Lisbon School of Economics & Management
Universidade de Lisboa

Department of Economics

Carlos Lourenço, Els Gijsbrechts

Details and Big Pictures: Consumer Use of Actual Prices and Price Images When Choosing a Store

WP02/2022/DE/SOCIUS

WORKING PAPERS

ISSN 2183-1815

LISBOA
UNIVERSIDADE DE LISBOA

Details and Big Pictures:

Consumer Use of Actual Prices and Price Images

When Choosing a Store

Carlos J.S. Lourenço
Assistant Professor
ISEG – Lisbon School of Economics and Management
SOCIUS/CSG – Research in Social Sciences and Management
University of Lisbon
Email: carloslourenco@iseg.ulisboa.pt

Els Gijsbrechts
Professor of Quantitative Marketing
Tilburg University
P.O. Box 90153, 5000 LE Tilburg, The Netherlands
Email: e.gijsbrechts@uvt.nl

This version: April 2015

[Preliminary version. Do not cite or circulate without permission.]

We thank (in alphabetical order) Nuno Camacho, Bas Donkers, and Richard Paap for fruitful discussions and comments on an earlier draft. We also thank conference participants at Marketing Science 2009 (Michigan, USA), Marketing Dynamics 2010 (Istanbul, Turkey), Pricing Conference 2011 (Syracuse, NY, USA), and Advances in National Brands and Private Labels in Retailing 2014 (Barcelona, Spain), as well as seminar participants at Catholic University of Portugal (Lisbon), Erasmus University Rotterdam (Erasmus School of Economics and Rotterdam School of Management), University of Amsterdam, and University of South Carolina. We are also thankful to GfK/AiMark for providing us the data.

Details and Big Pictures:

Consumer Use of Actual Prices and Price Images When Choosing a Store

ABSTRACT

In this paper, we develop a model of consumer patronage decisions to evaluate the effect of store price images vis-à-vis that of objective basket prices. Within this dual retail price model, the two types of price information are linked through the dynamic formation of price images over time, itself based on actual prices. We show that not accounting for the effect of (dynamic) price perceptions may seriously bias store traffic estimation in response to price changes. Finally, we explore which demographic and shopping characteristics of consumers may explain or shed light on differences in sensitivity to different price information.

Keywords: Retail store choice, store price image, consumer learning

Prices are ubiquitous in consumer decisions about where to shop. While early store choice papers remained agnostic or at least ambiguous about the store price information adopted by consumers, recent literature suggests that consumers may rely on two distinct types of price cues: (1) observed or expected week-to-week basket prices and (2) overall store price images (e.g. Mägi and Julander 2005; van Heerde, Gijsbrechts, and Pauwels 2008). Store price image (SPI) has in fact become an increasingly popular pricing tool among retailers. So much so, that managing SPI is considered essential in profitable retail pricing strategies (Levy et. al 2004) and grocery retailers are spending hundreds of millions of dollars to develop their SPIs (Kalyanam, Lal, and Wolfram 2006). In 2009 alone, France-based Carrefour, the largest hypermarket chain in the world, has invested more than half a billion dollars in its price image (MarketWatch 2009), and in April 2010, Wal-Mart cut the prices of 10,000 items in the U.S. market, with the goal of "polishing its discount image" (Wall Street Journal 2010).

Despite its managerial relevance, surprisingly little is known about the effect of SPIs on observed store choices, let alone in combination with actual prices (see Hamilton and Chernev 2013 for a review of price image in retail management). For one, very few empirical studies include SPI as a determinant of observed store selection, an exception being van Heerde, Gijsbrechts, and Pauwels (2008). Moreover, papers that do consider the impact of SPI, either separately or in conjunction with weekly actual prices, typically ignore the fact that SPIs themselves are adjusted over time based on actual price levels. Disregarding this "mediating role of price image on store traffic" (Fox, Postrel, Semple 2009) may have serious consequences. If price changes have an impact on consumer choices not only directly but also through their effect on SPI, this dual effect must be accounted for to obtain accurate price response estimates. This is important for academics to correctly understand the over-time effect of price, relative to other store choice determinants like assortment or location (Bell, Ho, and Tang 1998; Briesch, Chintagunta, and Fox 2009; Gauri, Sudhir, and Talukdar 2008). It is also crucial for retailers aiming to fine-tune their store pricing.

Apart from market-level effects, there is a lack of understanding about who are the price-sensitive consumers and, among them, who are the ones more prone to use one type of price information or the other. Even households who do not immediately tailor their store choices to weekly prices may still integrate these prices into their SPIs, and adjust their store patronage in the longer run. Identifying and profiling these price-image sensitive consumers would further enhance our understanding of price response, and prove useful for retailers to develop targeted pricing strategies.

In this paper we address these pressing issues, and aim at answering to three main questions. First, do prices also influence store choice *through* SPI and, if so, what is the size of this effect? Second, do consumers who attend to weekly actual prices for store selection, also adjust their store patronage to (price-based) changes in SPI? Or, are these routes rather exclusive? Third, can we profile households who rely on different sources of price information? To answer these questions, we develop an individual-level model of store choice that includes both short-term weekly prices and long-term shaped store price images. These SPIs, in turn, are spelled out explicitly as a function of past store prices, using a Bayesian updating specification. This specification is consistent with earlier analytical work on SPI formation over time (e.g. Büyükkurt 1986; Feichtinger, Luhmer, and Sorger 1988), and its parameters can be used as indicators of adaptive consumer learning (Erdem and Keane 1996).

We estimate these models on an extensive and unique data set, which combines scanner panel information on store choice and spending, with longitudinal survey data on store price images held by the same individual panel members. Taking the perspective that shopping activity is part of a household's production process (Becker 1965), we relate our household-level estimates of price sensitivity with extensive background data, thereby exploring which demographic and shopping characteristics trigger consumers to use one or the other type of price information (see e.g. Hoch et. al 1995; Urbany, Dickson, Kalapukaral 1996, for a similar approach).

Our results provide several new and important insights. First, we obtain clear evidence of a dual price effect. Actual price changes influence store choice both directly, and indirectly through their effect on SPIs, and ignoring this second effect leads to an underestimation of the long-term impact of store price shifts. Second, we show that while these two types of price sensitivity may coincide in a small group of consumers, the majority of price-sensitive consumers adjust their store patronage to only one type of price cues (either actual prices or SPI). Third, we find that households who attend to actual prices ('Eye-For-Detail' consumers) differ from those guided by SPI ('Big Picture' consumers) on various socio-demographic and behavioral characteristics, including media usage. These new insights contribute to the academic debate on the relative importance of price in a store choice context, and are relevant for retailers who thus become empowered with valuable knowledge to set prices while maintaining profitability (Grewal and Levy 2007; Levy et. al 2004).

In the next section, we briefly present our conceptual framework. We then discuss the unique features of our data and the models we estimate. The results are summarized afterwards, together with an analysis of price- and SPI-sensitive consumer profiles. We illustrate the implications of our findings by simulating the over-time impact of price changes among consumers with different types of price sensitivity. We conclude with a discussion of limitations and opportunities for future research.

Conceptual Framework

Background literature on prices and store choice

Prices influence choices because they constitute objective indicators of the monetary costs of purchasing (Monroe 2002). Consistent with this premise, academic contributions present price as a major determinant of consumers' variable cost of shopping at a particular store, and – hence – of store selection (Bell and Lattin 1998; Bell, Ho, and Tang 1998). Similarly, the prevailing industry wisdom is that (promotional) price changes drive store traffic (Urbany, Dickson, and Sawyer 2000). These views are further underscored by consumer surveys, ranking price as one of the top determinants in store selection (e.g. Nielsen 2008). Yet, empirical evidence on this effect seems less overwhelming, with several studies reporting small or insignificant market-level effects of price changes on weekly store choice (e.g. Bell, Ho, and Tang 1998; Briesch, Chintagunta, and Fox 2009). Similarly, individual-level analyses have revealed the segment of consumers who cross-shop to benefit from weekly price changes, to be very small (Gauri, Sudhir, and Talukdar 2008). This discrepancy has led some researchers to conclude that the impact of price has been over-estimated (Urbany, Dickson, and Sawyer 2000).

However, failing to uncover strong immediate effects does not mean that actual prices are unimportant for store choice. Even if consumers do not adjust their weekly store selection to actual, week-to-week price changes, their store patronage may still be guided by the overall image they hold of the stores' expensiveness. Psychology and marketing have long acknowledged the subjective nature of prices, and have found support for the existence and effects of price perceptions (Zeithaml 1988). In a retail context, store price images are defined as consumer perceptions or beliefs about stores' overall price levels (Brown 1969, 1971; Nyström 1970; Nyström, Tamsons, and Thams 1975). Considered a distinct retail price dimension (Mägi and Julander 2005), several studies – indeed – have found consumers' self-reported store price images one of the most important determinants of store patronage (Arnold, Oum, and Tigert 1983; Finn and Louviere 1990, 1996; Nielsen 2008; Severin, Louviere, and Finn 2001; Srivastava and Lurie 2004), over and above objective weekly store prices. Moreover, such store price images do not come 'out of the blue'. Instead, they are themselves affected by actual prices charged in the store (Ailawadi and Keller 2004). As argued by Feichtinger, Luhmer, and Sorger (1988) and Büyükkurt (1986), and, as shown by Lourenço, Gijsbrechts, and Paap (2015), store price image formation is a dynamic process, by which consumer beliefs about the overall expensiveness of stores, are learned adaptively over time based on basket prices.

Bringing together these insights, actual weekly prices can drive store choice in two ways. First, they can exert a direct influence on the consumers' store selection – an effect focused on in most empirical studies on store traffic and choice. Second, they can shape the store's overall image of expensiveness held by consumers and, through this adjusted SPI, affect store patronage over time. This indirect effect of actual prices on store selection has – to the best of our knowledge – received far less attention conceptually, and has not been fully addressed empirically. Some studies measure the effect of prices on store price image (Büyükkurt 1986; Desai and Talukdar 2003; Lourenço, Gijsbrechts, and Paap 2015), but not the ensuing store choice effect. Others consider the impact of price image (Mägi and Julander 2005; Mazumdar, Raj, and Sinha 2005), or of both actual prices and price image (van Heerde, Gijsbrechts, and Pauwels 2008), but treat price image as an exogenous variable. Moreover, these studies do not shed light on the size of consumer segments responding to one or the other type of price information, nor on the profile of these shopper segments.

Below, we present a framework of consumers' dual response to store prices, which guides our study and will be empirically investigated in subsequent sections. We note upfront that our emphasis is on store choice (or store traffic) as the dependent variable, not on promotion-induced shifts in spending once the consumer is inside the store. Focusing the attention on store traffic is important and an worth-taking perspective, given that "store traffic is essential to retailer profitability" (Fox, Postrel, and Semple 2009, p.709) and that stealing traffic from competitors is the primary reason for retailers to engage in temporary price promotions (Urbany, Dickson, and Sawyer 2000).

Consumer sensitivity to store-level prices and price images

In line with the discussion above, consumers can be sensitive to prices in their store selection in two main ways. They can directly respond to changes in actual, objective basket prices, and they can also be influenced by subjective, holistic summaries of stores' overall expensiveness, which – themselves – may be gradually adjusted to changes in actual prices. Viewing households as a production unit (Becker 1965), the extent to which consumers search for and respond to grocery price information is driven by the cost of acquiring price information on the one hand, and the expected gains of this price search on the other. These, in turn, depend on a number of contextual and household-specific characteristics and constraints (Gauri, Sudhir, and Talukdar 2008; Urbany, Dickson, and Kalapurakal 1996). We propose that these costs and gains, and their antecedents, may differ between the response to the two types of price information, such that consumers may fall into four possible segments, depicted in Figure 1: (1) convenience, (2) eye-for-detail, (3) big picture, (4) and combined use.

