternative types of search price behavior. We also summarize the household’s actual ability to take advantage of price variations in the market based on their revealed purchase choices using a construct called “price search efficiency.” We evaluate the retailer profitability of households using alternative price search patterns for the first time in the literature.

Using a unique and labor intensive data collection approach, we compare revealed price search efficiency against stated price search patterns and personality traits from survey data. We found that people who state they search more are indeed more efficient and obtain lower average prices in general. We also found through the survey that there are some consumers who enjoy shopping even without financial returns (market mavens) and as expected, these consumers did not obtain greater price search efficiency from their price search. By comparing findings from objective revealed purchase data and survey data, we were able to offer interesting insights on
this long-standing research question in the literature on price search about the comparability of the two types of data.

We discuss some key empirical insights from our analysis and potential implications for managers and researchers.

(1) Spatial patterns have a significant impact on both stated price search patterns and 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).

Further, locations and opportunity costs 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 locations should be an important variable in explaining store choice.

(2) 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 who shop both across 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 advantage of substantial amount of the promotion by sheer chance.

Contrary to conventional wisdom that people who shop across stores are more likely to save more, we find that households who do spatial search across stores do marginally worse (who obtain 66% of potential savings) compared to store loyal households who search temporally across time (who obtain 68% of potential savings).

(3) Though incidental price searchers (i.e., those who don’t search, but are not loyal) are the most profitable in terms of profits margins per dollar sold, store-loyal inter-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 keeping 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 who do inter-temporal price search may shift to a competing store to take advantage of inter-temporal 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 intensive price search segment (cross-store inter-temporal) provide an average margin and total weekly profits that are about 20% and 10% below of 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 households make a net negative contribution and these net losses are around 0.2% 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**

There are certain limitations in this study that suggest interesting possibilities for future research. First, our 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 these 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 provide additional insights to marketing managers. Examples of studies on category characteristics are (Narasimhan, Neslin and Sen 1996, Bell et al, 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 cross-store efficiency more, while displays may affect inter-temporal efficiency more. Overall, there is an opportunity to understand how price search efficiency varies as a function of (1) market characteristics, (2) category characteristics and (3) marketing mix variables.
In this study we focus on two dimensions of cherry picking: cross-store (the “where” dimension) and inter-temporal (the “when” dimension). A third dimension in which consumers can choose to get lower prices for their groceries is through brand-switching (the “what” dimension). Accounting for this third dimension could mean that the information value and the opportunity for savings in the market could be greater. But incorporating the “brand switching” dimension of price search in estimating price search efficiency 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. A systematic study of the effect of brand switching on price search efficiency is beyond the scope of this study and needs to 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 branded categories. As expected, the estimated price search efficiency is marginally higher for non-branded 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 are 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 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 cross-sectional cherry picking across stores, but does not model inter-temporal cherry picking. A model incorporating inter-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 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., Fox, Montgomery and Lodish 2004). We hope our paper serves as an impetus for launching such an interesting stream of research.

References


Effectiveness,” Kluwer, Boston.


Figure 1: Segmentation by Price Search Patterns

<table>
<thead>
<tr>
<th>Cross Store Price Search</th>
<th>Inter-temporal Price Search</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>Incidental Price Search</td>
</tr>
<tr>
<td></td>
<td>Store-Specific Inter-Temporal Price Search</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td></td>
<td>Trip-Specific Cross-Store Price Search</td>
</tr>
<tr>
<td></td>
<td>Cross-Store Inter-Temporal Price Search</td>
</tr>
</tbody>
</table>

