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An Empirical Analysis of the Extreme Cherry Picking Behavior of Consumers in the Frequently Purchased Goods Market☆

Debabrata Talukdar[a,*], Dinesh K. Gauri[b,1], Dhruv Grewal[c,2]

[a] Marketing, SUNY, 215 E Jacobs Center, Buffalo, NY 14260, United States
[b] Marketing, Whitman School of Management at Syracuse University, 721 University Ave, Syracuse, NY 13244, United States
[c] Babson College, United States

Abstract

Extreme cherry pickers are customers who seek price deals and excessively avail themselves of deep discount offers, which generates negative profits for retailers. This study uses market transaction and primary consumer survey data to provide insights into the determinants, prevalence, and profit impacts of such behavior in the frequently purchased goods market. We find that the extreme cherry picking segment is small (about 2% of all shoppers), but its relative value varies across stores, and consumers manifest this behavior only in secondary stores. An inverse U-shaped relationship marks consumers' opportunity costs for cross-store price search and likelihood of extreme cherry picking behavior. Finally, we also find that a loss leader promotional strategy adds to retailers' bottom lines, despite the pure loss generated by extreme cherry pickers.

Keywords: Price search; Loss leader promotions; Profit impact; Shopping trip incidence models

Retailers use price promotions as both an offensive mechanism to attract competitors' customers and a defensive strategy to retain current customers (Gupta 1988; Inman and McAlister 1993; Raghubir, Inman, and Grande 2004). U.S. retailers across all product categories in 2004 spent about $429 billion in such promotions; a more recent estimate by ACNielsen (2007) suggests that promotional sales account for as much as 36% of total grocery sales.

A prevalent price promotion strategy uses "loss leaders" or products temporarily discounted heavily to a selling price at or below the retailers' cost as a way to offer additional incentives to deal-prone, store-switching consumers. These loss leaders generally appear in the largest ads in a retailer's promotions and in the biggest display space, to facilitate their rapid sales. Duncan, Hollander, and Savitt (1983) argue that the economies of scale associated with shopping encourage consumers to buy goods other than loss leaders once they are in the store. Therefore, stores offer loss leaders to attract consumers, then price their other products to compensate for the deals offered on the loss leaders, with the expectation that loss leaders not only increase store traffic but also lead to net incremental profits from the sales of other products to shoppers who visit to buy loss leaders.

As retailers intensify their price promotions, consumers have the opportunity to obtain frequently purchased goods at lower prices merely by shifting their purchase timing or quantities to a given store or by engaging in cross-store shopping. Past research suggests that consumers respond to price promotions by engaging in price search and by trading off the benefits of price search against the opportunity costs of time for undertaking the search (Putrevu and Ratchford 1997; Ratchford 1982; Urbany, Dickson, and Kalapurakal 1996). Many consumers spend considerable time and effort bargain hunting and enjoy the thrill of getting bargains, in addition to the price savings (Karolefski 2002; Lin-Fisher 2007; Marmorstein, Grewal, and Fiske 1992; Tedeschi 2003). They efficiently and systematically track down information about relevant price deals and even form local or Internet-based interest groups to share this information (Lin-Fisher 2007).

In the context of the loss leader promotions, retailers also face the threat of "devils" or "extreme cherry pickers" (Gauri, Sudhir, and Talukdar 2008; McAlister, George, and Chien 2009). These consumers visit specific retailers exclusively to buy loss

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* Corresponding author. Tel.: +1 716 6453243; fax: +1 716 6453261.
E-mail addresses: dtalukda@buffalo.edu (D. Talukdar), dkgauri@syr.edu (D.K. Gauri), dgrewal@babson.edu (D. Grewal).
[1] Tel.: +1 315 4433672; fax: +1 315 442146.
[2] Tel.: +1 781 239 3902; fax: +1 781 239 5139.

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leaders or items with deep discounts and, as a consequence, generate negative profit contributions for the retailer. Retail managers remain apprehensive about the size of this segment of consumers. According to Brad Andersen, CEO of Best Buy, approximately 20% of its 500 million annual customer visits feature "devils" who "buy the products, apply for rebates, return the purchases, and then buy them back at returned merchandise discounts . . . load up on 'loss leaders' and flip the goods at profit on eBay" (McWilliams 2004, p. A1; see also Elberse, Gourville, and Narayandas 2005).

Existing academic literature provides little insight into such extreme loss-inducing customer behavior, at either the individual customer or the aggregate store level. Additionally, recent reviews of the retailing literature have called for research to examine cherry picking behavior across stores (Grewal and Levy 2007, 2009). Therefore, we focus on extreme cherry pickers as a customer segment in the frequently purchased goods (FPG) grocery market, which accounts for approximately half a trillion dollars in the United States and takes up a significant part of household consumption expenditures (U.S. Census Bureau 2006). This market is also characterized by widespread loss leader pricing to entice customers (Drèze 1995). Marketers and retailers need to be cognizant of the financial implications of their marketing strategies (Kumar 2008; Petersen et al. 2009; Shankar 2008). Grocery retailers need to know the extent of systematic extreme cherry picking (ECP) behavior among their customers, who these customers are, and how their behavior adversely affects store profits. Using both survey and market data to match the stated attitudes and revealed behaviors of consumers, we provide comprehensive empirical insights into the scope and profit impact of ECP behavior. Specifically, we: (1) estimate the size of the ECP segment across different stores in different competitive market contexts, (2) identify the key market and individual consumer characteristics that drive ECP behavior, and (3) estimate the incremental net impact of loss leader pricing on a retailer's profit in the presence of ECP behavior by its customers.

The rest of this article is organized as follows: In the next section, we summarize the existing research, followed by discussions of the conceptual framework we use to guide our empirical analyses and the data for the analyses. Next, we present the results from our analyses. We conclude with some implications and future research directions.

Relevant existing research

A well-established stream of empirical research investigates consumers' responses to price promotions by considering their deal proneness (Bawa and Shoemaker 1987; Blattberg et al. 1978) or their promotion proneness (Lichtenstein, Netemeyer, and Burton 1990). This definition conceptualizes deal proneness as consumers' psychological propensity to buy goods on promotion, not their actual purchase. That is, deal-prone consumers respond to price-based benefits because they appear in the form of a deal, rather than because they offer lower prices (i.e., buying on deal has psychological benefits, irrespective of the financial consequences; Lichtenstein, Netemeyer, and Burton 1990). This conceptualization also is consistent with observations of the "thrill" or "transaction value" consumers often get from finding price deals (Grewal, Monroe, and Krishnan 1998).

Previous research on deal proneness tends to investigate the extent of deal-seeking behavior and the correlates or drivers of that behavior. Such research falls into two distinct streams based on the type of data used: consumer survey data regarding consumers' stated price search propensity or deal-seeking behavior (e.g., Beatty and Smith 1987; Putrevu and Ratchford 1997; Urbany, Dickson, and Kalapurakal 1996; Urbany, Dickson, and Sawyer 2000) and field or scanner data pertaining to consumers' observed purchase and deal-seeking behavior (e.g., Carlson and Gieseke 1983; Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2008; Mace and Neslin 2004; Neslin, Henderson, and Quelch 1985; Shankar and Bolton 2004). Observed behaviors include the percentage of deal purchases, stockpiling, purchase accelerations or delays, store and brand switching, and visits to multiple competing stores during the same shopping trip.

Estimates of the size of the deal-prone segment in the FPG market range from 3% to 50% (Blattberg et al. 1978; Lichtenstein, Burton, and Netemeyer 1997; Vanhuele and Drèze 2002). Urbany, Dickson, and Sawyer (2000) find that approximately 19% of consumers regularly shop for price specials at multiple stores, which imply that retail managers generally overestimate the proportion of such consumers when they claim one-third of customers do so. Fox and Hoch (2005) similarly find that consumers who visit multiple stores in the same shopping trip constitute approximately 18% of all consumers. Existing research also identifies several consumer demographic (e.g., income), psychographic (e.g., opinion leadership), and market characteristics (e.g., distance between competing stores) characteristics that influence deal-seeking behavior (Putrevu and Ratchford 1997; Urbany, Dickson, and Kalapurakal 1996).

Unfortunately, prior research has been unable to provide insights into the impact of consumers' deal-seeking behavior on retailers' profit (Ailawadi and Harlam 2004; Fox and Hoch 2005). Despite the significant managerial interest in this impact (McAlister, George, and Chien 2009), existing literature lacks studies that investigate the link between consumers' deal-seeking behavior and their profit contributions to retailers. Using individual level data from two stores in the home improvement product market, Mulhern and Padgett (1995) find that regular price purchases are highly correlated with promotional price purchases. They find that among shoppers who identify promotions as one of the reasons for visiting the stores, about three quarter of them make regular purchases also. This provides support for the underlying rationale for loss leader promotions—that 'deep discount' items may enhance the sale of other items at individual consumer level. Ailawadi et al. (2006), using drugstore data, find that more than half of the individual promotions are not profitable, but they induce a significant positive halo effect. However, they do not explicitly analyze the profit impact of loss leader promotions or consumers' ECP behavior.

We investigate the prevalence of ECP behavior in the FPG market by analyzing a data set of customer-level transaction data of over 52 weeks from approximately 1.5 million customers across 152 stores. Furthermore, we provide the first systematic analysis – in both conceptual and empirical terms – of the key market and consumer characteristics that drive ECP behavior. Our novel data set, which combines actual purchase data with survey data from households, enables us to develop a detailed comparative profile of extreme cherry pickers based on both observable and attitudinal measures.

Because extreme cherry pickers represent an unavoidable cost of a deep discount or loss leader pricing strategy for retailers, if the proportion of these consumers is larger, the loss leader pricing strategy may be unprofitable or ineffective (Drèze 1995). The limited existing studies on the impact of loss leader pricing strategy on store performance or profit (Walters and MacKenzie 1988; Walters and Rinne 1986) use aggregate store-level data. In contrast, we employ individual customer-level data to test the profitability of loss leader pricing strategy in the presence of ECP behavior and to decompose and estimate the unavoidable cost of its negative profit contribution compared with the incremental positive profit contribution of loss leader pricing.