--- Insert Figure 1 about here ---

'Convenience' consumers correspond to the typical non-price sensitive grocery shoppers, whose store choice is driven by non-price marketing mix variables such as assortment (Briesch, Chintagunta, Fox 2009), or by convenience-factors such as distance (Gauri, Sudhir, and Talukdar 2008). Though these consumers may, as indicated by Gauri, Sudhir, and Talukdar (2008), incidentally benefit from in-store price offers, their store patronage decisions are not price-based. These consumers either do not care about grocery prices (e.g. for lack of financial constraints), or do not consider it worthwhile to keep an eye on detailed price information (e.g. because of time pressure, or mobility constraints).

‘Eye-for-detail’ consumers, in contrast, keep track of actual store prices to spot temporary price reductions, and then adjust their store choices to benefit from the resulting monetary savings. Such behavior implies two conditions. First, consumers need to collect and encode timely information on actual prices, through e.g. store feature-ads or flyers, word of mouth, or frequent (same week) store visits. Second, they need to adjust their shopping patterns so as to benefit from the temporary offers, either by shifting their entire trip to the store that has the lower temporary prices, or by splitting their purchases and adding ‘cherry-picking’ trips to stores that offer good deals. Both conditions imply substantial costs of information collection, and of shopping around: even if no extra store visits are added, the consumer must be willing to switch to less conveniently located or less familiar stores. As already suggested by Urbany, Dickson, and Kalapurakal (1996), “the benefits of such a regular, extensive search and store switching will exceed the costs for only a small minority of consumers” (p. 94).

‘Big Picture’ consumers keep track of stores’ overall expensiveness, such that stores with more favorable price images have a higher chance of being patronized, or that regularly visited stores can be abandoned if consumers come to perceive them as too expensive. Even if the stores’ SPI is updated based on actual price information (leading to an indirect actual price-effect), the search and shopping costs of this behavior are quite different from those in the previous segment. For one, instead of actively having to search for specific weekly price information prior to store selection, consumers may simply ‘take in’ price cues as they shop around in the store, and integrate this information with prior beliefs for future use (Desai and Talukdar 2003; Hoch and Deighton 1989). This process of price encoding need not be effortful or time consuming, and can even take place unconsciously or be incidental (Mazumdar and Monroe 1990). Moreover, acting upon SPIs does not require consumers to visit multiple stores or change stores on a weekly basis – as SPI changes tend to come about gradually (Alba et. al 1994). Hence, even consumers with high costs of time, or important mobility constraints, can be expected to exhibit Big-Picture price response – as long as they experience some type of budget constraint and/or find it important, psychologically, to get good value for money.

Finally, even though we do not expect this segment to be large, consumers may simultaneously exhibit both types of price-sensitivity. This can be true, for instance, if consumers' actual weekly price information is (perceived to be) incomplete, such that they supplement it with a more stable subjective indicator of store expensiveness. Or, consumers' willingness/ability to shop around may be driven by situational factors, making them rely more on one or the other type of price cue depending on the circumstances. We label such consumers 'Combined' price users.

Our methodology will allow us to assess the size of these different segments. Moreover, within each segment, we will quantify the strength of the households' response to actual store prices, either directly (Eye-for-Detail consumers), indirectly through the formation of SPI and its impact (Big Picture consumers), or both (Combined segment). Last but not least, we will explore how the nature and strength of these responses varies with a set of household characteristics, related to the costs and benefits of price search.

Data and models

Empirical setting and data

For our empirical analysis, we have access to an exceptionally rich data set. This includes scanner panel data from a national GfK panel covering purchases of 4400 households, at all Dutch grocery retailers, over a period of four years (from January 2002 to December 2005). For N = 1076 of these panel members, we have access to a broad set of background characteristics, including socio-demographics, shopping behavior and media usage, and attitudinal variables. These data are complemented with information from Reed Business, specifying store floor spaces and store locations (zip-code of all available outlets of a chain, on a bi-annual basis) for each of the grocery chains, and from IRI and Publi-Info, specifying weekly price cuts, and feature and display activities by retailer.

In the analysis below, we focus on the S = 10 major chains, which, together, comprise 88% of all store visits among Dutch grocery chains. We include trips made by households for whom background data are available, over a period of 209 weeks. In total, our data set consists of 349,586 shopping trips. Table 1 provides choice shares and descriptive statistics aggregated over the entire period of analysis for the non-price variables in our model, by retail chain. The leading chain is Albert Heijn, with almost a third of the Dutch market (in shopping trips), the broadest coverage (average distance of 2.3 km), and the second largest assortment. On average, households patronize or switch among 3.2 different stores during the period of analysis, and shop for groceries approximately twice a week.

--- Insert Table 1 about here ---

A unique feature of our data set is that, for the same individual panel members and in the same time period, we have information on the chains' price perceptions. These price perceptions are measured on an ordinal scale from 1 (= most favorable) to 9 (= least favorable) and vary at the household-, time-, and store-level. The data were collected semi-annually by GfK among their panel members, using store-intercept interviews. The surveys took place in weeks 16 and 40 of every year, with an additional survey in week 5 of 2004. Each of the 9 survey waves was conducted throughout the whole week, allowing households to judge the overall price level of more than one store.

The average (and standard deviation) values for actual store prices and store price images are given in Table 2, together with two rankings of the stores based on each type of price information. Two stores, Aldi and Lidl, are hard discounters and practice an everyday low price (EDLP) policy with virtually no price promotions (they have the lowest mean and standard deviation values for prices). Together with Jumbo, these chains are the ones enjoying the lowest (i.e. most favorable) average store price image among consumers. All other stores have higher average prices and promote their products regularly (HiLo policy), with the market leader Albert Heijn practicing the highest average prices. However, the most unfavorable store price image is associated with Konmar, not Albert Heijn. In general, the relative position of a store based on its average price image does not align perfectly with the store's average price level, but, except for Edah and Jumbo, there are only small differences.

--- Insert Table 2 about here ---

To illustrate the evolution of average price images, we zoom in on the HiLo market leader Albert Heijn and the EDLP chain Aldi. Table 3 shows the evolution of SPI for these two stores (where higher SPI values correspond with less favorable perceptions), together with their average price levels. The average price image of Albert Heijn first deteriorates, from the beginning of the period until the end of 2003, but then consistently improves again. A similar pattern applies to Albert Heijn's average price levels. The average price image of Aldi, however, has the opposite pattern: it is lower than the overall average until the start of 2004, and higher afterwards. Taken together, Tables 2 and 3 suggest that price images vary not only across chains, but also over time within a chain, as do actual week-to-week prices, thus providing preliminary support for the link between SPI learning and store prices. In the next section, we model the individual-level store choice and learning mechanism.

--- Insert Table 3 about here ---

Model specification

Our model is designed to capture direct as well as indirect effects of actual weekly prices on store patronage. The logic is as follows. At a given point in time t-1, the consumer holds beliefs about the overall expensiveness of each available store. These store price images, together with actual store price information, may affect his selection of a specific store on his next purchase occasion. Upon visiting a store, the consumer will update his beliefs about the expensiveness of that store based on the prices encountered inside. We first explain the store choice model, followed by the model of store price image updating.

Store choice. On each shopping trip t, we observe consumer i's multinomial discrete store choice y_{it}=s among S mutually exclusive stores (for s=1,…,S).[1] T_i is the number of shopping trips observed for consumer i and the total number of observations is thus given by $\sum_{i=1}^{N} T_i$. Consumers attach a (partly observed) utility to each store and choose the store with maximum utility. Let $u_{it}^*=\{u_{it1}^*,\ldots,u_{itS}^*\}$ denote the vector of store-specific latent utilities underlying choices. Hence, the multinomial outcome variable y_{it} takes the value s if $\max(u_{it}^*)=u_{its}^*$. The latent utilities are modeled as a function of a systematic component of K store-specific variables in the vector w_{its} (for k=1,…,K) and a normally distributed stochastic component v_{its} representing the effect of unobservables. Formally,

[1] $$u_{its}^*=w_{its}^{'}\beta_i+v_{its}, \qquad v_{its}\sim N(0,\Omega),$$

where Ω is a symmetric matrix, with non-zero off-diagonal elements. To solve the location identification problem present in Equation [1] we use differences in utilities.[2] Specifically, we subtract the utility equation of an arbitrarily chosen store – the market leader – from each of the remaining S-1 equations. Stacking together the S-1 equations of individual i in shopping trip t results in the following system of equations

[2] $$u_{it}=X_{it}\,\beta_i+\varepsilon_{it}, \qquad \varepsilon_{it}\sim N(0,\Sigma),$$

where u_{it} is a vector of S-1 differenced utilities and $X_{it}=[I_{S-1}\ W_{it}]$, where I_{S-1} is an identity matrix of size S-1 (containing S-1 store-specific dummy variables for the store intercepts) and W_{it} is a matrix of K differenced marketing-mix variables for each of the S-1 stores. The

[1] Throughout the paper we use store and retail chain, and shopping trip and time period, interchangeably. We consider only single-store shopping trips. See Vroegrijk, Gijsbrechts, and Campo (2013) for a recent study of multiple-store shopping trip behavior.

[2] A choice model like the one in Equation [1] has both a locational and a scale identification problem, as adding or multiplying the underlying utilities by a scalar, respectively, leads to the same likelihood value. The use of differences in utilities is a common practice with an unrestricted Ω (see e.g. McCulloch and Rossi 1994). There is no location identification problem if Ω is restricted to be diagonal. However, models with a diagonal Ω in which choice alternatives are not allowed to be correlated are, in our view, an unrealistic representation of store choice decisions. In the estimation section we explain how we deal with the scale identification problem.

coefficient vector β_i of individual i contains store-specific intercepts representing the intrinsic preferences for the S-1 stores relative to the market leader store, and the response coefficients for the K marketing-mix variables. The stochastic components in the (differenced) error term ε_{it} represent the effect of factors known to the consumer but unobserved to the researcher, and are assumed to follow a multivariate normal distribution $N(0,\Sigma)$. We assume a random coefficients structure for β_i with a normal distribution, i.e. $\beta_i \sim N(\mu_\beta, V_\beta)$. Note that with a full covariance matrix the model does not suffer from the restrictive IIA property. We acknowledge that little correlation may remain in the error terms once we account for unobserved heterogeneity, but we let the data reveal the extent to which Ω is a full covariance matrix. The model in Equation [2], together with the distributional assumption for β_i, is thus a multinomial probit (MNP) model with random coefficients.