Table 1: Likely Spatial Layout and Price Search Pattern

<table>
<thead>
<tr>
<th>Price Search Pattern</th>
<th>Spatial Layout of Most Likely Segment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Incidental</td>
<td>LLL</td>
</tr>
<tr>
<td></td>
<td><img src="#" alt="LLL Diagram" /></td>
</tr>
<tr>
<td>Store-Specific Inter-temporal</td>
<td>LSL</td>
</tr>
<tr>
<td></td>
<td><img src="#" alt="LSL Diagram" /></td>
</tr>
<tr>
<td></td>
<td><img src="#" alt="LLS Diagram" /></td>
</tr>
<tr>
<td>Trip-Specific Cross-Store</td>
<td>SLL</td>
</tr>
<tr>
<td></td>
<td><img src="#" alt="SLL Diagram" /></td>
</tr>
<tr>
<td>Cross-Store Inter-temporal</td>
<td>SSS</td>
</tr>
<tr>
<td></td>
<td><img src="#" alt="SSS Diagram" /></td>
</tr>
</tbody>
</table>
### Table 2: Summary of Hypotheses and Empirical Results

<table>
<thead>
<tr>
<th>Consumers’ Stated Cherry Picking Behavioral Pattern</th>
<th>Determinants of Cherry Picking Patterns</th>
<th>Effect of Cherry Picking Patterns on Price Search Efficiency and Profit Margins</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Most likely consumer-store spatial pattern</td>
<td>Market mavenism</td>
</tr>
<tr>
<td>Incidental Cherry Picking</td>
<td>LLL √ Most Negative √ Most Positive √ Most Negative √</td>
<td>Lowest √</td>
</tr>
<tr>
<td>Store-Specific Inter-temporal Cherry Picking</td>
<td>LSL or LLS √</td>
<td>Most Positive √</td>
</tr>
<tr>
<td>Trip-Specific Cross-Store Cherry Picking</td>
<td>SLL √</td>
<td>Most Positive √</td>
</tr>
<tr>
<td>Cross-Store Inter-temporal Cherry Picking</td>
<td>SSS √ Most Positive √ Most Negative √ Most Positive √</td>
<td>Highest √</td>
</tr>
</tbody>
</table>

Note: √ indicates support of a hypothesis based on our empirical results at p < 0.05.

### Table 3: “Information Value” from Price Search in Grocery Markets

<table>
<thead>
<tr>
<th>Shopping Basket Value</th>
<th>Average Values of Maximum Potential Savings (std. dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Trip-Specific Cross-Store</td>
</tr>
<tr>
<td>&lt;$30</td>
<td>$2.98 (2.90)</td>
</tr>
<tr>
<td>$30 -$60</td>
<td>$9.64 (5.79)</td>
</tr>
<tr>
<td>$61 -$90</td>
<td>$16.41 (7.45)</td>
</tr>
<tr>
<td>&gt;$90</td>
<td>$28.02 (11.56)</td>
</tr>
<tr>
<td>Sample average:</td>
<td>$31.22</td>
</tr>
</tbody>
</table>
Table 4a: Stated Cherry Picking Patterns

<table>
<thead>
<tr>
<th>Distance Between Stores</th>
<th>Percentage of</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
</tr>
<tr>
<td>&lt;=0.3 miles (Close)</td>
<td>156</td>
</tr>
<tr>
<td>&gt;2 miles (Far)</td>
<td>99</td>
</tr>
<tr>
<td>Average</td>
<td>255</td>
</tr>
</tbody>
</table>

Table 4b: Observed Location patterns

<table>
<thead>
<tr>
<th>Distance Between Stores</th>
<th>Percentage of</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
</tr>
<tr>
<td>&lt;=0.3 miles (Close)</td>
<td>156</td>
</tr>
<tr>
<td>&gt;2 miles (Far)</td>
<td>99</td>
</tr>
<tr>
<td>Average</td>
<td>255</td>
</tr>
</tbody>
</table>

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

Table 5: Multinomial Logit Regression: Determinants of Price Search Patterns
(Cross-Store Inter-temporal Price Search and SSS is Base Case)