Conceptual framework

Antecedents/characteristics of extreme cherry picking behavior

Conceptual framework for our study is represented in Fig. 1. We start with some fundamental, logical inferences that are consistent with the grocery retail market dynamics and customer-level outcomes of ECP behavior. The usual frequency and coverage of items across categories that are subject to loss leader price promotions means customers find only a fraction of items on promotion. That is, they likely cannot patronize a single store for any substantial share of their overall market basket and still generate a net negative profit contribution for that store. For customers to generate a net negative profit contribution they likely visit the store only occasionally to specifically take advantage of loss leader promotions for their items of interest; otherwise, they purchase at another store. That is, the negative profit impact appears only with respect to a secondary store. We focus on understanding the factors that should lead to such outcomes for any cross-store shopping behavior.

Two theories from the economics literature are especially relevant and form the conceptual basis of our study. One is the Becker's (1965) theoretical framework of household production, which has been used as a guiding force for understanding the role of various consumer and market characteristics on consumers' valuation of times and how such valuations affects various facets of consumer behavior (Horsky 1990). The other is the Stigler's (1961) economics of information theory that serves as a seminal foundation to understanding consumers' information search behavior including price search (Ratchford 1982). These two theories essentially complement each other.

A fundamental premise underlying both the aforesaid theories (Becker 1965; Stigler 1961) is that consumers perceive their time as especially valuable, and they use an implicit cost–benefit framework to make trade-offs between the opportunity cost of time for engaging in a specific activity and the expected benefit enjoyed from engaging in that activity. In the context of

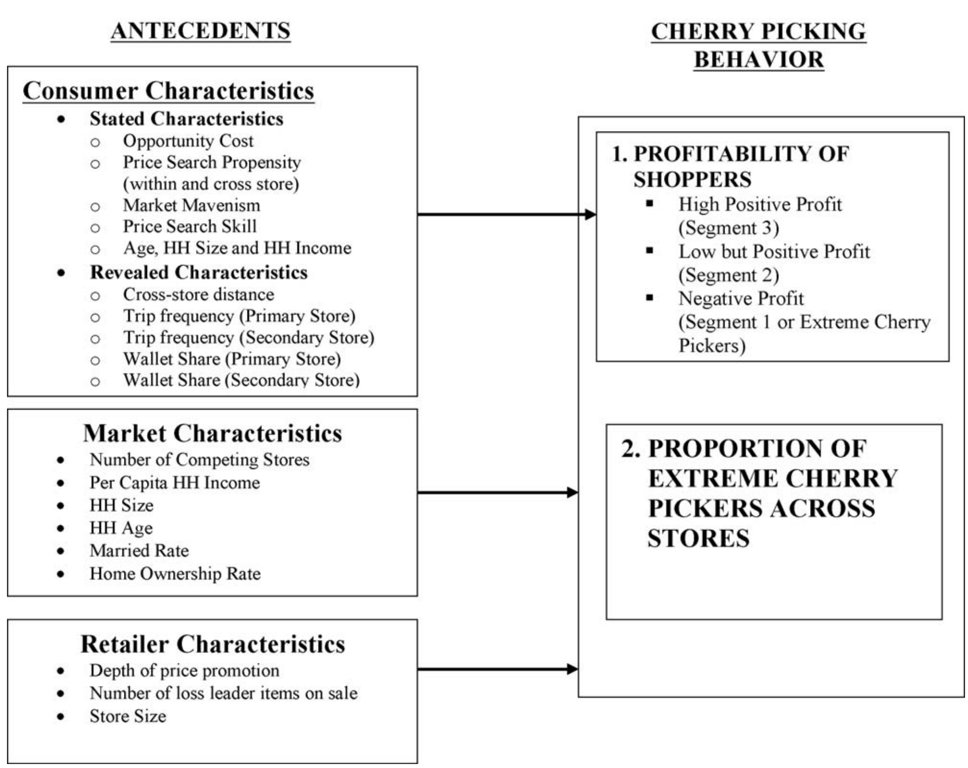

Fig. 1. Conceptual framework.

our study, this cost–benefit conceptual framework posits that customers would choose a cross-store search strategy that maximizes their potential savings, net their costs (e.g., Marmorstein, Grewal, and Fiske 1992; Putrevu and Ratchford 1997). We now discuss how Becker's (1965) theoretical framework of household production can be used to analytically characterize this cost–benefit framework behind a consumer's cross-store search strategy.

For any given customer, we consider two grocery stores, the primary store and the main secondary store. The use of only the two most frequently visited grocery stores reflects both supply- and demand-side considerations. On the supply side, the regional market we analyze represents a de facto duopoly grocery market structure, with two regional supermarket chains accounting for more than 80% of market shares (see Lal and Matutes 1994; Lal and Villas-Boas 1998; Rao and Syam 2001). On the demand side, several recent studies (e.g., Gauri, Sudhir, and Talukdar 2008) note that a household's grocery spending typically concentrates in just one or two stores.[3] In this context, according to Progressive Grocer (2005), an average consumer shops in 2.17 supermarkets and the percentage share of spending done in the primary supermarket is 73%. Further, it is important to recognize that the focus of our study is on systematic ECP behavior of a customer with respect to a store.[4] Thus, it is especially reasonable in our study to abstract way from the marginal stores in a household's grocery store choice set.

As per Becker's (1965) theoretical framework of household production, a consumer must decide which market goods to purchase and how to allocate her time so that she "produces" the utility maximizing mixture of "commodities" to satisfy her regular household needs. On any given decision cycle time, the consumer maximizes a utility function which has as arguments m different commodities, Z_i, (e.g., household grocery shopping; household entertainments) that satisfy her regular household needs. Following Horsky (1990) and using similar notations, the consumer decision process in our current study context can then be specified as:

$$\max U = F(Z_1, Z_2, \ldots\ldots, Z_m) \quad \text{such that :} \tag{1}$$

$$Z_i = f_i(x_{i0}, x_{i2}, \ldots, x_{in_1}; t_{i1}(1 + h_0 x_{i0}), t_{i2}, \ldots, t_{in_2}; D), \quad i = 1, \ldots, m \tag{1a}$$

$$-g_{i0}x_{i0} + \sum_{i=1}^{m}\sum_{j=1}^{n_{1t}} p_j x_{ij} = I = wt_w + V \tag{1b}$$

$$h_0 t_{i1} x_{i0} + \sum_{i=1}^{m}\sum_{l=1}^{n_{2t}} t_{il} + t_w = T \tag{1c}$$

$$x_{i0} = 0, 1 \tag{1d}$$

Constraint (1a) above shows the household production functions that reflect how the various commodities are produced by a combination of market goods, the consumer's time and other inputs. The amount of market good j which is used in the production of commodity i is x_{ij}, and the amount of time spent on activity l for the production of commodity i is t_{il}. In the production function of commodities, D represents a vector of characteristics such as household size. Thus, for example, a larger household may require more market goods and time inputs for producing a specific commodity. In general, there can be n_{1i} different frequently purchased market goods and n_{2i} different time intensive activities which go into the production of commodity i. For example, if commodity i is household grocery shopping, then its production requires various grocery items needed by the household, shopping trip times, etc. In order to achieve price savings, the consumer may consider a cross-store trip (between her primary and main secondary stores) as part of her shopping trip. If she decides not to make a cross-store trip, then $x_{io} = 0$. On the other hand, if she decides to make a cross-store trip, then $x_{io} = 1$ and it increases her total shopping trip time, t_{i1}, by a fraction h_0. At the same, let g_{io} be the typical price savings gain she can have from a cross-store trip that splits her shopping basket between her primary and main secondary stores. The law of triangles (i.e., sum of two sides is always greater than the third side) reveals that it will always be cheaper for this consumer to undertake a common shopping trip rather than separate trips.

The choices the consumer makes concerning market goods and time allocation are constrained by both her income and time. For instance, the total expenditure on market goods is limited by each period's money income, I, which is the sum of her earned wages, wt_w, and other income, V (see constraint (1b)); w is the wages rate of the consumer and t_w is the time spent working. The unit price of the frequently purchased market good j is p_j. Constraint (1c) divides the total time available, T, for the given decision time cycle into working time and time devoted to the production of various commodities, including rest and sleep. The income and time constraints can be combined into a single constraint by substitution of the working time, t_w, from (1c) into (1b) to yield:

$$(h_0 w t_{i1} - g_{i0})x_{i0} + \sum_{i=1}^{m}\sum_{j=1}^{n_{1t}} p_{ij} x_{lj} + w\sum_{i=1}^{m}\sum_{l=1}^{n_{2t}} t_{il} = wT + V = S \tag{2}$$

The new combined constraint indicates that the "full" income, S, which would be realized if all time were devoted to work, and is spent partly on goods and partly by foregoing earnings to use time in household production. The consumer's decision problem (1) on how to allocate her income and time among the various commodities to maximize her utility can

[3] As we discuss later, our own data show that a household's grocery store choice set size is essentially two with an almost exclusive concentration of its grocery spending (90%-100%) at the top two visited stores in its choice set with the other stores being very marginal in terms of spending share.

[4] To capture such systematic ECP behavior of a customer with respect to a store in the FPG market context of our empirical analysis, we only look at those customers who has visited the store at least on 12 occasions over the year and still generated negative profit contribution to the store.

then be solved through the following Lagrangian (Horsky 1990):

$$\max L = F[f_1(x_{11}, \ldots), \ldots\ldots, f_i(x_{i0}, x_{i1}, \ldots., t_{i1}(1 + h_0 x_{i0}), t_{i2}, \ldots.), \ldots., f_m(x_{m1}, \ldots.)] + \lambda\{S - [(h_0 w t_{i1} - g_{i0})x_{i0} + \sum_{i=1}^{m}\sum_{j=1}^{n_{1t}} p_{ij}x_{ij} + w\sum_{i=1}^{m}\sum_{l=1}^{n_{2t}} t_{il}]\} \quad (3)$$

As shown by Horsky (1990) in the analogous consumer decision context of whether to adopt a time saving new product, conditions under which a consumer decided whether to engage in cross-store search strategy can be drawn from the above analytical optimization framework. Specifically, assuming that cross-store trip is not made (i.e., $x_{i0} = 0$), the Lagrangian defined in (3) can be solved to determine the total amount of time, t^*_{i1}, that the consumer should spend on shopping trip. The consumer is then indifferent between either engaging or not engaging in cross-store search when the additional time, $h_0 t^*_{i1}$, spent on cross-store search reaches a level at which $h_0 w t^*_{i1} = g_{i0}$. The indifferent consumer thus faces an "opportunity cost" (Stigler 1961) $C = h_0 w t^*_{i1}$ for undertaking cross-store search on a shopping trip that is equal to the typical price savings gain, g_{i0}, from such cross-store search. The additional time, $h_0 t^*_{i1}$, spent on cross-store search by a consumer will consist of $A + d/s$, where A is the additional time (e.g., separate checkout, parking) required to shop at another store (Fox and Hoch 2005), d is the distance traveled to perform the cross-store search, and s is the speed of the typical mode of transport. Thus, taken together, the opportunity cost faced by a consumer for undertaking cross-store search can be characterized as:

$$C = w\left(\frac{A + d}{s}\right) \quad (4)$$

The above cost–benefit framework of consumers' shopping trip implies three consumer segments that correspond to three distinct cases for the magnitude of the opportunity cost (C) of cross-store search relative to the typical savings (g_{i0}) from such search:

Segment 1 (*Seekers*: Occasional basket splitters): For seekers, the opportunity cost of a cross-store search is approximately the same as the typical savings g_{i0} of their search. Therefore, they buy almost exclusively from the primary store, though they may occasionally split their shopping baskets when loss leader promotions in the secondary store provide more savings. In other words, these customers do not find it cost effective to engage in regular cross-store search, except in response to deep discounts by the secondary store on the items of interest. Thus, they reveal a disproportionate concentration of deeply discounted loss leader item purchases from secondary stores. These customers generate negative profit margins at their secondary stores but positive profit margins at their primary store.