The focal price variables are observed week-to-week prices, P_{its}, and observed consumer price perceptions about the overall expensiveness or price image of store s in the previous period, $MSPI_{i,t-1,s}$. To guide the selection of variables to be included in each utility function u_{its}, other than the two focal price variables, we use the framework of Bell, Ho, and Tang (1998). While the price variables capture the variable costs of shopping, store distance ($Dist_{is}$) is included as a proxy for fixed transportation costs (monetary units and traveling time). We further include store size as a proxy for assortment size ($Assort_{is}$), promotional feature advertising ($Feat_{its}$), consumer-specific loyalty or trip share ($Loyal_{is}$), and past store visit ($y_{i,t-1,s}$). The utility function of a consumer i on shopping trip t at store s can thus be written as follows (recall that all values enter the utility function in differences),

[3] $u_{its}=\beta^{s}_{0i}D_s+\beta_{1i}Dist_{is}+\beta_{2i}Assort_{is}+\beta_{3i}Loyal_{is}+\beta_{4i}P_{its}+\beta_{5i}MSPI_{i,t-1,s}+\beta_{6i}Feat_{its}+\beta_{7i}y_{i,t-1,s}+\varepsilon_{its}$,

where D_s is a dummy for store s (further details on the variable operationalizations are given below). Equation [3] accounts for two sources of choice dynamics, through a loyalty and a lagged choice variable (see Ailawadi, Neslin, and Gedenk 2001; Gijsbrechts, Campo, and

Nisol 2008 for a similar approach). The loyalty variable captures the store's trip share for the household, and, given positive state dependence (e.g. due to switching costs from reduced store familiarity), we expect the effect of this variable to be positive. As for the lagged choice variable, which equals one if the particular store was chosen on the previous store visit, the effect may go both ways. It may be positive for consumers with a tendency to always re-visit the same store. At the same time, we notice from the data that consumers, on average, exhibit switching behavior among a subset of stores (among 3.2 different stores, on average), often on multiple trips within one week. A negative coefficient for lagged choice, combined with a positive effect for trip share, might then point to consumers alternating visits among stores in their preferred set (Finn and Louviere 1990), in line with the notion of multiple store loyalty (Gijsbrechts, Campo, and Nisol 2008; Leenheer et. al 2007). Hence, the model already captures a rich pattern of choice dynamics based on consumer inertia and variety seeking behavior. Still, in line with our conceptual framework, we allow for price changes to trigger an additional type of dynamic response. While current prices in the utility function in Equation [3] measure the same-period effect of prices on store choice, the dynamic effect of prices is captured through the formation of store price image.

Store price image formation. We assume that consumers hold beliefs about the overall price level for each available store s. Because the acquisition of exhaustive price information is prohibitive, consumers will be uncertain in their evaluation of stores' overall price levels (Desai and Talukdar 2003). Let $S\overline{P}I_{i,t-1,s}$ be consumer i's *mean* belief about the overall expensiveness of store s at time t-1, and let $\sigma^2_{SPI_{i,t-1,s}}$ be the uncertainty (variance) of his store price belief. Upon a store visit, the consumer has access to the prices actually charged by the store, PI_{its}. According to adaptive learning, the consumer adjusts his mean store price perceptions using a weighted average of his previous SPI beliefs and this new price information (Feichtinger, Luhmer, and Sorger 1988, Nyström 1970):

$$[4] \qquad \bar{SPI}_{its} = w_{0,its}\bar{SPI}_{i,t\text{-}1,s} + w_{1,its}PI_{its}$$

where $w_{0,its}$ and $w_{1,its}$ are consumer i's weights attached to his previous price image held about store s, and to observed prices, respectively. Although prices themselves are not ambiguous, the large amount of price information to be processed creates uncertainty surrounding the price signals (Mägi and Julander 2005), as a result from difficulties in encoding, comparing or remembering prices for inclusion in SPI.

In line with recent marketing studies (see e.g. Erdem, Keane, and Sun 2008 and Erdem and Keane's 1996 seminal paper; Ching, Erdem, and Keane 2013 provide an up-to-date overview), we adopt a Bayesian framework similar to the SPI model of Lourenço, Gijsbrechts, and Paap (2015) to operationalize the updating learning process (i.e. the weights) in the very general Equation [4]. The Bayesian model offers a simple account of consumer learning that can explain a considerable range of phenomena, is found to make sensible predictions (Shin, Misra, and Horsky 2012), and fits well with the SPI formation process described in the literature (see Alba et al. 1994; Büyükkurt 1986; Feichtinger, Luhmer, and Sorger 1988; Nyström 1970). Consumers combine prior SPI beliefs with new price evidence to obtain posterior beliefs (which constitute priors for the next update), such that incoming information becomes less important (and SPI beliefs become less uncertain). This is consistent with the notion that store-price perceptions change slowly (Desai and Talukdar 2003, Hamilton and Chernev 2013) and that store-profile effects may persist even after exposure to in-store price information (Büyükkurt 1986).

In the Bayesian framework, assuming that consumer i's prior SPI beliefs (in t-1) and the overall price signal (in t) are normally distributed (with means $\bar{SPI}_{i,t\text{-}1,s}$ and PI_{ts}, respectively), his posterior belief about the overall expensiveness of store s at time t is normally distributed as well, with mean $\bar{SPI}_{its}$ and variance $\sigma^2_{SPI_{its}}$ given by (DeGroot 1970):

[5] $$\overline{\mathrm{SPI}}_{\mathrm{its}} = \sigma^2_{\mathrm{SPI_{its}}} \left(\frac{1}{\sigma^2_{\mathrm{SPI_{i,t\text{-}1,s}}}} \overline{\mathrm{SPI}}_{\mathrm{i,t\text{-}1,s}} + \frac{1}{\sigma^2_{\eta_i}} \mathrm{PI}_{\mathrm{ts}} \right)$$

[6] $$\sigma^2_{\mathrm{SPI_{its}}} = \left(\frac{1}{\sigma^2_{\mathrm{SPI_{i,t\text{-}1,s}}}} + \frac{1}{\sigma^2_{\eta_i}} \right)$$

In Equation [5], the weights attached to previous and new information, are proportional to the 'precision' (inverse of the variance) of each piece of information: the precision of the prior belief, $1/\sigma^2_{\mathrm{SPI_{i,t\text{-}1,s}}}$, and the precision of price signals, $1/\sigma^2_{\eta_i}$, respectively. Equation [6] implies that the posterior SPI variance – a combination of the prior belief's variance and the variance of the price signals – decreases over time (the posterior precision of the SPI belief is obtained as the prior precision plus the price-signal precision, both positive numbers). In other words, consumers who are more exposed to price information have higher objective, but also 'subjective', store price knowledge (Mägi and Julander 2005), i.e. they feel more confident about their judgements.

The individual-specific overall price signal variances $\sigma^2_{\eta_i}$ are model parameters to be estimated and are not to be confused with the variances of the actual prices, which reflect the variation in overall prices as observed in the store. The 'price signal variance' in the Bayesian model (i.e., its inverse) reflects the extent to which price signals are informative of the store's SPI; higher levels of $\sigma^2_{\eta_i}$ implying the consumer learns less from prices about the store's expensiveness.[3]

Model estimation

To estimate the MNP model, we use a block-based Bayesian estimation approach, like the one of McCulloch and Rossi (1994). In particular, we use a Gibbs sampler to draw from the full conditional posteriors of the parameters (see Gelfand and Smith 1990). As mentioned above,

[3] We estimated a simplified multiple-price signal model similar to Lourenço, Gijsbrechts, and Paap's (2015) model with individual- and category-specific learning parameters (details can be obtained from the first author). Hence, for the purposes of the current SPI formation model with a single overall price signal of store s, i.e. $\sum_c r_{c,i}\mathrm{PI}_{c,st}$, the individual-specific learning parameters are obtained by making $\sigma^2_{\eta_i} = \sum_c r^2_{c,i}\sigma^2_{\eta_{c,i}}$, where $r_{c,i}$ is category's c shopping basket weight for individual i, and $\mathrm{PI}_{c,\,st}$ is category's c price signal mean in t.

a scale identification problem remains in the MNP model in Equation [2]. The Bayesian approach, however, does not require fixing the scale of the latent utilities (e.g. by setting the first diagonal element of Σ equal to one) to achieve identification. With proper priors, a posterior in the unidentified space of Σ (and β) can be defined. We therefore 'margin down' and report the posterior of the identified quantities $\tilde{\beta}$ and $\tilde{\Sigma}$ by normalizing with respect to one of the diagonal elements of Σ, say the first one (see Rossi, Allenby, and McCulloch 2005),[4] $\tilde{\beta} = \frac{\beta}{\sqrt{\sigma_{11}}}, \tilde{\Sigma} = \frac{\Sigma}{\sqrt{\sigma_{11}}}$. The advantage of this approach is the simplicity of the sampler needed and its good mixing properties (Rossi, Allenby, and McCulloch 2005), as all draws are sampled from familiar distributions. The expressions of the full conditional posterior distributions of the unknowns in the random coefficients MNP component are derived in the Appendix.

As indicated above, a unique feature of our data set is the information on individuals' store price image perceptions at different points in time. This implies that, rather than having to treat SPI as a latent construct within the store choice equation, we can explicitly link it with past store prices and estimate the formation process as a separate equation. This greatly enhances identification, and increases our confidence that we actually capture the effect of store price image – and not some other mediating construct. To deal with the ordinal scale of the image data, we add an extra layer to the model, which maps the latent, unobserved store price image SPI_{its} onto the measured $MSPI_{ist} = j$ if:

[7] $$\alpha_{j-1} < SPI_{its} + \theta_{its} \leq \alpha_j,$$

where the α_j are threshold parameters to be estimated (j=1,…,J), and θ_{its} is an independent, normally distributed random term, $\theta_{its} \sim N(0, \sigma_\theta^2)$, which leads to the well-known ordered probit model. To estimate the SPI formation model in Equations [4] to [7] we again rely on Bayesian estimation procedures (for details see Lourenço, Gijsbrechts, and Paap 2015).[5]

[4] A prior put on the full set of unidentified parameters (β and Σ) induces a prior on the identified parameters ($\tilde{\beta}$ and $\tilde{\Sigma}$), as in McCulloch and Rossi (1994).
[5] To initialize the recursive relation in Equation [5] we obtain the initial mean for each store as the average

Variable operationalization and estimation results

Variable operationalization

We use data on the households' shopping histories to generate the dependent variable for the store choice model, i.e. the household i's multinomial discrete store choice y_{it}=s among S mutually exclusive stores on each shopping trip t. To obtain household- and store-specific price (P_{its}) and feature variables ($Feat_{its}$), we use a procedure similar to van Heerde, Gijsbrechts, and Pauwels (2008) and Fox, Montgomery, and Lodish (2004): we combine the average weekly price and feature information for each chain and product category (out of a set of 58 representative product categories as defined by GfK), with households' shopping basket weights for these categories in an initialization period.[6] Promotions are run on a weekly basis and hence prices and feature faced by a household are constant across multiple shopping trips made to one same store in any particular week.

Our measure of store price image, $MSPI_{i,t-1,s}$, is based on GfK survey responses. Since we do not have these measures for all panel members in each of the 209 weeks, we impute missing values in the choice model using the same procedure as van Heerde, Gijsbrechts, and Pauwels (2008). Estimation of the store price image formation model is based only on the actually observed SPI measures. As a proxy for assortment size of each chain's store nearest to the household ($Assort_{is}$), we use store size in square meters (data available on a yearly basis). Similarly, store locations are combined with the GfK household panelists' zip codes to compute the Euclidean distance between a household and the closest store from each chain ($Dist_{is}$). Finally, as a measure for household-specific loyalty ($Loyal_{is}$) we compute, for each household, the average trip share across all visited stores on a

---

across the prices of a large, representative set of 58 product categories. The initial variance for each store is the variance of the initial beliefs across households (similar to Lourenço, Gijsbrechts, and Paap 2015).