<table>
<thead>
<tr>
<th></th>
<th>Incidental Estimate (Std. Err)</th>
<th>Store-Specific Inter-Temporal Estimate (Std. Err)</th>
<th>Trip-Specific Cross-Store Estimate (Std. Err)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>3.06** (1.48)</td>
<td>-0.10 (1.35)</td>
<td>-6.19*** (1.30)</td>
</tr>
<tr>
<td>LSL/LLS</td>
<td>1.96*** (0.67)</td>
<td>2.59*** (0.51)</td>
<td>-0.54 (1.15)</td>
</tr>
<tr>
<td>SLL</td>
<td>0.48 (0.72)</td>
<td>0.29 (0.59)</td>
<td>2.55*** (0.58)</td>
</tr>
<tr>
<td>LLL</td>
<td>5.52*** (0.91)</td>
<td>2.59*** (0.89)</td>
<td>-3.57*** (1.18)</td>
</tr>
<tr>
<td>Opportunity Cost</td>
<td>0.24*** (0.03)</td>
<td>0.14*** (0.02)</td>
<td>0.16*** (0.03)</td>
</tr>
<tr>
<td>Market Mavenism</td>
<td>-0.70** (0.32)</td>
<td>-0.17 (0.24)</td>
<td>0.36 (0.26)</td>
</tr>
<tr>
<td>Perceived Search Skills</td>
<td>-2.09*** (0.49)</td>
<td>-0.89** (0.39)</td>
<td>0.03 (0.34)</td>
</tr>
</tbody>
</table>

* 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 6: Regression results for observed price search efficiency across tracked multiple shopping trips

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Dependent Variable: Observed price search efficiency across multiple shopping trips</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate (Std. Err)</td>
<td>Estimate (Std. Err)</td>
<td>Estimate (Std. Err)</td>
<td></td>
</tr>
<tr>
<td>Stated Cherry Picking Behavioral Pattern</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-store inter-temporal</td>
<td>0.221*** (0.033)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Store-specific inter-temporal</td>
<td>0.143*** (0.039)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trip-specific cross-store</td>
<td>0.129*** (0.045)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incidental (used as “base” category)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer-Store Spatial Patterns</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSS</td>
<td>0.327*** (0.045)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSL/LLS</td>
<td>0.250*** (0.046)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLL</td>
<td>0.230*** (0.045)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LLL (used as “base” category)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to the primary store</td>
<td></td>
<td>-0.011* (0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance between stores</td>
<td></td>
<td>-0.019* (0.008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to primary store × Distance between stores</td>
<td></td>
<td>-0.003* (0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit opportunity cost of time</td>
<td></td>
<td>-0.003* (0.001)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market mavenism</td>
<td>0.007 (0.015)</td>
<td>0.001 (0.015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived search skills</td>
<td>0.011 (0.023)</td>
<td>0.031 (0.022)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary shopper with respect to focal store</td>
<td>-0.008 (0.045)</td>
<td>-0.086 (0.047)</td>
<td>0.032 (0.045)</td>
<td></td>
</tr>
<tr>
<td>Average number of items per tracked shopping trip</td>
<td>0.001 (0.001)</td>
<td>0.001 (0.001)</td>
<td>-0.000 (0.001)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.536 (0.051)</td>
<td>0.516 (0.094)</td>
<td>0.654 (0.098)</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.164</td>
<td>0.260</td>
<td>0.222</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>228</td>
<td>222</td>
<td>222</td>
<td></td>
</tr>
</tbody>
</table>

* 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 7: Averages of Retailer Performance Measures at the Cooperating Chain