Segment 2 (*Opportunists*: Regular basket splitters): Opportunists experience low opportunity costs of cross-store search between primary and secondary stores and enjoy savings ΔS that are much greater than their opportunity costs. These customers regularly split their shopping baskets to take advantage of market price variations. This split loyalty avoids any disproportionate concentration of loss leader item purchases at either store, so they generate low but positive profit margins for both stores.

Segment 3 (*Loyalists*: Rare basket splitters): In direct contrast, with opportunists, loyalists have high opportunity costs for cross-store search and experience much lower g_{i0} than their opportunity cost of cross-store search. This trade-off implies that these customers are one-store loyal shoppers with little incentive to seek price deals. They likely buy almost exclusively from their primary store with rare, if any, shopping trips to secondary stores, which mostly represent fill-in rather than deal-seeking trips. These customers will generate high, positive profit margins for both primary and secondary stores.

This discussion of price search underscores two important points. First, the framework decomposes the deal-prone segment, typically identified as a single segment in the existing literature (e.g., Blattberg et al. 1978; Urbany, Dickson, and Kalapurakal 1996), into two distinct segments. Thus, we can recognize explicitly and investigate the two materially distinct impacts of deal-seeking behavior on the key operational variable of interest to retailers, namely, customer profit contribution. Second, somewhat counter intuitively, it suggests customers who are most likely to generate negative profit contributions are not those with the lowest opportunity cost for cross-store shopping. Rather, we consider an inverse U-shaped relationship between customers' opportunity cost and likelihood of exhibiting ECP behavior (see Fig. 2). At the aggregate market level, this inverse U-shaped relationship should be evident between the mean opportunity cost of cross-store search (nearest competing store) for customers of a store and the proportions of customers exhibiting ECP behavior. As one of its key goals, our study empirically tests for this inverse U-shaped relationship at both the individual customer and aggregate store levels.

Furthermore, we hope to gain systematic empirical insights into the comparative consumer characteristics of those who exhibit ECP behavior and the effects of market (e.g., competition) and retail (e.g., store size) characteristics. We offer a priori conceptual expectations about these insights on the basis of our cost–benefit framework, as well as relevant prior research.

Comparative consumer characteristics

Consumer characteristics can be classified as stated and revealed. Stated characteristics include self-reported attitudinal and behavioral measures, as well as socio-economic demographics. Revealed characteristics pertain to observed purchases that capture consumers' actual shopping behavior and related measures. To gain insights into both types, we consider the three customer segments identified by our conceptual cost–benefit framework; specifically, we compare the expected levels of selected consumer characteristics among ECP customers (Segment 1: Seekers) with those for low, positive profit margin

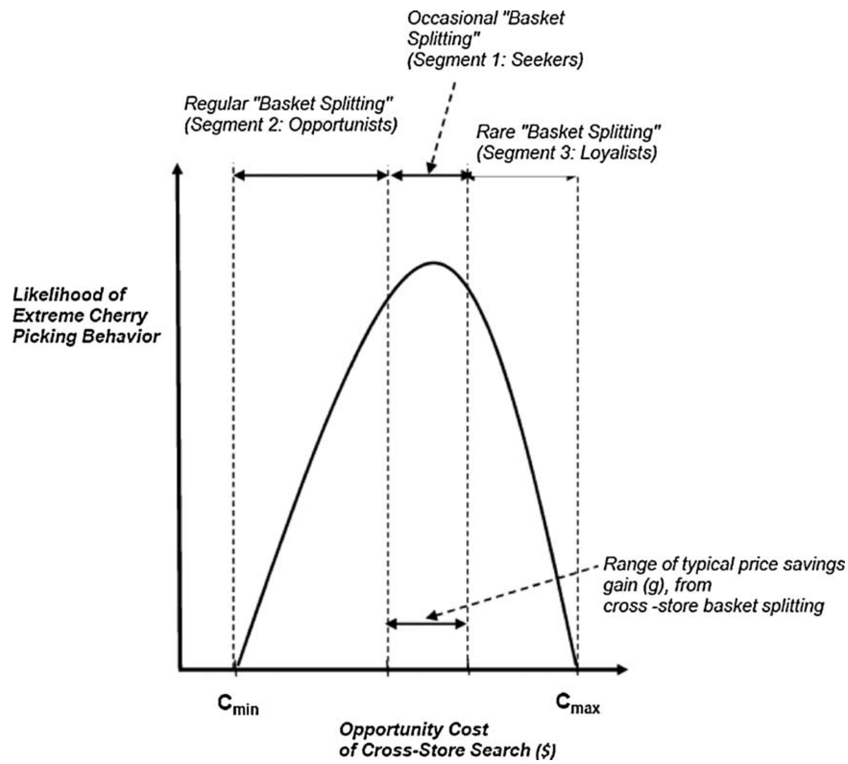

Fig. 2. Conceptual relationship between cross-store search cost and likelihood of extreme cherry picking behavior.

customers (Segment 2: Opportunists) and high, positive profit margin customers (Segment 3: Loyalists).

As we noted in our conceptual framework, a key comparative difference across the segments is their total opportunity cost of cross-store price search. Eq. (1) also implies that the unit opportunity cost of time and cross-store distance will be lower for seekers and opportunists than for loyalists. Furthermore, regarding differences in relevant behavioral outcomes, only seekers and opportunists should exhibit price deal-seeking behavior, though we expect a substantive difference in the nature of such behavior. That is, opportunists visit both stores regularly to seek all types of price deals, whereas seekers visit their secondary store only occasionally to take advantage of specific, deep discount, or loss leader price deals.

We expect trip frequency to the primary store to be higher for seekers and opportunists than for loyalists and trip frequency to the secondary store to be lower for seekers and loyalists than for opportunists. Moreover, wallet share should concentrate at the primary store for seekers and loyalists, more so than for opportunists, which splits its share of wallet more evenly. Regarding attitudinal characteristics, we use various measures identified in prior research that offers evidence of a positive correlation between deal-seeking behavior and measures of cross- and within-store search propensities, market mavenism, and perceived search skills (Dickson and Sawyer 1990; Feick and Price 1987; Gauri, Sudhir, and Talukdar 2008; Putrevu and Ratchford 1997; Urbany, Dickson, and Kalapurakal 1996). Therefore, attitudinal measures should be higher for seekers and opportunists than for loyalists. However, because of the difference in cross-store search behavioral outcomes, we also expect that the measure of cross-store search propensity will be lower for seekers than for opportunists.

Existing evidence about the impact of individual demographic characteristics on deal proneness and price search behavior appears mixed. Some studies indicate a weak or nonexistent relationship (Magi and Julander 2005; Montgomery 1971; Rossi and Allenby 1993); others find mild to strong associations between demographic characteristics and price or coupon responses (Bawa and Shoemaker 1987; Blattberg et al. 1978; Carlson and Gieseke 1983; Inman, Shankar, and Ferraro 2004; Narasimhan 1984; Urbany, Dickson, and Kalapurakal 1996). We thus consider the differences across segments in terms of age or household size empirically open questions. However, because household income acts as a proxy for unit opportunity cost of time, we expect it to be lower for seekers and opportunists.

We summarize our a priori conceptual expectations for the selected consumer characteristics in Table 1. The relationship of consumer characteristics across the three segments (and thus with customer profitability) is not strictly monotonic or linear, as suggested by existing literature. Furthermore, by using the conceptual framework to decompose deal-prone consumers into two segments, we recognize the materially distinct impacts of deal-seeking behavior on customers' profit contributions and test empirically the unexplored non-monotonic relationships between several key consumer characteristics and customer profitability. Appendix C presents a complete list of the items for various attitudinal measures, their corresponding reliability coefficients, and sources.

Table 1
Expected comparative profiles of extreme cherry pickers by selected consumer characteristics.

Consumer characteristics	Expected relative[a] levels			Related prior research	Variables included[a]
	Negative profit margin or ECP segment (# 1): Seekers	Low positive profit margin segment (# 2): Opportunists	High positive profit margin segment (# 3): Loyalists		
Stated characteristics				Blattberg et al. (1978) [b]	(6[c], 8)
1. Opportunity cost of cross-store search	Moderate	Low	High	Carlson and Gieseke (1983) [d]	(6, 7, 8)
2. Cross-store search propensity	Moderate	High	Low	Dickson and Sawyer (1990) [d]	(2, 3, 5)
3. Within-store search propensity	High	High	Low	Feick and Price (1987) [d]	(4)
4. Market mavenism/enjoyment	High	High	Low	Gauri, Sudhir, and Talukdar (2008) [e]	(1–8)
5. Perceived price search skill	High	High	Low	Magi and Julander (2005) [d]	(7, 8)
6. Age	Not clear	Not clear	Not clear	Marmorstein, Grewal, and Fiske (1992) [d]	(1, 5)
7. Household size	Not clear	Not clear	Not clear	Putrevu and Ratchford (1997) [d]	(1, 4, 5)
8. Household income	Low	Low	High	Ratchford (1982) [d]	(1)
				Urbany, Dickson and Kalapurakal (1996) [d]	(1, 4–8[f])
Revealed characteristics					(1–3)
1. Cross-store distance	Low	Low	High	Fox and Hoch (2005)[e]	(1–5)
2. Trip frequency at the primary store	High	High	Low	Gauri, Sudhir, and Talukdar (2008) [e]	
3. Trip frequency at the secondary store	Low	High	Low		
4. Wallet share at the primary store	High	Moderate	High		
5. Wallet share at the secondary store	Low	Moderate	Low		

[a] Each number in the "variables included" column indicates the inclusion of the corresponding numbered variable in that study.
[b] This study uses the presence of children in the house under 6 years of age as an indicator for less time available for shopping.
[c] The focus domain of this study is on identifying characteristics of deal prone households.
[d] The focus domain of this study is only on consumers' price search behavior.
[e] The focus domain of this study is on both consumers' price search behavior and consumer promotion.
[f] This study uses the number of children in the house less than 5 years of age as an indicator for less time available for shopping.