[6] To ensure comparability across product categories, we express category prices as an index (relative to the average category price across stores, in an initialization period), before aggregating to the store level (see Fox, Montgomery, and Lodish 2004; van Heerde, Gijsbrechts, and Pauwels 2008, for a similar approach). The period from week 27 of 2001 till week 4 of 2002 was used as the initialization period in both cases (see van Heerde, Gijsbrechts, and Pauwels 2008).

household's trip history, while the lagged choice variable ($y_{i,t-1,s}$) is simply an indicator of the household's chosen store on the previous trip. These variables and their operationalizations are well established, and similar to earlier literature.

Estimation results

Store choice. Estimation results of the MNP model are based on a Gibbs sampler with a total of 20 000 draws, 10 000 of which were discarded as burn-in to eliminate the effect of the initial values. The mean posterior values of the off-diagonal elements of the error covariance matrix are all close to zero, suggesting that with a random coefficients structure across households there is little covariance among stores remaining in the data (the posterior mean variances are reported in the rightmost column of the second panel of Table 4). Visual inspection suggests convergence of both the individual and the mean parameters (Fig. 2 plots the draws for the two price variables). The model correctly classifies 71,95% of shopping trips, a figure that favorably compares to a 10% random assignment.

--- Insert Figure 2 about here ---

Table 4 reports the identified quantities $\tilde{\beta} = \frac{\beta}{\sqrt{\sigma_{11}}}$ and $\tilde{\Sigma}=\frac{\Sigma}{\sqrt{\sigma_{11}}}$ for the estimated parameters. All store-specific intercepts (from Aldi to Super de Boer), measuring intrinsic consumer preferences in comparison to the reference store Albert Heijn, are negative (see second half of Table 4). Only for Dekamarkt the 95% highest posterior density (HIPD) of the intercept includes zero.[7] These results confirm the position of Albert Heijn as the market leader in the Netherlands and strengthen the face validity of our estimates. The first panel of Table 4 summarizes the mean effects of all benefit and cost variables in the MNP model. The estimated effects of distance, assortment size and loyalty have the expected sign. Stores located farther away from consumers have a lower likelihood of being patronized. Assortment

[7] Inference within a Bayesian estimation approach is conducted by assessing whether a specific highest posterior density interval (HPDI) of a parameter includes zero (and is thus 'significant' in a frequentist sense). We use a 95% HPDI.

has a positive effect on store patronage: stores with bigger assortments (measured by store floor space) have a higher likelihood to be chosen. The estimated effect of loyalty is positive. This indicates that consumers have a tendency to stick to (a subset of) earlier visited chains – possibly because of switching costs inherent to visiting less familiar stores. The parameter measuring the effect of lagged choices has a negative sign, in line with the notion of multiple-chain loyalty and consumers alternating between chains. The effect of out-of-store feature advertising is non-significant, perhaps because store-level changes in the number of feature ads are rather limited. Moreover, its effect may be taken up by price changes.

--- Insert Table 4 about here ---

As expected, the posterior means of the parameters for price image and actual price are negative: all else equal, the higher the actual practiced prices or the more unfavorable the price image of a particular store, the higher the actual and perceived monetary costs of shopping in that store, which decreases its likelihood of being chosen on a given shopping trip. The mean coefficient values are -0.027 for price image and -0.390 for actual price. However, these are average figures, which do not hold equally among consumers. The histograms of the household-level posterior means, for the parameters of price image and actual price, are displayed in the two leftmost panels of Figure 3. These histograms point to quite some dispersion (see also Table 4), especially for the actual price variable. The correlation between the two sets of parameters is significant and positive, but very low ($r=.103$; $p<.01$), suggesting that actual price and SPI sensitivity are two distinct constructs.

--- Insert Figure 3 about here ---

SPI formation. The estimates for the threshold parameters that allow mapping unobserved beliefs SPI_{its} into the observed, discrete $MSPI_{i,t-1,s}$ (see Equation [3]) are summarized in the third panel of Table 4. The middle thresholds are further apart than the extremes, in line with the fact that respondents use extremes relatively less than other values of the SPI scale (recall that the SPI scale ranges from 1 to 9 and that for identification, α_0, α_1, α_9 are set to $-\infty$, 0, and

+∞, respectively). The SPI formation model correctly predicts about one third of all observed SPI scores (29.8%), a figure that favorably compares to random assignment (11.1%).[8] Figure 3 depicts the distribution of the price learning parameters across households.

Next, we explore which household characteristics drive the different price-related parameters. Our goal is to gain a better understanding of the determinants of the dual price response across households, and lay the ground for targeted pricing strategies.

Profiling price and price-image sensitive households

We run exploratory regressions with the price-related parameters as the dependent variables and a range of potential antecedents or correlates, as independent variables. We consider three groups of independent variables, related to (1) the households' self-reported attention to and use of prices and price cuts, (2) their socio-demographic characteristics, and (3) variables reflecting the households' shopping behavior and media use (see Table 5 for details on the operationalization of these variables). To account for the estimation error in the price coefficients, we use weighted least squares, with weights equal to the inverse of the posterior standard deviations. Table 6 lists the regression results.[9] A first and striking observation is that the pattern of significant effects strongly differs across the three regressions. Factors related with sensitivity to weekly prices do not drive responsiveness to overall store price images, or the strength with which these are updated based on price signals – corroborating that different households react to different price cues. For the sake of clarity, we discuss the effects by type of variable and describe only the significant effects.

--- Insert Table 5 about here ---

Attitude towards prices and price cuts

[8] In 57.7% of the cases, the difference is less than 2 points. The non-parametric Spearman correlation is .29 and the mean absolute deviation (MAD) is 1.28.

[9] Increased price sensitivity implies lower response coefficients, but for the sake of readability we have reversed the estimations signs, such that a positive (negative) sign represents an inrease (decrease) in the sensitivity towards the two types of price information and an increase in learning (which is regressed directly as $1/\sigma^2_{\eta_i}$; see Equation [5]).

As a first group, we consider the survey measures that reflect consumers' self-reported attention to various price cues. Some of these statements relate to price awareness and attention in more general terms. While those measures do not influence the degree of store switching in response to weekly price changes, we find them to be significantly correlated with SPI-sensitivity ('importance of low prices when choosing a supermarket': $\gamma=.0048$; $p<.05$, 'price awareness': $\gamma=.0221$; $p<.1$, 'note discount offers': $\gamma=.0108$; $p<.1$). In contrast, 'buy more of a brand when on price cut', a statement reflecting consumers' actual purchase shifts of specific brands, only increases sensitivity to basket prices ($\gamma=.0476$; $p<.05$), but not SPI responsiveness or learning. Consumers who state that they 'take advantage of price promotions, regardless of the amount of money saved', exhibit weaker price and SPI sensitivity ($\gamma=-.0562$; $p<.01$, $\gamma=-.0076$; $p<.05$). Interestingly, the only measure in this group that is significantly linked with learning, is the 'importance of low prices when choosing a supermarket' ($\gamma=-.0277$; $p<.05$).

--- Insert Table 6 about here ---

Economic and socio-demographic characteristics

The second group of variables is formed by economic and socio-demographic characteristics of households, which are related with the costs and gains of collecting and responding to price information. Table 6 reveals that higher education levels and membership to a higher social class significantly decrease consumer sensitivity to week-to-week prices ($\gamma=-.0176$; $p<.05$ and $\gamma=-.0626$; $p<.05$, respectively). Being a tenant of a house significantly increases sensitivity to both week-to-week prices and SPI ($\gamma=.0685$; $p<.1$ and $\gamma=.0125$; $p<.05$, respectively). Interestingly, higher dispersion of stores neighboring a household, significantly increases sensitivity to week-to-week detailed prices ($\gamma=.0064$; $p<.05$). Higher price learning is associated with larger households ($\gamma=-.0269$; $p<.1$), as household size may be an incentive to keep track of prices.

Shopping behavior

The third group of variables characterize a household's purchasing and shopping behavior. Not unexpectedly, consumers sensitive to week-to-week prices in their store selection are less store-loyal (γ=–.1654; p<.05), buy smaller baskets (γ=–.0043; p<.05), buy more private labels (γ=.0143; p<.05), and are less brand-loyal (γ=–.0338; p<.05); observations that do not hold for SPI-sensitive households. Also, weekly-price sensitive shoppers buy more brands that others will adopt (γ=.0535; p<.01), while SPI-sensitive shoppers tend to try less new brands(γ=–.0054; p<.01). Households that never visited the high-price high-service chain leader in the market, are significantly more sensitive to weekly prices (γ=.3040; p<.01) and to SPI (γ=.0140; p<.01) in their store choice.

Finally, increased readership of different newspapers is significantly related with increased sensitivity to one type of price information but not to the other, which makes these findings important for targeting and communication purposes. NRC Handelsblad, which has a wider reach in the Dutch society, is weakly related to higher actual price sensitivity (γ=.0362; p<.1), whereas higher SPI sensitivity is associated with Het Parool (γ=.0078; p<.05), a newspaper associated with somewhat more liberal views.

Implications

The estimation results indicate that consumers adjust their store choice to actual prices directly, through the actual price coefficient, or indirectly, through the learning and SPI parameters. At the same time, we find substantial heterogeneity in each of these coefficients (explained by different consumer characteristics). These findings raise two additional questions. First, what is the size of the segments of consumers that do/do not react to the different types of price information? Second, what is the immediate and long term impact of changes in store price, on traffic in each of these segments? We address these two questions in turn.

Segmenting consumers: Eye-for-Detail or Big Picture?

To identify which consumers are influenced by both, none, or one of the two types of price information, we use the individual-level draws from the Gibbs sampler, for the actual price and SPI parameters in the store choice model. We compute highest posterior density intervals for each individual and parameter, and then check whether they include zero (in which case the individual is said to be non-responsive to the price cue) or not (in which case the individual is said to be responsive to the price cue). Since we have a clear expectation regarding the signs of both the price image and the actual price effects, we use one-tailed 90% posterior density intervals.

We find that 68.5% of all households do not exhibit any significant price response. These consumers select stores based on only non-price attributes, such as distance or assortment, and/or display some form of choice dynamics (persistence and or varied choice among a subset of stores). The remaining 31.5% of the households *do* adjust their store selection in response to price cues (see Figure 4). Among these price-oriented consumers, we find that the great majority uses only one of the two types of price information, only 11.5% (3.6% of all households) making use of both actual prices and price perceptions. Detailed week-to-week prices intervene in the decision making process of 16.2% of all consumers, and 11.7% of all consumers resort exclusively to their price perceptions to assess stores' expensiveness and to guide their choices.

--- Insert Figure 4 about here ---

Linking these figures with earlier findings from the literature leads to some interesting observations. In previous *survey* studies, about two-thirds of consumers self-report hardly ever comparing prices, the remaining consumers claiming to be price sensitive (Urbany, Dickson, and Sawyer 2000). At the same time, several authors suggest that far fewer consumers *actually* cross-shop to benefit from price deals (e.g. Bodapati and Srinivasan 2001;

Urbany, Dickson, and Key 1991; Urbany, Dickson, and Sawyer 2000). Our results appear to reconcile these views. On the one hand, the total size of our price-sensitive segment (31.5% of all households) is surprisingly consistent with the self-report data – corroborating the importance of price. We note that shopping trips made by this segment comprise 35.1% of all grocery trips (see last line of Table 7, columns 3 to 5), and their spending represents nearly half of the total spending in the market (47.4%) – further underscoring their economic relevance. On the other hand, our dual-effect framework reveals that far fewer households (only half of these price-sensitive households: the Eye-for-Detail segment) adjust their store choice to weekly price changes – in line with earlier empirical findings based on actual purchase behavior. This finding may help explaining why many researchers did not find any significant effect of price promotions on store traffic (e.g. Srinivasan et. al 2004).