<table>
<thead>
<tr>
<th>Store Performance Related Measures at the cooperative retail chain</th>
<th>For All Shoppers</th>
<th>By Stated Cherry Picking Behavioral Pattern</th>
<th>By Observed Household-Store Spatial Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Cross-store inter-temporal</td>
<td>Store-specific inter-temporal</td>
</tr>
<tr>
<td>Surveyed Sample (N = 255)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. profit margin(^1,2)</td>
<td>0.23</td>
<td>0.21</td>
<td>0.22</td>
</tr>
<tr>
<td>Avg. trip frequency(^1)</td>
<td>0.94</td>
<td>1.18</td>
<td>1.12</td>
</tr>
<tr>
<td>Wallet share(^1,3)</td>
<td>0.61</td>
<td>0.62</td>
<td>0.67</td>
</tr>
<tr>
<td>Avg. trip basket size(^2)</td>
<td>$35.43</td>
<td>$25.30</td>
<td>$33.28</td>
</tr>
<tr>
<td>Avg. weekly profit(^1,2)</td>
<td>$7.20</td>
<td>$6.83</td>
<td>$8.67</td>
</tr>
<tr>
<td>All Households at two of the stores included in study (N = 21,963)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. profit margin(^1,2)</td>
<td>0.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. trip frequency(^1)</td>
<td>0.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. trip basket size(^2)</td>
<td>$33.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. weekly profit(^1,2)</td>
<td>$5.58</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\(^1\) Based on actual purchase scanner data over one year (2002).
\(^2\) Scaled for confidentiality reasons.
\(^3\) Based on self-reported data from survey (2003).
Table 8: Retailer Profit Analysis

<table>
<thead>
<tr>
<th>Explanatory Variable</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stated Cherry Picking Behavioral Pattern</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-store inter-temporal</td>
<td>-0.060* (0.013)</td>
<td>-2.186 (1.030)</td>
<td>-0.045** (0.016)</td>
<td>1.487 (1.217)</td>
</tr>
<tr>
<td>Store-specific inter-temporal</td>
<td>-0.031* (0.016)</td>
<td>-1.996 (1.235)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Incidental (used as “base” category)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer-Store Spatial Patterns</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSS</td>
<td>0.151*** (0.019)</td>
<td>-5.731*** (1.637)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSL/LLS</td>
<td>-0.095*** (0.019)</td>
<td>-1.859 (1.639)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SLL</td>
<td>-0.098*** (0.018)</td>
<td>-4.199*** (1.612)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LLL (used as “base” category)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary shopper with respect to focal store</td>
<td>0.044*** (0.014)</td>
<td>5.981*** (1.083)</td>
<td>0.063*** (0.015)</td>
<td>6.662*** (1.315)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.002 (0.004)</td>
<td>3.190*** (0.311)</td>
<td>0.009*** (0.004)</td>
<td>3.583*** (0.334)</td>
</tr>
<tr>
<td>Unit opportunity cost of time</td>
<td>0.000 (0.000)</td>
<td>0.003 (0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market mavenism</td>
<td>-0.008 (0.005)</td>
<td>-0.153 (0.461)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Perceived search skills</td>
<td>-0.023*** (0.008)</td>
<td>-1.360 (0.729)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.219*** (0.022)</td>
<td>-8.665*** (1.757)</td>
<td>0.350*** (0.036)</td>
<td>-2.469 (3.180)</td>
</tr>
<tr>
<td>R²</td>
<td>0.09</td>
<td>0.31</td>
<td>0.30</td>
<td>0.35</td>
</tr>
<tr>
<td>N</td>
<td>254</td>
<td>254</td>
<td>228</td>
<td>228</td>
</tr>
</tbody>
</table>

* p < 0.1; ** p < 0.05; *** p < 0.01
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. Inter-Temporal Cherry Picking 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. 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 2 or 3 trips. 1

2. Cross-Store Cherry Picking Propensity (5 items; Cronbach’s alpha=0.89)
   - 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/fliers. 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 2 or 3 different stores. 3

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. 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 (8 items; Cronbach’s alpha=0.71)
   - 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 pre-sort my coupons before going grocery shopping. 3

1 New item developed in this study.
2 From Urbany et al. (1996).
3 From Putrevu and Ratchford (1997).