Role of market and retailer characteristics

Various market- and retailer-level characteristics may influence deal-seeking behavior (see Table 2). For example, competition has a significant impact on search behavior (Ratchford and Srinivasan 1993) and a store's net profits (Ailawadi et al. 2006); we similarly expect that as the number of competitors within a store's trading area increases, the number of extreme cherry pickers will increase, because they have more stores from which to choose. Hoch et al. (1995) reveal a significant impact on price sensitivity of the income, size, and age of households in a trading area, and Ailawadi et al. (2006) report positive effects of income and proportion of single-family homes on net profits. However, they find a negative impact on profits of the proportion of households with more than three people. Blattberg et al. (1978) reveal

Table 2
Expected role of selected market and retailer characteristics on extreme cherry picking behavior of consumers.

Characteristics	Expected role	Related prior research	Variables included[a]
Market characteristics			(1[b], 2, 3, 6)
1. Number of competing stores	+	Ailawadi et al. (2006) [c]	(6)
2. Per capita income of households	–	Blattberg et al. (1978) [d]	(1, 4)
3. Mean household size	+	Boatwright, Dhar, and Rossi (2004) [c]	(2, 3, 4)
4. Mean age	+	Hoch et al. (1995) [c]	(2, 3, 4)
5. Married rate	Not clear	Mace and Neslin (2004) [c]	(1)
6. Home ownership rate	Not clear	Ratchford and Srinivasan (1993) [e]	
Retailer characteristics			(1, 3)
1. Mean depth of price promotion	+	Ailawadi et al. (2006) [c]	(1)
2. Mean number of loss leader items on sale	+	McAlister, George, and Chien (2009) [c]	(2)
3. Size of store	+	Walters and MacKenzie (1988) [c]	(2)
		Walters and Rinne (1986) [c]	

[a] Each number in the "variables included" column indicates the inclusion of the corresponding numbered variable in that study.
[b] This study depicts competition as population divided by the number of stores.
[c] The focus domain of this study is only on consumer promotion.
[d] The focus domain of this study is on identifying characteristics of deal prone households.
[e] The focus domain of this study is only on consumers' price search behavior.

a positive impact of home ownership on deal proneness; Mace and Neslin (2004) suggest significant impacts of household size and age on promotion elasticities but not of income.

Increased discount depth by a retailer may attract deal-seeking customers who boost store sales (Ailawadi et al. 2006; McAlister, George, and Chien 2009; Shankar and Bolton 2004); we posit that increased depth of loss leader promotions should be positively associated with an increased proportion of ECP shoppers. Walters and Rinne (1986) also find that certain products promoted as loss leaders have a greater impact on store traffic, store sales, and deal sales, yet no portfolios of loss leaders have significant impacts on retailer profits. In another study, Walters and MacKenzie (1988) find that two (of eight) categories influence store profits—one positively and one negatively. We expect that when more loss leaders are on sale, ECP should increase. Also, we expect that the proportion of ECP shoppers will increase with the size of the store.

Prevalence of extreme cherry picking behavior

To identify the prevalence of ECP behavior among its customers, a retailer must analyze the proportion of customers who generate negative profit contributions. An important consideration entails the time window over which to evaluate the profit contribution. At a minimum, the window should take into account the typical industry price cycle period and consumers' shopping frequency; in the grocery retail market, both these periods are weekly.

We analyze customer-level transaction data for a given store to identify the proportion of customers who generate negative profit contributions in any given week and over the course of an entire year. The weekly measure may include some customers who exhibit ECP behavior, even if they do not price shop systematically. The annual measure likely includes only customers who exhibit ECP behavior on a sustained basis. In other words, while the weekly measure indicates the extent of temporal or short-term incidence of ECP behavior, the annual measure reveals the extent of long-term or systematic ECP behavior among a store's customers.

Store profit impacts from extreme cherry picking behavior

Taking advantage of the availability of store-specific detailed transaction and profit contribution data in our data set, we propose a disaggregate customer-level analysis approach to investigate the underlying cost–benefit trade-off implicit in the rationale for loss leader pricing. For each store-week case, we use transactional and profit data to analyze all customers who make purchases. In analytical terms, we decompose the profit contribution p_{ijt} of any customer i at store j on week t as:

$$p_{ijt} = l_{ijt} + g_{ijt}, \tag{5}$$

where l_{ijt} is the negative profit contribution (or loss) generated from the purchase of loss leader item(s), and g_{ijt} is the positive profit contribution (gain) generated from the purchase of non–loss leader item(s). On the basis of the composition of their shopping baskets, we segment customers into three mutually exclusive and exhaustive subsets: $S^{(1)}$, $S^{(2)}$ and $S^{(3)}$. In Appendix A, we provide the expression for computing the profit contribution ($P_{jt}^{(i)}, i = 1, 2, 3$) of each of the subsets.

To justify the cost–benefit rationale for loss leader pricing, the profit contribution $P_{jt}^{(3)}$ from $S^{(3)}$ must more than offset the unavoidable pure loss $P_{jt}^{(2)}$ imposed by $S^{(2)}$. Moreover, $P_{jt}^{(3)}$ represents the upper profit boundary, with the assumption that the loss leader pricing strategy is solely responsible for inducing customers in $S^{(3)}$ to make the shopping trip (and thus generate the positive profit contribution $P_{jt}^{(3)}$). This premise may not hold for all customers in the subset.

To estimate the incremental profit gain $P_{jt}^{*(3)}$ for store j from the loss leader pricing strategy in week t, we adjust $P_{jt}^{(3)}$ as follows:

$$P_{jt}^{*(3)} = \sum_i (a_{ijt} P_{ijt}^{(3)}), \quad \forall i \in S_{jt}^{(3)}, \tag{6}$$

where a_{ijt} is an adjustment factor that captures the incremental impact of store j's loss leader pricing strategy on customer i's likelihood of undertaking a shopping trip to store j in week t. For the loss leader pricing strategy to be effective, the incremental profit gain $P_{jt}^{*(3)}$ must be greater than the unavoidable pure loss $P_{jt}^{(2)}$. One way to conceptualize and measure the value of the adjustment factor uses:

$$a_{ijt} = 1 - Pr_{ijt}, \tag{7}$$

where Pr_{ijt} is the probability that customer i would make the shopping trip to store j in week t even in the absence of the loss leader promotion. The value of this adjustment factor a_{ijt}, by definition, should equal 0 and 1 for households in subsets $S^{(1)}$ and $S^{(2)}$, respectively.

We also propose two alternative approaches to estimate the adjustment factor. A heuristic approach computes the probability Pr_{ijt} as the ratio of the number of non–loss leader items to all items in the shopping basket of customer i during the trip to store j in week t. This measure captures the conceptually consistent expectation that the presence of a relatively larger proportion of loss leader items in the shopping basket indicates that the loss leader pricing strategy plays a significant incremental role in triggering that shopping trip. This approach represents a simple yet intuitive use of information embedded in readily available scanner data and thus gives retail managers an initial but relevant insight into the underlying profit dynamics behind weekly loss leader pricing. Such strategic information is consistent with the notion of creating a marketing dashboard for managers (Marketing Science Institute 2006). A more theoretical method uses a statistical approach based on shopping trip incidence or purchase timing probability is described in Appendix B.

Data

For this research, we obtain data from a major grocery supermarket chain in the northeastern region of the United States. This stock keeping unit (SKU)-level scanner database includes all product items that the chain sells in its stores. The data include 52 weeks (2002) and 152 stores of the chain across distinct geographic markets. During this time period, we observe all customer-level transactions made in each of the stores, including information about the time and date of the transactions, loyalty card holder information, dollar volume, quantity, unit price, unit profit contributions, and price deals offered for each SKU sold.

The stores of the participating chain use a Hi-Lo pricing strategy, enjoy a loyalty card usage rate of approximately 95%, and make store price promotion deals (loss leader or not) available only to store loyalty card holders. Thus, households likely cannot engage in ECP behavior without holding a loyalty card and using that card for transactions. Rather, we argue that an ECP household would be especially likely to own and use the loyalty card, because of its deal proneness. Therefore, a household engaged in an ECP price search strategy at the participating store will appear identified as such in our data.

The item cost data from the participating retail chain is the average marginal cost or average acquisition cost (AAC), based on the chain's inventory costing system for wholesale prices and various trade deals (Besanko, Dube, and Gupta 2005; Chevalier, Kashyap, and Rossi 2003; Gauri, Sudhir, and Talukdar 2008). These data also cover 100% of the universal product codes in the stores during the 52 weeks. Therefore, we can compute the gross profit margin of each item on weekly basis and the gross profit contributions from store customers. We consider an item subject to a loss leader promotion when its gross margin is negative and sold at a loss according to its AAC (Gauri, Sudhir, and Talukdar 2008). Similarly, we define a customer as an extreme cherry picker for the store if he or she generates a negative gross profit contribution from purchases in that store on a sustained basis (52 weeks); that is, according to the AAC of the items purchased by that customer, the retailer suffers a loss. The retailer also provided upstream accounting cost data, which it uses to identify loss leader items for operational decisions.

We complement the scanner data with various relevant secondary data, including information about the nearest competitor, number of competitors in the trading region, and floor area for each store. We geo-code the address (longitude, latitude) of each store and spatially linked it to the census block group (CBG) polygon to which the store belongs. For each store, we use this geo-coding to compute the distance from the nearest competing grocery store. Using sociodemographic data at the CBG level from the U.S. Census Bureau, we compute distance-weighted averages of sociodemographic variables (e.g., household size, income) associated with each CBG in the trading area. Because car ownership rates are available only at the five-digit zip code, rather than CBG, level, we measure car ownership rates by the zip code of the location.