--- Insert Table 7 about here ---

While these segment sizes pertain to the total market, retailers have an interest in the segment-decomposition of their *own clientele*. As revealed in the top panel of Table 7, the market shares of the different stores differ across consumer segments. This holds in particular for the top two players, Albert Heijn and C1000, which comprise more than half of the market. C1000 is more attractive to Eye-for-Detail price-sensitive consumers (i.e. obtains a 27.4% choice share within that segment), and less attractive to those monitoring SPI (17.4% choice share among SPI sensitive consumers), relative to its overall market share (22.6%). Albert Heijn, in contrast, is relatively more (less) attractive to SPI-sensitive (detailed price-sensitive) consumers (5.8 percentage points higher and 4.7 percentage points lower than its market share, respectively). Focusing on the composition of the stores' customer base (bottom panel of Table 7), we find that the % of the store clientele that belongs to the convenience segment is far lower for the hard discounters (Aldi and Lidl) and the more price-oriented HiLo stores (Jumbo and Dekamarkt) than the market average. Interestingly, these discounter stores do not necessarily have the highest proportion of weekly-price sensitive shoppers (e.g. 18.3% of Lidl customers, compared to 21.7% for C1000), an important fraction of their customers being price-image oriented (e.g. 17.3% for Lidl versus 10.1% for C1000).

Even though the customer classification is relevant conceptually, it does not yet paint a full picture of the impact of price. First, the segmentation reflects responsiveness based on statistical significance, but does not shed light on the size of the price effects. Second, for Big Picture consumers, the extent to which actual price changes affect store choice depends on the strength of the learning process, which governs the adjustments in SPI. Third, the response coefficients reflect the immediate impact of weekly price, and the one-period lagged effect for SPI, but do not capture the full dynamic influence of actual prices over time. For instance, a price change will, through the updating process, affect the store's SPI level over multiple subsequent periods. In the next section, we address these issues.

Impact of price changes across segments

To shed light on the importance of the dual price effect, we use our data and estimated models as a basis for simulation. We start by drawing parameters from the store choice model (i.e. the individual-level β_i, which include the effect of actual prices and of price perceptions, and the covariance matrix Σ) as well as the SPI formation model (i.e. the thresholds α_j and the individual-level price learning parameters $1/\sigma^2_{\eta_i}$). We then use those parameters, in conjunction with the actual database, to predict the effect of a price drop under two scenarios. The benchmark scenario is one without price learning and, therefore, no store price image updating. This benchmark is compared with the results of a model where price learning does take place, and price perceptions are formed dynamically over time based on price signals. For illustrative purposes, we conduct our simulation for the market leader (Albert Heijn), and consider the effect of a price drop from a given week on (the 30th week of the year 2002), by 5 10 15, and 20%. The results are summarized in Table 8, where we break down the simulated effects across segments. In the benchmark case without learning, price decreases lead to gains in weekly traffic due to immediate changes in consumer choices. In this static SPI scenario, by construction, no trip increases can be attributed to the SPI sensitive segment, and most of the gained trips take place among basket price-sensitive consumers. Even within those price sensitive-segments, the absolute elasticity of trip share with respect to actual price changes is smaller than one – in line with earlier findings (Fox, Postrel, and Semple 2009) – and amounts to approximately .70.

--- Insert Table 8 about here ---

In the dynamic SPI scenario, the learning effect becomes apparent due to the impact on store price perceptions. Depending on the level of the price change, the total number of shopping trips gained is approximately 15% higher than if only the direct effect of prices is accounted for, a difference attributable to the price responses in the Big Picture and Combined segments. While the Combined segment is much smaller in size (3.6% of the total market, compared to 11.7% for the Big Picture group), it accounts for many of the indirect (SPI-induced) traffic gains, indicating that this 'hard core' group of price mavens not only keeps track of both price cues, but is highly responsive in its store selection. Hence, a store choice model not accounting for the dynamic formation of store price images, clearly underestimates the impact of price cuts, and disproportionately so among specific segments.

We further note that, while this 15% difference is already sizable, it is likely to be a conservative estimate of the indirect effect. For one, while our simulations also account for changes in the 'lagged choice' variable, we keep the loyalty variable the same. Differently stated, our model does not yet allow SPI changes to alter the consumer's set of 'frequently visited stores'. No doubt, changes in SPI may, in the long run, also affect the degree to which stores are included in the loyal set, thereby further adding to the indirect price influence. Moreover, as argued in the conceptual part, Big Picture consumers are more likely to shift their entire purchase basket to the selected store, rather than engage in cherry picking visits. Hence, an extra trip among these Big Picture consumers is likely to bring in more spending than an extra Eye-for-Detail customer visit.

Conclusions, limitations and future research

Conclusions

In this paper, we advocate that actual store prices may affect store patronage in two main ways: *directly*, by making consumers shop in stores with low prices in that particular week, and *indirectly*, by affecting the overall image of expensiveness of the visited stores and, hence, their propensity to be visited on future trips. To empirically test this dual price effect, we consider an individual-level store choice model including both week-to-week basket prices and overall store price images. To account for the fact that store price images themselves are affected by basket prices, we complement this choice model with a model of SPI formation over time, using a Bayesian learning framework. We use this specification to illustrate how a price change may affect store traffic not only through a direct, same-week effect of basket prices but also in subsequent weeks, due to the mediating role of store price perceptions updated by consumers.

By considering this comprehensive price effect, our study underscores the importance of pricing strategies in the context of consumers' store selection, often overshadowed by the 'location, location, location' mantra prevailing in the retailing industry. In particular, we find that more than one third of consumers use some type of price information to guide their over-time store selection. The economic relevance of these basket price- and SPI-sensitive consumers is clearly demonstrated by the fact that their grocery shopping trips represent more than one third of the total number of trips, and comprise nearly fifty percent of the total spending in the market. An interesting finding, also, is that compared to mainstream retailers, a higher proportion of (hard) discounters' clientele is SPI-sensitive.

The fact that the remaining two thirds of consumers use only non-price or convenience cues, may help to explain why previous research did not find any significant effects of price promotions on store traffic (see e.g. Srinivasan et. al 2004).

Interestingly, only half of the price-sensitive consumers keep track of actual weekly prices and use those to adjust their weekly store visits. The other half, tailor store selection to overall beliefs about stores' expensiveness. These beliefs, in turn, are updated dynamically, based on price signals received in-store – leading to an indirect actual price effect. Accounting for this indirect effect increases the over-time impact of actual permanent overall price changes by approximately 15%, enhancing the importance of pricing as a strategic instrument for retailers.

Moreover, we find that the majority of consumers attend to only one type of price cue, very few households adjusting their store patronage to both weekly price changes and store price images. The two subgroups of households differ in the timing of their reactions: while consumers sensitive to weekly actual prices exhibit an immediate traffic change, SPI-sensitive consumers respond with a delay, as they learn about overall price changes. This underscores the importance of monitoring over-time price response – as suggested by Fox, Postrel, and Semple (2009). While those authors already documented the presence of lagged price effects, we offer a complementary explanation for these effects through SPI formation. We also expect visits from SPI-sensitive consumers to be economically more important, as these consumers typically shift their entire shopping basket when changing stores.

This is confirmed by our exploratory analysis, which links our individual-level estimates to a broad range of household characteristics. We find that consumers more sensitive to weekly prices (*Eye-for-Detail*) are those who, in surveys, report using store price information to direct *specific* brand purchases. In line with previous research (e.g. Gauri, Sudhir, and Talukdar; Hoch et. al 1995), we find these households to be tenants rather than home owners, to exhibit lower education levels, and to belong to lower social classes. In addition, weekly-price sensitive consumers are less store or brand loyal, buy more private labels, and have smaller purchase baskets – corresponding to the profile of cherry picking consumers (see e.g. Bell and Lattin 1998; Fox and Hoch 2005).

Households more responsive to stores' overall price images (*Big Picture*) do not exhibit these characteristics. These are the households who, when surveyed, attest to a general attention to prices. In line with this price focus but, also, a desire for efficient shopping, they are less inclined to try new brands. Moreover, while SPI-sensitivity is also more prevalent among tenants rather than house owners, it is found in all social classes and education levels. Similarly, the degree to which these consumers *adjust their SPI beliefs* to actual incoming price information does not seem related with their socio-demographic profile, except for the fact that larger households exhibit stronger SPI updating. Finally, we find that the type of price response is linked to actual store patronage and journal readership: consumers adjusting their store choice to weekly prices, self-selecting different stores, and reading different magazines than those sensitive to overall store price beliefs. In all, these findings lead to a better understanding of who are the price-sensitive consumers, and enable effective segmentation and targeting strategies.

Limitations and future research

Our empirical analysis pertains to only one country (the Netherlands), and one retail format (supermarkets). It would be interesting to verify the presence of a dual price effect, but also the size and profile of the Eye-for-Detail vs Big-Picture vs Combined Segments, in other settings. Similarly, while we consider the grocery setting, the dual price impact may appear in other categories such as apparel or consumer durables – an issue we leave for future study.

Second, our findings reveal that households can be responsive to SPI, but only weakly update it using prices. For those households, managing other SPI determinants becomes strategically important. Unfortunately, our data did not allow to assess the possible impact of non-price cues such as store layout on SPI – effects that future studies may incorporate.

Third, while our focus was on traffic, it would be interesting to analyze the dual price effect on consumers' in-store purchase behavior and spending. An intriguing question is whether households who select stores based on their SPI (rather than low weekly prices) are also less responsive to in-store promotion announcements or, in contrast, make up for their lower responsiveness in store choice by selecting items on deal within the store. While we expect the former to be true, future research should verify this.

Last but not least, our analysis shed light on *household* differences in the use of actual weekly prices versus price images. In addition to such household heterogeneity, the type of price cue used to pick stores may be affected by the type of shopping trip – situational factors or differences in shopping mission favoring the use of one price indicator rather than another. Shedding light on such trip-specific responses may further fine tune our understanding and management of price as a crucial retail marketing instrument.

REFERENCES

Ailawadi, Kusum L. and K. L. Keller (2004), “Understanding Retail Branding: Conceptual Insights and Research Priorities,” *Journal of Retailing*, 80, 331–342.

Ailawadi, Kusum L., Scott A. Neslin, and Karen Gedenk (2001), “Pursuing the Value-Conscious Consumer: Store Brands Versus National Brands Promotions,” *Journal of Marketing*, 65, 71–89.

Joseph W. Alba, Susan M. Broniarczyk, Terence A. Shimp, and Joel E. Urbany (1994) “The Influence of Prior Beliefs, Frequency Cues, and Magnitude Cues on Consumers’ Perceptions of Comparative Data,” *Journal of Consumer Research*, 21, 219–235.

Arnold, S. J., T. Oum, and D. J. Tigert (1983), “Determinant Attributes in Retail Patronage: Seasonal, Temporal, Regional, and International Comparisons,” *Journal of Marketing Research*, 20 (May), 149–157.

Becker, Gary. (1965), “A Theory of the Allocation of Time,” *Economic Journal*, 75, 493–517.

Bell, David R. and James M. Lattin (1998), “Shopping Behavior and Consumer Preference for Store Price Format: Why ‘Large Basket’ Shoppers Prefer EDLP,” *Marketing Science*, 17(1), 66–88.

Bell, David R., T-H Ho, and C. S. Tang (1998), “Determining Where to Shop: Fixed and Variable Costs of Shopping,” *Journal of Marketing Research*, 352–369.

Bodapati, Anand V. and V. Srinivasan (2001), “The Impact of Out-of-Store Advertising on Store Sales,” Working Paper, University of California at Los Angeles.

Briesch, Richard A., Pradeep K. Chintagunta, and Edward J. Fox (2009), “How Does Assortment Affect Grocery Store Choice?,” *Journal of Marketing Research,* 46 (April), 177–189.

Brown, Francis E. (1969), “Price Image Versus Price Reality,” *Journal of Marketing Research*, 6(2), 185–191.

Brown, Francis E. (1971), "Who Perceives Supermarket Prices Most Validly?," *Journal of Marketing Research*, 8(1), 110–113.

Büyükkurt, B. Kemal (1986), "Integration of Serially Sampled Price Information: Modeling and Some Findings," *Journal of Consumer Research*, 17(3), 357–373.

Ching, Andrew T., Tülin Erdem, and Michael P. Keane (2013), "Learning Models: An Assessment of Progress, Challenges and New Developments," *Marketing Science*, 32 (6), 913–38.

Desai, K. K. and Debabrata Talukdar (2003), "Relationship Between Product Groups' Price Perceptions, Shopper's Basket Size, and Grocery Store's Overall Store Price Image," *Psychology and Marketing*, 20(10), 903–933.

Erdem, Tülin and Michael P. Keane (1996), "Decision-Making Under Uncertainty: Capturing Dynamic Choice Processes in Turbulent Consumer Goods Markets," *Marketing Science*, 15 (1), 1–20.

Erdem, Tülin, Michael P. Keane, and Baohong Sun (2008), "A Dynamic Model of Brand Choice When Price and Advertising Signal Product Qual- ity," *Marketing Science*, 27 (6), 1111–25.

Feichtinger, G., A. Luhmer, and G. Sorger (1988), "Optimal Price and Advertising Policy for a Convenience Goods Retailer," *Marketing Science*, 7(2), 187–201.

Finn, A. and J. Louviere (1990), "Shopping-Center Patronage Models: Fashioning a Consideration Set Segmentation Solution," *Journal of Business Studies*, 21(3), 259–275.

Finn, A. and J. Louviere (1996), "Shopping Center Image, Consideration, and Choice: Anchor Store Contribution," *Journal of Business Studies*, 35(3), 241–251.

Fox, Edward J. and Stephen J. Hoch (2005), "Cherry-Picking," *Journal of Marketing*, 69(1), 46 – 62.

Fox, Edward J., Alan L. Montgomery, and Leonard M. Lodish (2004), "Consumer Shopping and Spending Across Retail Formats," *The Journal of Business*, 77(2), 25–60.

Fox, Edward J., Steven Postrel, and John H. Semple (2009), "Optimal Category Pricing with Endogenous Store Traffic," *Marketing Science*, 28(4), 709–720.

Gauri, Dinesh K., K. Sudhir, and Debabrata Talukdar (2008), "The Temporal and Spatial Dimensions of Price Search: Insights from Matching Household Survey and Purchase Data," *Journal of Marketing Research*, 45(2), 226 – 240.

Gelfand, Alan E. and Adrian F. M. Smith (1990), "Sampling-Based Approaches to Calculating Marginal Densities," *Journal of the American Statistical Association*, 85(410), 398–409, June.

Gijsbrechts, Els, Katia Campo, and Patricia Nisol (2008), "Beyond Promotion-Based Store Switching: Antecedents and Patterns of Systematic Multiplestore Shopping," *International Journal of Research in Marketing*, 25(1), 5–21.

Grewal, Dhruv and Michael Levy (2007), "Retailing Research: Past, Present, and Future," *Journal of Retailing*, 83(4), 447–464.

Hoch, Stephen J., Byung-Do Kim, Alan L. Montgomery, and Peter E. Rossi. (1995), "Determinants of Store-Level Price Elasticity," *Journal of Marketing Research*, 32, 17–29, February.

Hoch, Stephen J. and John Deighton (1989), "Managing What Consumers Learn from Experience," *Journal of Marketing*, 53 (April), 1–20.

Hamilton, Ryan and Alexander Chernev (2013), "Low Prices Are Just the Beginning: Price Image in Retail Management," *Journal of Marketing*, 77 (November), 1–20.

Kalyanam, Kirthi, Rajiv Lal, and Gerd Wolfram (2006), "Retailing in the 21st Century: Current and Future Trends," chapter Future Store Technologies and Their Impact on Grocery Retailing, pages 95–112. Springer, Berlin-Heidelberg.

Leenheer, Jorna, Harald J. van Heerde, Tammo H.A. Bijmolt, and Ale Smidts (2007), “Do Loyalty Programs Really Enhance Behavioral Loyalty? An Empirical Analysis Accounting for Self-Selecting Members,” *International Journal of Research in Marketing*, 24(1), 31–47.

Levy, M., D. Grewal, Pravin K. Kopalle, and J. D. Hess (2004), “Emerging Trends in Retail Pricing Practice: Implications for Research,” *Journal of Retailing*, 80:xiii–xxi. Editorial.

Lourenço, C.J.S., Gijsbrechts, E., and Paap, R. (2015), “The Impact of Category Prices on Store Price Image Formation: An Empirical Analysis,” *Journal of Marketing Research*, 52(2), April, 200-216.

Mägi, A.W. and C-R Julander (2005), “Consumers’ Store-Level Price Knowledge: Why Are Some Consumers More Knowledgeable Than Others?,” *Journal of Retailing*, 81, 319–329.

MarketWatch (2009), “Carrefour Pushes Hard to Restore Its Price Image (accessed September 29, 2009) [http://www.marketwatch.com/story/carrefour-detemined-to-restore-price-image].

Mazumdar, T. and Kent B. Monroe (1990), “The Effects of Buyers’ Intentions to Learn Price Information on Price Encoding,” *Journal of Retailing*, 66(1), 15–32.

Mazumdar, T., S. P. Raj, and I. Sinha (2005), “Reference Price Research: Review and Propositions,” *Journal of Marketing*, 69(4), 84–102.

McCulloch, Robert and Peter Rossi (1994), “An Exact Likelihood Analysis of the Multinomial Probit Model,” *Journal of Econometrics*, 64, 207–240.

Monroe, Kent B. (2002), “Pricing: Making Profitable Decisions,” McGraw-Hill/Irwin, 3rd edition.

Nielsen, A.C. (2008), “Grocery Store Choice and Value for Money: A Global Nielsen Consumer Report,” Technical report, January.

Nyström, H. (1970), “Retailing Pricing – An integrated economic and psychological approach,” PhD thesis, Economic Research Institute at the Stockholm School of Economics.

Nyström, H., H. Tamsons, and R. Thams (1975), “An experiment in price generalization and discrimination,” *Journal of Marketing Research*, 12, 177–181, May.

Rossi, Peter E., Greg M. Allenby, and Robert McCulloch (2005), “Bayesian Statistics and Marketing,” Wiley Series in Probability and Statistics, Wiley, West Sussex, England.

Severin, Valerie, Jordan J. Louviere, and Adam Finn (2001), “The Stability of Retail Shopping Choices Over Time and Across Countries,” *Journal of Retailing*, 77, 185–202.

Srinivasan, Shuba, Koen Pauwels, Dominique M. Hanssens, and Marnik G. Dekimpe (2004), “Do Promotions Benefit Manufacturers, Retailers, or Both?,” *Management Science*, 50(5), 617–629.

Srivastava, Joydeep and Nicholas H. Lurie (2004), “Price-Matching Guarantees as Signals of Low Store Prices: Survey and Experimental Evidence,” *Journal of Retailing*, 80(2), 117–128.

Urbany, Joel E., Peter R. Dickson, and Rosemary Key (1991), “Actual and Perceived Consumer Vigilance in the Retail Grocery Industry,” *Marketing Letters*, 2(1), 15–25.

Urbany, Joel E., Peter R. Dickson, and Rosemary Kalapurakal (1996), “Price Search in the Retail Grocery Market,” *Journal of Marketing*, 60, 91–104.

Urbany, Joel E., P. R. Dickson, and A. G. Sawyer (2000), “Insights Into Cross- and Within-Store Price Search: Retailer Estimates vs. Consumer Self-Reports,” *Journal of Retailing*, 76(2), 243–258.

van Heerde, Harald, Els Gijsbrechts, and Koen Pauwels (2008), “Winners and Losers in a Major Price War,” *Journal of Marketing Research*, 45, 117–128, October.

Vroegrijk, Mark, Els Gijsbrechts, and Katia Campo (2013), “Close Encounter with the Hard-Discounter: A Multiple-Store Shopping Perspective on the Impact of Local Hard-Discounter Entry,” *Journal of Marketing Research*, Vol. 50 (5), 606–626, October.

Wall Street Journal (2010), “Wal-Mart Bets on Reduction in Prices,” (accessed April 27, 2010) [http://online.wsj.com/article/SB10001424052702304198004575172271682347064.html].

Zeithaml, Valarie A. (1988), “Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence,” *Journal of Marketing*, 52 2–22.

TABLE 1
DESCRIPTIVES: MEAN (STANDARD DEVIATION) VALUES FOR NON-PRICE VARIABLES AND MARKET SHARES BY RETAIL CHAIN

Store	Number of visits	Market share	Weekly visits[a]	Distance[b]	Floor space[c]	Loyalty	Feature[d,e]
Albert Heijn	102153	29%	0.55	2.00 (2.57)	1.38 (0.57)	0.31 (0.38)	1.68 (1.23)
Aldi	33310	10%	0.21	2.95 (2.86)	0.43 (0.13)	0.09 (0.18)	1.99 (4.71)
C-1000	78981	23%	0.41	2.56 (2.92)	0.98 (0.35)	0.21 (0.33)	1.00 (1.00)
DekaMarkt	11133	3%	0.06	36.36 (31.76)	0.87 (0.36)	0.03 (0.14)	0.95 (0.81)
Edah	22394	6%	0.12	6.42 (5.42)	1.00 (0.36)	0.08 (0.20)	1.87 (1.36)
Jumbo	9042	3%	0.05	12.48 (9.21)	1.41 (0.69)	0.02 (0.11)	0.05 (0.31)
Konmar	12744	4%	0.07	17.81 (15.30)	2.61 (0.51)	0.05 (0.17)	1.40 (1.10)
Lidl	12350	4%	0.08	4.27 (3.76)	0.68 (0.15)	0.02 (0.07)	2.57 (5.41)
Plus	23208	7%	0.12	5.98 (5.20)	0.89 (0.33)	0.05 (0.18)	2.58 (1.50)
SdB	44271	13%	0.23	4.01 (4.71)	1.01 (0.31)	0.14 (0.29)	1.76 (1.15)
Total	**349586**	**100%**					

[a]Given by the households' number of visits to the store divided by the households' total number of weeks.
[b]In kilometers (Km).
[c]In square meters (m2) and rescaled (divided by 1000).
[d]To compute this variable we use households' typical shopping basket weights among a representative set of product categories.
[e]Given by the percentage of stores in the chain carrying feature promotion times the percentage of products promoted. It varies from 0 (no feature promotional activity) to 10,000 (100% of the products in 100% of the stores are promoted).