Finally, we augment these data with responses from a primary consumer survey that we mailed to a subset of the chain's customers (i.e., those with loyalty cards and who made at least 12 shopping trips to stores = 1430). On the basis of the customers' net profit margins at the individual level, we identify three sample groups: (1) negative values (i.e., ECP customers); (2) low, positive values; and (3) high, positive values. Based on our conceptual framework, these customers should be occasional, regular and rare basket splitters. The respondents are the primary grocery shoppers in their respective households. We received 529 surveys, for an overall response rate of 37%. The distribution of the 529 customers across the three profit groups is close to equitable, with 168 negative values; 178 low, positive values; and 183 high, positive values.

For each customer, we gather information about household size, income level, names and addresses of the primary and main secondary stores, approximate shares of wallet at each store, and the main reason for shopping at the secondary store. The address information enables us to geo-code and compute the inter-store distance. As Putrevu and Ratchford (1997) point out, it is very difficult to develop a multi-item scale for the unit opportunity cost measure that exhibits high scale reliability; we follow them, Gauri, Sudhir, and Talukdar (2008), and Marmorstein, Grewal, and Fiske (1992) and employ a single-item measure that asks respondents to indicate the hourly wage rate at which they would be willing to undertake an extra hour of work.

We use self-reported consumer survey information to construct the various attitudinal and behavioral measures. All items in our constructs are based on previous studies in consumer price search literature. Appendix C presents a complete list of the items, their corresponding reliability coefficients, and their sources.

Empirical analyses results

What characterizes extreme cherry pickers?

The cost–benefit conceptual framework suggests that a key determinant of ECP behavior is the opportunity cost of a cross-store shopping trip. Specifically, at the aggregate store level, the framework hypothesizes an inverse U-shaped relationship between the proportions of ECP customers across stores and the mean opportunity costs of cross-store shopping; at the individual customer level, it hypothesizes an inverse U-shaped relationship between customers' opportunity cost of cross-store shopping and their likelihood of exhibiting ECP behavior. We test for this relationship at both the store and customer levels.

Aggregate store-level analysis. For the aggregate store-level analysis, we run a regression analysis of the proportions of ECP customers of each store in our data set vs. the mean opportunity costs of cross-store shopping. First, we treat mean opportunity cost as a continuous measure and include both linear and quadratic terms as explanatory variables. Second, we treat the mean opportunity cost as a discrete measure and use it as an explanatory variable with five mutually exclusive and exhaustive levels (Morck, Shleifer, and Vishny 1988). To obtain a relative measure of the mean opportunity cost of cross-store shopping for customers, we use Eq. (4) and measure distance d in terms of the distance between the store and its nearest competing grocery store and the unit opportunity cost of time w according to the imputed hourly wage rate from the mean per capita income for the population in the store's trading region. We assume the additional trip time A and travel speed s are the same for all customers, equal to 15 min and 35 miles/h, respectively. These

Table 3
Regression results for the proportion of extreme cherry picking shoppers across stores.

Independent variable	Model 1		Model 2	
	Coefficient	Std. error	Coefficient	Std. error
Market characteristics				
Mean opportunity cost of cross-store shopping trip to the nearest competing store ($)	0.019 E−02 ***	0.007 E−02		
Square of the mean opportunity cost of cross-store shopping trip	−0.149 E−04 ***	0.032 E−04		
Mean opportunity cost of cross-store shopping trip in discrete ranges				
Less than $3			−0.363 E−02***	0.132 E−02
$3–less than $6			−0.114 E−02**	0.056 E−02
$6–less than $9 (Base)				
$9–less than $12			−0.143 E−02**	0.069 E−02
More than $12			−0.304 E−02***	0.097 E−02
Number of competing stores in the trading area	−0.009 E−01***	0.003 E−01	−0.009 E−01***	0.003 E−01
Mean per capita annual income for population in the trading area ($)	0.177 E−09	0.431 E−08	0.174 E−09	0.429 E−08
Mean household size for population in the trading area	0.041***	0.009	0.040***	0.009
Proportion of 60 years and above among population in the trading area	0.123***	0.041	0.122***	0.039
Proportion of married among adult population in the trading area	0.042*	0.023	0.043*	0.023
Home ownership rate among population in the trading area	−0.020	0.013	−0.020	0.014
Retailer characteristics				
Mean price promotion depth at the store (%)	0.060 E−03**	0.031 E−03	0.063 E−03**	0.032 E−03
Mean proportion of items on weekly loss leader promotions at the store	0.011 ***	0.003	0.012 ***	0.003
Floor area of the store (Sq. Ft.)	0.193 E−08***	0.483 E−09	0.193 E−08***	0.483 E−09
Intercept	−0.122***	0.028	−0.121***	0.029
N	152		152	
Adj. R^2	0.54		0.51	

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

specific values do not affect our analysis findings; they simply shift the relative scale used to measure customers' opportunity costs.

The opportunity cost of cross-store shopping reflects both customer (unit opportunity cost of time, w) and market competition (inter-store distance, d) characteristics. Although opportunity cost is our focal explanatory variable, we test the effects of several market, store, and customer characteristics on consumer deal-seeking behavior (Blattberg et al. 1978; Fox and Hoch 2005; Mace and Neslin 2004). Because of a high degree of correlation (>.7) with income, we exclude three customer variables – education level, car ownership rate, and housing value – from our final analysis.

The results of the aggregate store-level regression analysis appear in Table 3. Models 1 and 2 use opportunity cost as a continuous and discrete measure, respectively. The results from Model 1 show a statistically significant positive coefficient ($p<.01$) for the mean opportunity cost of cross-store shopping and a negative coefficient ($p<.01$) for the mean opportunity cost squared term. In Model 2, we also find significant coefficients of mean opportunity cost, such that the proportion of ECP customers decreases with either lower or higher opportunity costs. Both models thus provide strong empirical evidence of an inverse U-shaped relationship between the proportion of ECP customers across stores and the mean opportunity costs of cross-store shopping for those customers.

Most of the other explanatory variables are statistically significant ($p<.1$ and below), with signs consistent with previous findings or a priori expectations (Table 2). The proportion of ECP behavior increases with greater household sizes, higher proportions of seniors (60 years and older), and higher proportions of married people in the focal store's customer base. However, income and house ownership levels have no significant ($p>.1$) effects; the effect of income appears partially accounted for by the opportunity cost of cross-store shopping. More competing stores in the trading area have a significant ($p<.01$) negative effect on the proportion of customers at a focal store who exhibit ECP behaviors, which may suggest a split effect. In terms of store characteristics, the proportion of customers who exhibit ECP behaviors increases with the weekly mean depth of price promotions at the focal store, as well as the weekly mean breadth of items on loss leader promotion. We also find a strong ($p<.01$) positive relationship between a store's size and its proportion of ECP customers.

Disaggregate customer-level analysis. We complement our insights from the store-level aggregate analysis with customer-

Table 4
Nature of relationship between customer profitability and selected consumer characteristics: regression results.

Independent variables: consumer characteristics	Dependent variable: customer profit margin[a]				
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Intercept	0.26 (0.01)***	0.46 (0.02)***	0.23 (0.04)***	0.57 (0.12)***	0.14 (0.01)***
Opportunity cost of cross-store search	−0.12 (0.00)***				
Square of opportunity cost of cross-store search	0.01 (0.00)***				
Cross-store search propensity		−0.25 (0.01)***			
Square of cross-store search propensity		0.03 (0.00)***			
Trip frequency at the primary store			−0.22 (0.07)***		
Square of trip frequency at the primary store			0.07 (0.02)***		
Wallet share at the primary store				−0.02 (0.00)***	
Square of wallet share at the primary store				0.1E−3 (0.00)***	
Wallet share at the secondary store					−0.6E−2 (0.00)***
Square of wallet share at the secondary store					0.1E−3 (0.00)***
N	529	529	529	529	529
Adj. R^2	0.76	0.49	0.02	0.07	0.06

[a] Standard errors are shown in parentheses after the respective coefficient estimates.
*** $p<.01$.

level analyses to test and develop a detailed comparative consumer profile of ECP customers (Table 1). Specifically, we combine market transaction and consumer survey data from 529 customers who represent the three distinct segments in terms of their profit margin contributions to the participating retail chain. We use Eq. (4) to obtain a relative measure of the opportunity cost of cross-store shopping for each customer, such that d is the distance between the primary and secondary stores, the unit opportunity cost of time w is the self-reported value from the survey, and the additional trip time A and travel speed s

Table 5
Empirical findings: comparative profiles of extreme cherry pickers by customer characteristics.

Customer characteristics	Customer segments			Statistical significance of difference between segments		
	Negative profit margin or ECP segment (# 1: Seekers) $N=168$	Low positive profit margin segment (# 2: Opportunists) $N=188$	High profit margin segment (# 3: Loyalists) $N=173$	Segment # 1 vs. Segment # 2	Segment # 1 vs. Segment # 3	Segment # 2 vs. Segment # 3
Stated characteristics						
Self-reported unit opportunity cost of time ($/h)	14.68	7.82	22.96	$p<.01$	$p<.01$	$p<.01$
Total opportunity cost of cross-store trip ($)	4.71	2.51	8.10	$p<.01$	$p<.01$	$p<.01$
Cross-store search propensity[a]	3.08	4.2	1.58	$p<.01$	$p<.01$	$p<.01$
Within-store inter-temporal search propensity[a]	4.01	4.06	1.54	$p>.1$	$p<.01$	$p<.01$
Market mavenism[a]	3.04	3.91	1.53	$p<.01$	$p<.01$	$p<.01$
Perceived price search skill[a]	3.96	4.01	1.93	$p>.1$	$p<.01$	$p<.01$
Agreement with price savings as the primary reason for shopping at the secondary store[a]	4.61	4.53	1.36	$p>.1$	$p<.01$	$p<.01$
Household size	3.32	3.45	2.85	$p>.1$	$p<.01$	$p<.01$
Household annual income (Th. $)	52.3	41.2	63.7	$p<.01$	$p<.01$	$p<.01$
% of households whose primary grocery shopper is 60 years and above in age	20.24	21.81	17.92	$p>.1$	$p>.1$	$p>.1$
Revealed characteristics						
Distance from home to the primary store (miles)	3.09	3.05	3.64	$p>.1$	$p<.01$	$p<.01$
Distance between the primary and secondary stores (miles)	2.95	2.75	3.83	$p>.1$	$p<.01$	$p<.01$
Weekly trip frequency at the primary store	1.03	1.45	0.96	$p<.01$	$p<.05$	$p<.01$
Weekly trip frequency at the secondary store	0.39	1.02	0.38	$p<.01$	$p>.1$	$p<.01$
Focal store is primary store (%)	0.00	56.91	100.00	$p<.01$	$p<.01$	$p<.01$
Wallet share at the primary store (%)	85.87	57.79	89.56	$p<.01$	$p<.01$	$p<.01$
Wallet share at the secondary store (%)	13.29	41.04	10.35	$p<.01$	$p<.01$	$p<.01$
Wallet share at the focal store (%)	13.29	51.43	89.56	$p<.01$	$p<.01$	$p<.01$
Avg. weekly grocery spending at all stores ($)	84.84	90.12	80.76	$p>.1$	$p>.1$	$p<.05$
Ratio of avg. profit contribution per week to the focal store (Base: Segment #2)	−0.10	1.00	4.60	$p<.01$	$p<.01$	$p<.01$

[a] These items are measured on a five point scale anchored by "strongly agree" (5) and "strongly disagree" (1).

again equal 15 min and 35 miles/h, respectively. We perform the customer-level analyses in two ways.

First, we run regression analyses between customer profit margin and several consumer characteristics, one at a time, to test for the nonlinear relationships conceptualized in Table 1 and provide the results in Table 4 for five consumer characteristics. To test for possible nonlinear relationships, we use both a linear term and a quadratic term for each consumer characteristic. The high statistical significance ($p < .01$) of both linear and quadratic terms indicates a strong, nonlinear relationship between customer profitability and the analyzed consumer characteristics.

Second, we compute the sample mean or proportion values of the various consumer characteristics across the three customer segments and test for their statistical differences. Table 5 contains the findings, which not only confirm the core implications from our cost–benefit conceptual framework (Table 1) but also shed light into who is likely to engage in ECP behavior. For example, a household's combined share of total grocery spending at its two most frequently visited stores varies from 90% to 100% across respondents, with an average of 98%. This finding is consistent with several past studies (e.g., Gauri, Sudhir, and Talukdar 2008; Urbany, Dickson, and Kalapurakal 1996; Urbany, Dickson, and Sawyer 2000) and our conceptual premise that a household's grocery store spending typically concentrates in one or two stores. The main secondary store for each household tends to be the competitor nearest the primary store, which indicates that cross-store shopping distance drives the choice of the major secondary store. Interestingly, although our survey did not preclude a respondent's two most frequently visited grocery stores from belonging to the same retail chain, they always came from different chains obviously reflecting the reality of spatial distributions of competitive store locations in the market analyzed. At the same time, for 96% of our sample respondents, their two most frequently visited grocery stores in fact belong to the two regional supermarket chains, which is not surprising given that these two chains represent a de facto duopoly grocery market structure (by accounting for more than 80% market shares) for the regional market analyzed.

The mean relative opportunity cost for seekers (i.e., ECP customers) is between those of customers who represent the loyalists (i.e., high positive profit margin customers) and opportunists (low positive profit margin customers). We thus again find strong empirical support for the hypothesized inverse U-shaped relationship between customers' relative opportunity cost of cross-store search and their likelihood of exhibiting ECP behavior. Customers' ECP behavior also appears only in their visits to their secondary stores, where they shop occasionally (average 2.5 weeks) to buy a small share (13% on average) of grocery needs.

Of equal interest are insights from contrasts of customers' stated price search involvement, skill, search motivation, and patterns across the three segments. Regarding market mavenism and perceived price search skills, the seekers and opportunist exhibit similar levels, which are significantly ($p < .01$) higher than those of the loyalists. In terms of their primary reason for shopping at the secondary stores, both the seekers and opportunists cite price savings significantly ($p < .01$) more than loyalists. However, these groups differ in their stated price search patterns. They engage in inter-temporal and cross-store price search behaviors more ($p < .01$) than do loyalists, but the level of cross-store search behavior among seekers is significantly lower (3.08 vs. 4.2, $p < .01$) than that of the opportunists.

These findings indicate that both the seekers and loyalists remain basically loyal to their primary stores but make occasional trips to secondary stores. However, seekers customers organize their occasional trips to secondary stores to buy deeply discounted items. They also actively engage in inter-temporal price search strategies for their purchases at primary stores. In contrast, the opportunists regularly shop and split their purchases between primary and secondary stores, and neither store bears the full brunt of their price search strategy or serves as an exclusive source of deep discount bargain hunts. As our conceptual framework and empirical results show, a key determinant of different shopping behaviors across customer groups is the underlying difference in the opportunity costs of cross-store search.

How prevalent is extreme cherry picking behavior?

We use both short-term (weekly) and long-term (annual) assessments to determine the prevalence of ECP behavior across different stores in different competitive market contexts. For the weekly analysis, we randomly select 4 weeks of transaction data per store for 25 stores, for a total of 100 store-week time periods. We compute the size of the ECP segment for each selected store-week as the proportion of a store's customers who generated net negative profit contributions. The proportion of the extreme cherry pickers has a mean value of .021 with a standard deviation of .006 (see Fig. 3, panel a).

For each of the 152 stores, we use the scanner database to identify the size of its regular customer base by counting customers who shopped at the store at least 12 different times during 2002. We then compute the size of the seeker (or ECP) segment as the proportion of a store's regular customer base that generated net negative profit contributions to the store during 2002. Across 152 stores, this annual measure shows that the mean proportion of extreme cherry pickers is .015 with a standard deviation of .011 (ranging from .04% to 5.96% in various locations; see Fig. 3, panel b).

The weekly measure indicates a relatively larger seeker (or ECP) segment, because it includes both occasional and systematic ECP behaviors. However, on an absolute level, both the weekly and annual measures suggest a small seeker (or ECP) segment (Gauri, Sudhir, and Talukdar (2008) also find a small ECP segment). This finding contrasts with the conventional wisdom (McWilliams 2004). Moreover, our findings indicate that despite the small size, the relative magnitude of the ECP segment varies across different stores and competitive market contexts.

How do extreme cherry pickers affect store profits?

A loss leader pricing strategy attempts to attract customers to the store and induce them to buy non–loss leader items in addition to the loss leader items. However, sev-

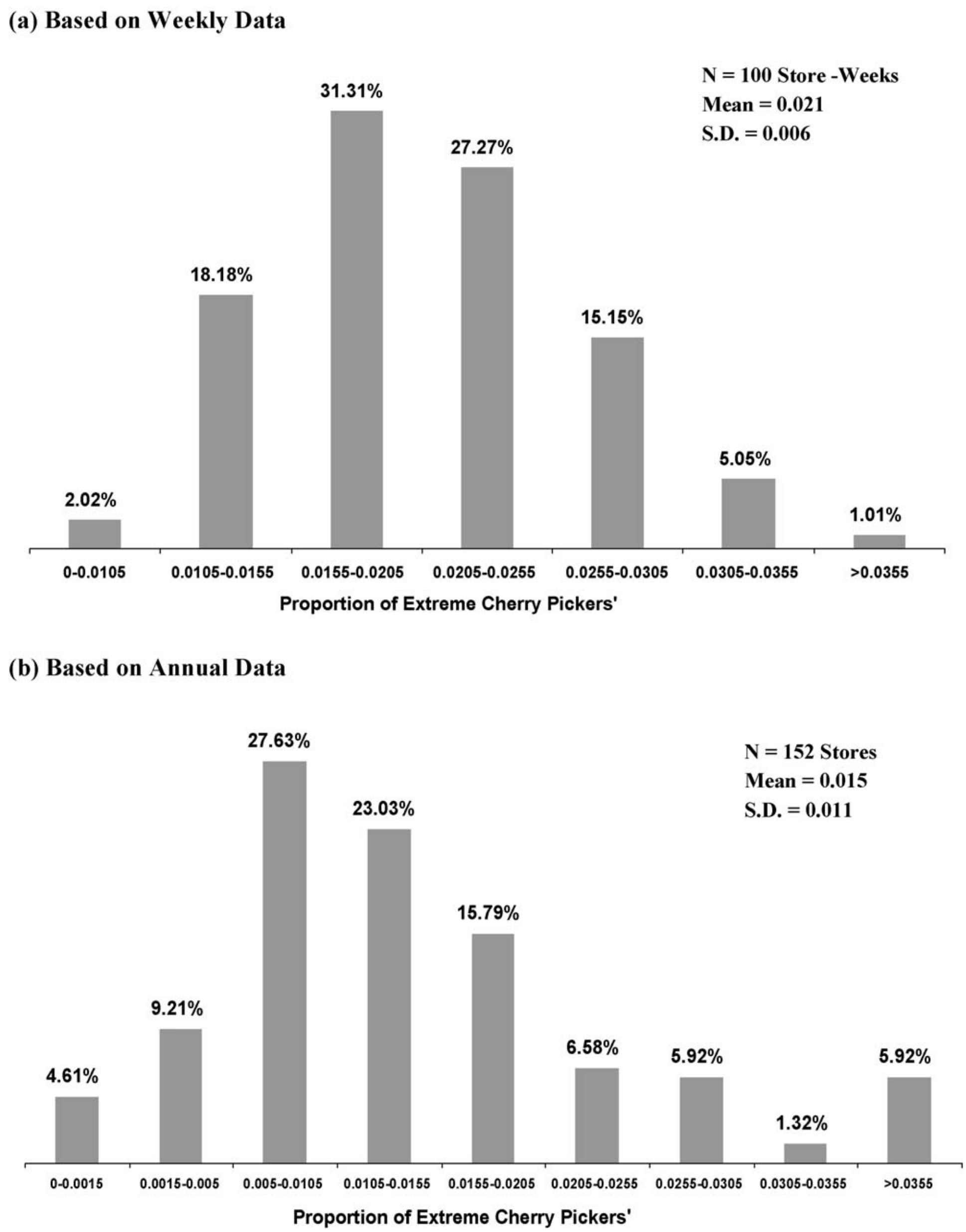

Fig. 3. Distribution of extreme cherry pickers: (a) based on weekly data and (b) based on annual data.

eral interesting questions remain regarding this rationale: (1) What proportion of customers buy non–loss leader items in addition to the promoted loss leader items? (2) How much of the profit generated by these customers is attributable to the loss leader pricing strategy? (3) Is the incremental profit great enough to cover the unavoidable pure loss of the negative profit contribution generated by the ECP customer s who buy only the loss leader items?

Heuristic approach to profitability. Using our store-specific transaction and profit contribution data, we perform a customer-level analysis. We use customer transaction data for 100 store-week combinations (4 randomly selected weeks, 25 randomly selected stores). For each case, we use transactional and profit data to analyze all customers who visit the store that week, or approximately 1.8 million customer trips, and summarize the findings in Table 6.