TABLE 2
DESCRIPTIVES: MEAN (STANDARD DEVIATION) VALUES FOR PRICE VARIABLES BY RETAIL CHAIN

Store	Price[a] (Index)	Rank price[b]	Price image[c]	Rank SPI[b]	Rank dif.[d]
Albert Heijn	1.215 (0.057)	10	4.45 (1.17)	9	+1
Aldi	0.589 (0.034)	1	3.12 (1.23)	2	-1
C-1000	0.975 (0.041)	3	3.76 (1.16)	5	-2
DekaMarkt	1.030 (0.055)	5	3.75 (1.14)	4	+1
Edah	1.022 (0.053)	4	4.06 (1.18)	7	-3
Jumbo	1.081 (0.061)	6	2.98 (1.25)	1	+5
Konmar	1.175 (0.077)	9	4.46 (1.14)	10	-1
Lidl	0.592 (0.036)	2	3.26 (1.25)	3	-1
Plus	1.123 (0.060)	7	4.04 (1.20)	6	+1
SdB	1.131 (0.050)	8	4.35 (1.20)	8	=0

[a]To compute this variable we use households' typical shopping basket weights among a representative set of product categories.
[b]Rank price ordered from cheapest (= 1) to most expensive (= 10) and rank SPI ordered from most favorable (= 1) to most unfavorable (= 10).
[c]Measured from 1 (= most favorable) to 9 (= least favorable).
[d]Extent to which price images among consumers align with average price levels (= rank price - rank SPI).

TABLE 3
EVOLUTION OF WEEKLY PRICES AND SPI WITHIN PRICING FORMATS

	HiLo (Albert Heijn)		EDLP (Aldi)	
Period[a]	Prices	SPI	Prices	SPI
2002 : 16	1.200	4.53	0.603	3.00
2002 : 40	1.196	4.60	0.585	2.93
2003 : 16	1.220	4.65	0.603	3.10
2003 : 40	1.229	4.72	0.596	3.07
2004 : 05	1.190	4.36	0.586	3.11
2004 : 16	1.198	4.31	0.583	3.31
2004 : 40	1.224	4.28	0.578	3.20
2005 : 16	1.243	4.21	0.584	3.20
2005 : 40	1.245	4.30	0.584	3.20

[a]Year:week. Average weekly prices computed from weeks before and after each survey week. A smaller number of weeks was used to compute the average price levels around the surveys 2003:40 and 2004:05.

TABLE 4
POSTERIOR RESULTS FOR THE MNP MODEL AND SPI THRESHOLDS

	Mean	S.d.	2,50%	50%	97,50%	Sigma
Benefits and costs						
Distance	-0.058	0.007	-0.069	-0.058	-0.048	
Assortment size	0.112	0.024	0.062	0.113	0.156	
Loyalty	2.498	0.065	2.369	2.500	2.617	
Price image	-0.027	0.005	-0.016	-0.027	-0.038	
Price	-0.390	0.045	-0.480	-0.390	-0.302	
Feature	-0.002	0.001	-0.004	-0.002	0.001	
Last visit	-0.037	0.011	-0.059	-0.037	-0.015	
Intercepts						
Aldi	-0.838	0.062	-0.948	-0.842	-0.707	1.000
C1000	-0.390	0.059	-0.497	-0.389	-0.274	0.540
Dekamarkt	-0.109	0.105	-0.301	-0.109	0.079	0.169
Edah	-0.480	0.070	-0.612	-0.477	-0.342	0.450
Jumbo	-0.323	0.070	-0.453	-0.325	-0.182	0.183
Konmar	-0.512	0.071	-0.629	-0.519	-0.367	0.403
Lidl	-1.121	0.063	-1.236	-1.123	-0.990	0.893
Plus	-0.720	0.081	-0.850	-0.732	-0.543	0.362
Super de Boer	-0.444	0.065	-0.566	-0.439	-0.319	0.426
SPI thresholds[a]						
Threshold α_2	0.375	0.005	0.366	0.376	0.386	
Threshold α_3	1.078	0.003	1.073	1.077	1.084	
Threshold α_4	1.515	0.006	1.503	1.515	1.523	
Threshold α_5	2.605	0.009	2.586	2.605	2.621	
Threshold α_6	3.505	0.029	3.451	3.505	3.570	
Threshold α_7	3.877	0.045	3.796	3.875	3.973	
Threshold α_8	4.552	0.118	4.332	4.547	4.796	

aFor identification, α_0, α_1, and α_9 are set equal to $-\infty$, 0, and $+\infty$, respectively.

TABLE 5
OPERATIONALIZATION OF CONSUMER CHARACTERISTICS

Fram.	Variables	Scale
Self-perceptions	Look first to the price	1 (=totally agree) to 5 (=totally disagree)
	Note discount offers	1 (=totally agree) to 5 (=totally disagree)
	Low prices choosing supermarket	1 (=very unimportant) to 9 (=very important)
	Price awareness	1=a lot/yes'; 0=more or less/no
	Check first whether cheaper somewhere else	1 (=totally agree) to 5 (=totally disagree)
	Price discounts can save consumers much money	1 (=totally disagree) to 5 (=totally agree)
	Pay more for better quality product	1 (=totally disagree) to 5 (=totally agree)
	Nice buy items w/ price cut whatever amount saved	1 (=totally disagree) to 5 (=totally agree)
	Buy more of a brand when on price discount	1 (=totally disagree) to 5 (=totally agree)
Demographics	Occupation level	1=low; 2=medium; 3=high
	Education household head	1 to 13
	Social class	1 to 5
	House owner/tenant	1=rents; 0=owns
	Household size	1 to 4 and 5+
	Net monthly income	1 to 19
	Housewife age	years
Shopping Behavior[a]	Albert Heijn customer	1=no; 0=yes
	Average quantity purchased	nr. of products
	Maximum loyalty share	0 to 1
	Average weekly private label quantity	nr. of products
	Mean nr. of weekly shopping trips	nr. weeks
	Proportion trips before 12:00 (after 18:00; EDLP to HiLo)	0 to 1
Opportunity Costs	Average distance and store dispersion	in km
	I consider myself a brand loyal consumer	1 (=totally disagree) to 5 (=totally agree)
	Buy brands that I think others will adopt	1 (=totally disagree) to 5 (=totally agree)
	Common to be first trying new brands	1 (=totally disagree) to 5 (=totally agree)
	Buy rare latest fashion trends before friends approve	1 (=totally disagree) to 5 (=totally agree)
	Put extra effort to shop in favorite supermarket	1 (=totally disagree) to 5 (=totally agree)
	NRC Handelsblad reading	1 (=never read) to 7 (=read all numbers)
	Parool reading	1 (=never read) to 7 (=read all numbers)

[a]Computed from purchasing data.

TABLE 6
EXPLAINING SPI AND BASKET PRICE SENSITIVITIES, AND LEARNING[a]

	PRICE	PRICE IMAGE	LEARNING
Note discount offers		0.0108*	
Low prices choosing supermarket		0.0048**	-0.0277**
Price awareness		0.0221*	
Nice buy items w/ whatever price cut	-0.0562***	-0.0076**	
Buy more of a brand when on price cut	0.0476**		
Education	-0.0176**		
Social class	-0.0626**		
House owner/tenant	0.0685*		
Household size			-0.0269*
Store dispersion	0.0064**		
Albert Heijn customer	0.3040***	0.0140**	
Average quantity purchased	-0.0043**		
Maximum loyalty share	-0.1654**		
Average weekly private label quantity	0.0143*		
I am a brand loyal coumer	-0.0338*		
Buy brands that others will adopt	0.0535**		
Common to be first trying new brands		-0.0054*	
NRC Handelsblad reading	0.0362*		
Parool reading		0.0078**	

[a]Weighted least squares with weights equal to the inverse of the posterior standard deviations. Mean imputation of missing values. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

TABLE 7
DISTRIBUTION OF TRIPS ACROSS STORES AND SEGMENTS (IN PERCENTAGE)

	Proportions					Percentage point (p.p.) difference				
Store	**All**	**Convenience**	**SPI**	**Price**	**Both**	**Convenience**	**SPI**	**Price**	**Both**	**Sum[a]**
Within Segment										
AH	29.2	29.3	35.1	24.5	29.7	0.1	5.8	-4.7	0.4	1.6
Aldi	9.5	8.3	10.2	12.3	15.5	-1.3	0.6	2.7	6.0	8.1
C1000	22.6	22.8	17.4	27.4	15.5	0.2	-5.2	4.8	-7.1	-7.3
Dekamarkt	3.2	3.9	2.8	1.6	0.1	0.7	-0.4	-1.6	-3.1	-4.4
Edah	6.4	6.4	6.0	6.6	6.4	0.0	-0.4	0.2	0.0	-0.2
Jumbo	2.6	2.2	3.6	3.0	4.2	-0.4	1.0	0.4	1.6	2.6
Konmar	3.7	3.6	5.8	2.5	2.8	-0.1	2.1	-1.1	-0.8	0.1
Lidl	3.5	3.3	4.6	3.6	3.6	-0.3	1.1	0.1	0.1	1.0
Plus	6.6	7.7	3.5	5.1	6.3	1.1	-3.1	-1.6	-0.4	-4.0
SdB	12.7	12.6	11.1	13.5	16.0	-0.1	-1.6	0.8	3.3	2.4
Sum[a]						**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Within Store										
AH		65.1	15.8	15.0	4.2	0.2	2.6	-2.9	0.1	0.0
Aldi		56.3	14.0	23.0	6.7	-8.6	0.9	5.1	2.6	0.0
C1000		65.4	10.1	21.7	2.8	0.5	-3.0	3.8	-1.3	0.0
Dekamarkt		79.5	11.7	8.7	0.1	14.6	-1.5	-9.1	-4.0	0.0
Edah		65.1	12.3	18.5	4.1	0.2	-0.8	0.6	0.0	0.0
Jumbo		54.6	18.3	20.5	6.7	-10.3	5.1	2.6	2.6	0.0
Konmar		63.7	20.8	12.4	3.2	-1.2	7.6	-5.5	-0.9	0.0
Lidl		60.2	17.3	18.3	4.2	-4.6	4.1	0.4	0.1	0.0
Plus		75.5	7.0	13.7	3.9	10.6	-6.2	-4.2	-0.2	0.0
SdB		64.3	11.5	19.0	5.2	-0.6	-1.7	1.2	1.1	0.0
All (Sum)[a]		**64.9**	**13.2**	**17.9**	**4.1**	**0.8**	**7.3**	**-8.0**	**-0.1**	**0.0**

[a]Sum of p.p. differences across the four segments (last column) and the ten stores (last row).