For any weekly loss leader pricing cycle, approximately 68% of customers (maximum 29.53% share buy 10–20% loss leader items, 25.28% buy 20–30%) buy both non- and loss leader items. Only 2.1% of customers are ECP customers who buy only loss leader items, and they buy fewer items on average (3.06) than those who buy either no loss leader items (5.51) or a mix of items (15.98). The typical unavoidable pure loss generated by the customers who buy only loss leader items is approximately .34% of net store profit, whereas the profit contribution from desirable customers averages 85.33% (Table 6). However, we cannot attribute this profit contribution to loss leader pricing entirely, because doing so would assume that these customers would not have shopped without the loss leader pricing promotion. Instead, we estimate the incremental profit contribution attributable to the loss leader pricing strategy, based on the adjustment factor a_{ijt}.

Table 6
Profit impact of loss leader (LL) pricing strategy: insights from heuristic approach ($N = 100$ store-weeks).

Subset of shoppers	Proportion of LL items in the shopping basket (x)	% of all shoppers[a]	Avg. number of items bought[a]	Profit from non-LL items (as % of store profit)[a]	Loss from LL items (as % of store profit)[a]	Net profit contribution (as % of store profit)[a]	Adjusted net profit impact due to LL pricing strategy (as % of store profit)[a]
Purchased only non-LL items	$x = 0$	29.91 (3.53)	5.51 (0.48)	15.03 (2.91)	0 (0.0)	15.0 (2.91)	0 (0.0)
Purchased both non-LL and LL items	$0 < x \leq 0.2$	29.53 (3.75)	25.5 (2.96)	58.57 (4.24)	−3.32 (0.24)	55.16 (4.14)	18.71 (1.27)
	$0.2 < x \leq 0.4$	25.28 (1.66)	19.91 (2.61)	31.28 (3.36)	−5.05 (0.75)	26.19 (2.72)	
	$0.4 < x \leq 0.6$	9.15 (0.98)	13.11 (2.06)	5.68 (1.02)	−2.10 (0.50)	3.59 (0.57)	
	$0.6 < x \leq 0.8$	2.9 (0.43)	10.18 (1.41)	1.13 (0.26)	−0.75 (0.23)	0.38 (0.15)	
	$0.8 < x < 1$	1.13 (0.12)	11.21 (1.33)	0.22 (0.07)	−0.21 (0.08)	0.009 (0.05)	
Purchased only LL items	$x = 1$	2.10 (0.51)	3.06 (0.50)	0 (0.0)	−0.34 (0.22)	−0.34 (0.22)	−0.34 (0.22)

[a] Mean value across the 100 store-week cases with the standard deviation shown in parentheses.

The adjusted profit contributions using the heuristic approach still indicate that the typical incremental profit contribution (18.71%) from customers who buy both types of items is significantly greater than the typical unavoidable pure loss generated by ECP customers (.34%). These results dissect the underlying cost–benefit trade-off dynamics of loss leader pricing strategy using a relatively easy computational approach that employs data readily available to most retailers. The findings in Table 4 thus provide a template for a useful and easy to implement gauge that retail managers can use to monitor and evaluate the effects of their strategic pricing decisions (Marketing Science Institute 2006).

Statistical approach to profitability. A similar profit impact analysis using the alternative statistical approach based on the PHM calibrates shopping trip incidence with transaction data for 700 randomly selected customers. On the basis of prior studies and conceptual expectations about the factors likely to influence a customer's shopping trip incidence, we choose several customer- and store-specific covariates for the hazard model (Gonul and Srinivasan 1993; Gupta 1991; Jain and Vilcassim 1991). To the best of our knowledge, ours is the first study to investigate explicitly the effect of loss leader pricing promotions on individual customers' shopping trip incidence.

The PHM calibration results in Table 7 show that the customer hazard function for shopping trip incidence depends on the various covariates, mostly consistent with prior studies and expectations. For example, the distance of the customer's home from the focal store has a significant and negative effect, whereas its distance to the nearest competing store has a significant and positive effect. The hazard function of shopping trip incidence also is positively affected for the primary shopper and negatively affected by the focal store price index. The key results from our model calibration relate to the effects of the depth and breadth of loss leader pricing at the store level; both have strong ($p < .01$) positive effects on customers' hazard function for shopping trip incidence.

We use the calibrated PHM to carry out a profit impact analysis with 40 separate, randomly selected store-week cases. For each case, we also select 300 random customers who shopped during that week at the store. Similar to our heuristic approach, for each of the 40 customer sample groups ($n = 300$), we compute the profit contributions by customers who purchased both non- and loss leader items and the pure loss generated by those who purchased only loss leader items. Finally, we adjust the profit contributions from the former customers using the calibrated PHM to estimate the adjustment factor a_{ijt}. Even after the adjustment, we again find that the typical incremental profit contribution (mean = 4.12%, std. dev. = .48%) from customers who buy both items is significantly more than the typical unavoidable pure loss generated by customers who buy only loss leader items (mean = .16%, std. dev. = .23%). That is, each of our alternative approaches for computing the adjustment factor provides strong empirical evidence that the loss leader pricing strategy generates incremental profit contributions to retailers, over and above the unavoidable pure loss produced by the ECP customer segment.

Table 7
Calibration results for the shopping trip incidence hazard model.

Variable	Coefficient	Std. Error
Customer characteristics		
Last trip basket size ($)	−0.0004	0.0002
Primary shopper dummy	0.51**	0.04
Time since last trip (weeks)	−0.14***	0.01
Primary shopper dummy × time since last trip	−0.01	0.02
Proportion of loss leader items bought in last trip	−0.08	0.05
Proportion of private label items bought in last trip	0.05	0.05
Median age	0.005***	0.001
Median income ($)	8.47E−07	7.50E−07
Distance to the focal store (miles)	−0.09***	0.03
Distance to the nearest competitor store (miles)	0.08***	0.03
Retailer characteristics		
Breadth of Loss leader promo × 100	0.09***	0.01
Depth of loss leader promo × 100	0.15***	0.003
Store price index ($)	−0.01***	0.004
Intercept	−9.65***	0.24
Number of subjects	705	
No. of parameters	13	
Log likelihood	12,244.49	
Schwarz information criterion (SIC)	−24,334.72	

** $p < .05$.
*** $p < .01$.

Conclusion

Summary and implications

Both business managers and academic researchers have noted consumers' price search and cherry picking behavior in retail markets, but an especially interesting phenomenon is the existence of the so-called extreme cherry pickers that generate negative profit contributions for retailers. Retailers strongly desire an in-depth understanding of such behavior; yet to the best of our knowledge, little systematic research attempts to investigate the prevalence, determinants, or profit impacts of ECP behavior. We focus exclusively on such ECP behavior in the context of frequently purchased goods. Our key findings are as follows.

Mean size of ECP segment is small and an inverse U-shaped relationship between customers' relative opportunity cost and their likelihood of exhibiting ECP behavior. On the basis of data from 152 grocery supermarket stores, we find that the mean size of the ECP customer segment for any store is quite small (1.5%), though the relative value varies substantially across stores in different competitive contexts. Although our study suggest a small size of ECP segment, we must point that domain of our study is grocery shopping and ECP is likely to be higher for other domains such as electronics (e.g. McWilliams (2004) suggests that proportion of such customers to be as high as 20% for the electronics retailer Best Buy). Thus retailers like Wal-Mart Supercenter, Target etc., which have grocery, electronics and other categories of merchandise, are likely to find higher proportion of cherry picking customers and as a consequence profitability ramifications for a retailer could be much more averse than what we find.

Using merged market transaction and consumer survey data at the consumer level, we find that the relative opportunity cost of cross-store price search represents the key determinant of ECP behavior. As with our aggregate store-level analysis, we find strong empirical support for an inverse U-shaped relationship between customers' relative opportunity cost and their likelihood of exhibiting ECP behavior. Customers who systematically generate negative profit contributions are not the ones with the lowest opportunity cost of cross-store price search.

At the individual level our results also provides a number of insights into extreme cherry picking behavior. If we consider the comparison of the ECP segment to the loyalist segment (Table 5), we can see a number of key differences between the two segments. ECP consumers are ones that demonstrate a greater cross-store and within-store inter-temporal search propensity, are market mavens, have higher price search skills and shop at the secondary store for price savings.

Consumers' ECP behavior pertains to their secondary stores alone. In particular, ECP customers shop for most of their household grocery items at a primary store, where they engage in within-store, inter-temporal price search. Their secondary stores serve only as destinations for occasional cross-store trips to take advantage of deep price discounts. These ECP customers and customers who generate low but positive profit contributions for retailers are similar in several price search behaviors, but there is a key difference. Secondary stores bear most of the adverse effects of price search for the ECP customers, whereas the effects get divided between primary and secondary stores for low profit customers. Our conceptual framework further shows that the main driver of this key behavioral difference is the difference in the opportunity costs of cross-store search. The ECP customers cause the worst profit impact, but they are not the customers with the lowest opportunity cost.

Loss leader pricing strategy adds to retailers' bottom lines. With regards to the effectiveness of the loss leader pricing strategy, we show that the majority (68%) of a grocery store's customers buy both non- and loss leader items while shopping. Only a very small percentage (2%) buy loss leader items alone and thus generate an unavoidable pure loss for retailers. This unavoidable pure loss is significantly less than the typical incremental profit contribution gained from incremental sales generated by customers who buy non–loss leader items along with loss leader items. Thus, our findings offer strong evidence that the loss leader pricing strategy still adds to retailers' bottom lines, even in presence of an ECP customer segment that buys loss leader items almost exclusively.

Since our results suggest that the mean size of Extreme Cherry Pickers' can be small and that loss leader pricing adds to the retailer bottom line, retailers may not want to spend too much of their resources avoiding attracting this segment. Instead, they may want to develop creative promotions to help convert these consumers from viewing the given store as their secondary store to their primary store. These promotions could include targeted greater discounts as the size of the basket or the quantity of adjacent items increase.

Limitations and future research directions

Our study provides a good foundation and backdrop for several interesting research extensions. First, we perform a detailed cost–benefit analysis of the profit impact of a loss leader pricing strategy but do not investigate it from a normative perspective. Further research might explore the impact of loss leader pricing strategies relative to non–loss leader pricing strategies. Do their impacts differ for various key performance measures? Are certain product categories more effective in boosting store performance when they appear in a loss leader promotion?

Second, we use weekly AAC to compute the profit margins and identify loss leader items; an ideal theoretical cost measure would use weekly replacement costs. However, computing replacement costs requires detailed information about inventory turnover, wholesale prices, and trade deals for thousands of items, which makes this idea a challenging research extension.

Third, for the individual household level analysis in our study, we restrict our analysis to the two most frequently visited stores – the primary and the main secondary store – for each household. As discussed earlier, this restriction was not critical in our case because of the de facto duopoly competitive structure for the regional grocery market in our study. As a result, a household's grocery store choice set size was essentially two with an almost exclusive concentration (90–100%) of its grocery spending at the top two visited stores. However, in other competitive market contexts, it will be interesting to expand the analysis to encompass multiple secondary stores per household. We recognize that getting the relevant data will again represent a great challenge as it will require the difficult to get cost data from multiple retail chains. Still, the challenge may be worthwhile given the deeper insights such data is likely to provide about consumers' ECP behavior. In a similar fashion to work on deals and price comparison advertising (e.g., Grewal, Monroe, and Krishnan 1998; Lichtenstein, Netemeyer, and Burton 1990), it would be useful to undertake research to understand the underlying processes and interrelationships between these psychological variables (e.g., cross-store search propensity, within-store inter-temporal search propensity, market mavenism, etc.) and cherry picking behavior. It would be useful to also study how the role of opportunity cost or time on cherry picking behavior is moderated by a number of these individual characteristics. Lab experiments are likely to provided important insights regarding these relationships.

Fourth, we consider cross-sectional variation in price search efficacy among consumers; additional research could analyze the within-consumer temporal evolution and investigate how consumer, product, and market characteristics drive such evolution.

Fifth, our conceptual framework and empirical findings pertain to the context of FPG markets. Research should address other product markets, such as durables, to study the prevalence, determinants, and profit impacts of consumers' ECP behavior. An equally interesting and related avenue of additional research would be to understand the role of the Internet and appropriate shopping bots (e.g., Lindsey-Mullikin and Grewal 2006) on price search behavior and extreme cherry picking. As a consequence of these shopping bots reducing the cost of search, it is likely that the size of the extreme cherry picking behavior is likely to much higher for categories (e.g., electronics) that are covered by such search bots.

Finally, given the macroeconomic changes over the past few years (Grewal, Levy, and Kumar 2009), it is important for future research to utilize recent data from other chains to validate our findings. One would speculate that due to the recent economic crisis, the incidence of cherry picking has likely gone up.

Appendix A.

The profit contribution p_{ijt} of any customer i at store j on week t is described as follows:

$$p_{ijt} = l_{ijt} + g_{ijt} \tag{A1}$$

where l_{ijt} is the negative profit contribution (or loss) generated from the purchase of loss leader item(s), g_{ijt} is the positive profit contribution (gain) generated from the purchase of non–loss leader item(s).

Now let $S^{(1)}$, $S^{(2)}$ and $S^{(3)}$ represents three subsets of customers whose shopping baskets include zero, all and some loss leader items respectively.

The profit contribution $P_{jt}^{(1)}$ from the first subset ($S^{(1)}$) of customers at store j on week t is:

$$P_{jt}^{(1)} = \sum_i g_{ijt} = G_{jt}, \quad \forall i \in S_{jt}^{(1)} \tag{A2a}$$

where G_{jt} represents the total gain from purchases of non–loss leader items.[5]

The profit contribution $P_{jt}^{(2)}$ from the second subset ($S^{(2)}$) of customers at store j on week t is:

$$P_{jt}^{(2)} = \sum_i l_{ijt} = L_{jt}, \quad \forall i \in S_{jt}^{(2)} \tag{A2b}$$

where L_{jt} represents the total loss from the purchases of loss leader items.[6] Using the composition of their shopping baskets, we assume that shopping trips by customers in subset $S_{jt}^{(2)}$ respond completely to loss leader pricing strategy at store j on week t. Therefore, their negative profit contribution $P_{jt}^{(2)}$ represents the pure loss imposed by ECP customers. However, from retailers' perspective, this unavoidable cost may be less than the benefit this pricing strategy generates from the third subset of customers.

The third subset ($S^{(3)}$) consists of customers whose shopping baskets include both loss leader and non-leader items. Their profit contribution $P_{jt}^{(3)}$ to store j on week t is:

$$P_{jt}^{(3)} = \sum_i l_{ijt} + \sum_i g_{ijt} = L_{jt} + G_{jt}, \quad \forall i \in S_{jt}^{(3)}. \tag{A2c}$$

Appendix B.

Based on the proportional hazard model (PHM; Cox 1972; Gonul and Srinivasan 1993; Gupta 1991; Jain and Vilcassim 1991), we specify a customer's probability (or hazard function) of undertaking a shopping trip at a given store, conditional on the elapsed time (t) since the customer's previous shopping trip to the store, as follows:

$$h_i(t, X_t) = h_i(t) * \phi_i(X_t), \tag{A3}$$

where $h_i(t, X_t)$ is consumer i's hazard function at time t, X_t is a row-vector of covariates facing customer i at time t, $h_i(t)$ is customer i's baseline hazard at time t, and $\varphi_i(X_t)$ indicates customer i's covariate function at time t. In this multiplicative model, the baseline hazard represents the probability distribution that characterizes the customer's interpurchase trip times; the covariate function shifts this baseline hazard up or down depending on the values of the covariates.

The choice of the functional form for the covariate function depends on the requirement that the hazard function always be nonnegative. We use the following functional form to represent

[5] The first subset represents those whose shopping baskets do not include any loss leader items and who therefore provide no negative profit contribution (i.e., $l_{ijt} = 0$).

[6] The second subset of customers buys only loss leader items and thus offers no positive profit contribution (i.e., $g_{ijt} = 0$).

the covariate function (Seetharaman and Chintagunta 2003):

$$\phi_i(X_t) = e^{X_t * \beta_i}, \tag{A4}$$

where β_i represents a column-vector of parameters corresponding to the covariates contained in X_t (e.g., consumer-level variables such as last trip basket size, dummy variable for primary vs. secondary shopper, time elapsed since last trip, depth and breadth of loss leader pricing encountered). This function yields the standard PHM:

$$h_i(t, X_t) = h_i(t) * e^{X_t * \beta_i}, \tag{A5}$$

and the hazard function can be written as:

$$h_i(t, X_t) = \frac{f(t, X_t)}{1 - F(t, X_t)} = h_i(t) * e^{X_t * \beta_i}, \tag{A6}$$

where $f(t, X_t)$ represents the probability density function (pdf) that corresponds to customer i's hazard function at time t, and $F(t, X_t)$ is the corresponding cumulative density function (cdf). In our study context, $f(t, X_t)$ indicates the customer's probability of conducting a shopping trip to the given store at time t, and $1 - F(t, X_t)$ equals the probability that the customer has not made the trip before time t since the last trip. Rearranging Eq. (A6) yields the following estimable version of the continuous-time PHM (Seetharaman and Chintagunta 2003):

$$\begin{aligned} f(t, X_t) &= h_i(t, X_t) * e^{-\int_0^t h(u) * e^{X_u \beta}\, du} \\ &= h_i(t) * e^{X_t \beta} * e^{-\int_0^t h(u) * e^{X_u \beta}\, du} \end{aligned} \tag{A7}$$

We use the parameter estimates from the PHM to obtain empirical estimates of the probability Pr_{ijt} from Eq. (4) for customer i, based on the relevant covariate X values with respect to a shopping trip to store j in week t.

The baseline hazard function h_i (t) in the PHM can be flat, monotonically increasing, or monotonically decreasing; in turn, it can take various functional forms, such as exponential, Weibull, Gompertz, log-logistic, log normal, and so forth. Because of its flexibility, the Weibull distribution is the most popular baseline hazard specification; we use it to specify the baseline hazard function for our model. We also tried alternative specifications, but the model fit is best with the Weibull distribution specification. Hence, the hazard function is:

$$h(t, X_t) = h(t) * e^{X_t * \beta} = p * t^{p-1} * e^{\beta_0} * e^{X_t * \beta}, \tag{A8}$$

where p is an ancillary shape parameter estimated from the data, and the scale parameter is parameterized as $\exp(\beta_0)$. We suppress the subscript i for notational ease.

Appendix C.

Multi-item scale items

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 price search propensity*: Propensity to compare prices across multiple time periods in a particular store. (5 items; Cronbach's alpha = .84)
   - 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.[a]
   - There are times when I delay my shopping trip to wait for a better price deal.[a]
   - Although planned before making a shopping trip, I often do not buy some items if I think they will be on better deal shortly.[a]
   - I keep track of price specials offered for the grocery products at the stores I regularly buy from.[a]
   - To get the best price deals for my groceries I often buy the items I need over 2 or 3 trips.[a]
2. *Spatial price search propensity*: Propensity to compare prices across multiple stores in a particular week. (5 items; Cronbach's alpha = .86)
   - I often compare the prices of two or more grocery stores.[b]
   - I decide each week where to shop for my groceries based upon store ads/fliers.[b]
   - I regularly shop the price specials at one store and then the price specials at another store.[b]
   - Before going grocery shopping I check the newspaper for advertisements by various supermarkets.[c]
   - To get the best price deals for my groceries I often shop at 2 or 3 different stores.[c]
3. *Market mavenism*: "Individuals who have information about many kinds of products, places to shop, and other facets of markets, and initiate discussions with consumers and respond to requests from consumers for market information" (Feick and Price 1987, p. 85).
   (4 items; Cronbach's alpha = .87)
   - I like it when people ask me for information about products, places to shop, or sales.[b,d]
   - I like it when someone asks me where to get the best buy on several types of • products.[b,d]
   - I know a lot of different products, stores, and sales and I like sharing this information.[b,d]
   - I think of myself as a good source of information for other people when it comes to new products or sales.[b,d]
4. *Perceived search skills*: Proficient in shopping for groceries. (8 items; Cronbach's alpha = .73)
   - I know what products I am going to buy before going to the supermarket.[c]
   - I am a well organized grocery shopper.[c]
   - Before going to the supermarket, I plan my purchases based on the specials available that week.[c]
   - I can easily tell if a sale/special price is a good deal.[b]
   - It is very difficult to compare the prices of grocery stores (reverse coded).[b]
   - 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.[c]
   - I pre-sort my coupons before going grocery shopping.[c]

[a] Gauri, Sudhir, and Talukdar (2008).
[b] Urbany, Dickson, and Kalapurakal (1996).
[c] Putrevu and Ratchford (1997).
[d] Feick and Price (1987).

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