TABLE 8
EFFECTS OF PERMANENT PRICE CHANGES ON STORE TRAFFIC ACROSS SEGMENTS (HILO FORMAT)[a]

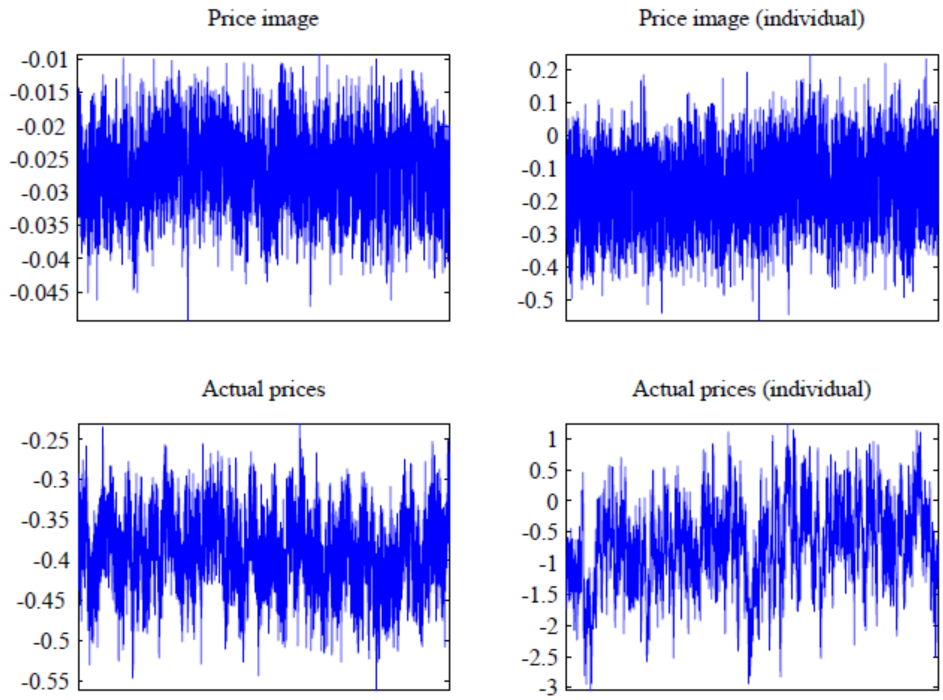
	Δ	SPI		Price		Both		Sum of
	in price	trips	% total	trips	% total	trips	% total	trips
static	5	0	0	491	80.2	121	19.8	612
dynamic	5	69	9.8	491	69.6	145	20.6	705
% dif		--	--	0.0	--	19.8	--	15.2
static	10	0	0	983	79.3	256	20.7	1239
dynamic	10	138	9.6	983	68.0	324	22.4	1445
% dif		--	--	0.0	--	26.6	--	16.6
static	15	0	0	1529	79.3	399	20.7	1928
dynamic	15	202	9.0	1529	68.2	511	22.8	2242
% dif		--	--	0.0	--	28.1	--	16.3
static	20	0	0	2090	79.3	546	20.7	2636
dynamic	20	272	8.9	2090	68.7	679	22.3	3041
% dif		--	--	0.0	--	24.4	--	15.4

[a]The total number of trips among the Convenience segment is equal to 62598. By construction, no trip changes can be attributed to this segment in response to any price changes.

FIGURE 1
GROUPS OF PRICE SENSITIVE CONSUMERS BASED ON USE OF BASKET PRICES AND STORE PRICE IMAGES.

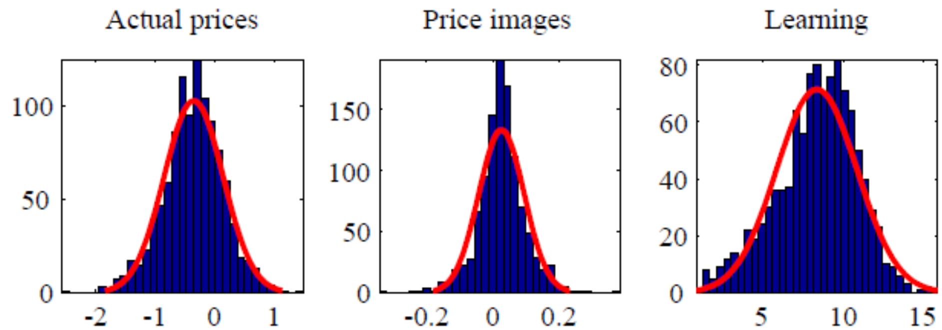
		Store price images	
		NO	**YES**
Store basket prices	**YES**	Eye-for-detail	Combined
	NO	Convenience	Big picture

FIGURE 2
CONVERGENCE OF GIBBS SAMPLER DRAWS FOR MEAN PARAMETERS



Gibbs sampler draws are plotted for the mean parameter (right panel) for price images (top panel) and actual prices (bottom panel), after discarding first 10000 draws for burn-in. For illustrative purposes, the left panel plots draws for the two types of price information of one particular household.

FIGURE 3
HOUSEHOLDS' POSTERIOR MEANS



Histograms (with superimposed normal curve) of households' posterior means for SPI, actual prices, and price learning parameters (after discarding burn-in draws).

FIGURE 4
DISTRIBUTION OF PRICE SENSITIVE CONSUMERS BASED ON USE OF BASKET PRICES AND STORE PRICE IMAGES

		Store price images	
		NO	**YES**
Store basket prices	**YES**	Eye-for-detail **16.2%**	Combined **3.6%**
	NO	Convenience **68.5%**	Big picture **11.7%**

APPENDIX. COMPLETE CONDITIONAL POSTERIORS

Priors

Σ^{-1}~W(ν_0,H_0), with ν_0=100 and $H_0=I_{S-1}$. (A1)

β_i~N(μ_β,V_β) (A2)

Second stage:

μ_β~N($\mu_{\beta0}$,$\Sigma_{\beta0}$), with $\mu_{\beta0}=0_{(S-1)\times K}$ and $\Sigma_{\beta0}=500\cdot I_{(S-1)\times K}$. (A3)

V_β^{-1}~W($\nu_{\beta0}$,$V_{\beta0}^{-1}$), with $\nu_{\beta0}$=(S-1)×K+4 and $V_{\beta0}=\nu_{\beta0}\cdot I_{(S-1)\times K}$. (A4)

Gibbs sampler

For the latent utilities:

$u_{its}|u_{it,-s},\Sigma^{-1},\beta,\mu_\beta,V_\beta\sim N(m_{its},\tau_{ss}^2)$, (A5)

where

$m_{its}=x'_{its}\beta_i+F'(u_{it,-s}-X_{it,-s}\beta_i)$, $F=-\sigma^{ss}\gamma_{s,-s}$, and $\tau_{ss}^2=1/\sigma^{ss}$, (A6)

where σ^{js} denotes the (js)th element of Σ^{-1} and $\gamma_{s,-s}$ refers to the *s*th row of Σ^{-1} with the sth element deleted. $X_{it,-s}$ is the matrix X_{it} with the sth column deleted.

For the individual coefficients:

$\beta_i|u,\Sigma^{-1},\mu_\beta,V_\beta\sim N(\beta_{i1},V_{i1})$, (A7)

where

$V_{i1}=(\sum_{t=1}^{T_i} X'_{it}\Sigma^{-1}X_{it}+V_\beta^{-1})^{-1}$ and $\beta_{i1}=V_{i1}(\sum_{t=1}^{T_i} X'_{it}\Sigma^{-1}u_{it}+V_\beta^{-1}\mu_\beta)$. (A8)

For the mean of the parameters:

$\mu_\beta|u,\Sigma^{-1},\beta,V_\beta\sim N(\mu_{\beta1},\Sigma_{\beta1})$, (A9)

where

$\Sigma_{\beta1}=(\Sigma_{\beta0}^{-1}+NV_{\beta1}^{-1})^{-1}$ and $\mu_{\beta1}=\Sigma_{\beta1}(\Sigma_{\beta0}^{-1}\mu_{\beta0}+V_{\beta1}^{-1}\sum_{i=1}^{N}\beta_i)$. (A10)

For the variance of the parameters:

$V_\beta^{-1}|u,\Sigma^{-1},\beta,\mu_\beta\sim W(\nu_{\beta1},V_{\beta1}^{-1})$, (A11)

where

$\nu_{\beta1}=\nu_{\beta0}+N$ and $V_{\beta1}^{-1}=[(V_{\beta0}^{-1})^{-1}+\sum_{i=1}^{N}(\beta_i-\mu_\beta)(\beta_i-\mu_\beta)']^{-1}$. (A12)

For the variance of the utilities:

$\Sigma^{-1}|u,\beta,\mu_\beta,V_\beta\sim W(\nu_1,H_1)$, (A13)

where

$\nu_1=\nu_0+\sum_{i=1}^{N}T_i$ and $H_1=[H_0^{-1}+\sum_{i=1}^{N}\sum_{t=1}^{T_i}(u_{it}-X_{it}\beta_i)(u_{it}-X_{it}\beta_i)']^{-1}$. (A14)

Starting values:

$\Sigma^{-1}=I_{S-1}$, $\beta_i=1_{(S-1)\times K}$ (for all *i*), $\mu_{\beta1}=1_{(S-1)\times K}$, $V_{\beta1}^{-1}=I_{(S-1)\times K}$, and $u=0_{\sum_{i=1}^{N}T_i\times 1}$

Profiling price and SPI-sensitive consumers: Full results

TABLE 9
EXPLAINING SPI AND BASKET PRICE SENSITIVITIES, AND LEARNING[a]

	PRICE		PRICE IMAGE		LEARNING	
	b	**t-stat**	**b**	**t-stat**	**b**	**t-stat**
Intercept	0.5247	1.452	-0.0613	-1.123	-1.8025***	-6.746
Look first to the price	0.0058	0.265	0.0028	0.842	0.0075	0.461
Note discount offers	0.0220	0.626	0.0108*	1.943	-0.0158	-0.601
Low prices choosing supermarket	0.0057	0.384	0.0048**	2.050	-0.0277**	-2.501
Price awareness	0.0203	0.276	0.0221*	1.951	0.0185	0.338
Check first somewhere else cheaper	-0.0108	-0.613	-0.0042	-1.546	0.0062	0.475
Price cuts save consumers much money	0.0161	0.623	0.0058	1.501	-0.0061	-0.316
Pay more for better quality product	0.0356	1.377	0.0042	1.047	0.0200	1.033
Nice buy items w/ whatever price cut	-0.0562***	-2.581	-0.0076**	-2.407	-0.0039	-0.243
Buy more of a brand when on price cut	0.0476**	2.162	0.000	0.011	0.0029	0.180
Occupation level	-0.0046	-0.110	0.0033	0.514	-0.0038	-0.123
Education	-0.0176**	-1.973	0.0004	0.308	-0.0038	-0.570
Social class	-0.0626**	-2.526	-0.0001	-0.017	-0.0118	-0.644
House owner/tenant	0.0685*	1.892	0.0125**	2.222	-0.0147	-0.545
Household size	0.0072	0.374	0.0012	0.419	-0.0269*	-1.875
Net monthly income	-0.0061	-1.138	0.0001	0.142	0.0053	1.329
Housewife age	-0.0013	-0.589	-0.0002	-0.507	0.0017	1.041
Average distance to all stores	-0.0073	-1.108	-0.0011	-1.088	0.0011	0.224
Store dispersion	0.0064**	2.030	0.0002	0.477	-0.0009	-0.407
Albert Heijn customer	0.3040***	6.417	0.0140**	2.134	-0.0098	-0.296
Average quantity purchased	-0.0043**	-2.124	-0.0002	-0.615	0.0010	0.659
Maximum loyalty share	-0.1654**	-2.006	0.0084	0.658	-0.0745	-1.206
Average weekly private label quantity	0.0143*	1.847	0.0002	0.215	0.0020	0.363
Mean nr of weekly shopping trips	-0.0218	-0.876	-0.0009	-0.250	-0.0074	-0.408
Proportion trips before 12:00	-0.0070	-0.100	-0.0037	-0.370	0.0091	0.176
Proportion trips after 18:00	-0.1765	-1.015	-0.0040	-0.153	-0.0803	-0.633
Proportion of trips EDLP to HiLo	-0.0020	-0.249	-0.0009	-0.954	0.0037	0.698
I am a brand loyal consumer	-0.0338*	-1.740	-0.0046	-1.583	-0.0107	-0.737
Buy brands that others will adopt	0.0535**	2.262	0.0048	1.340	0.0265	1.518
Common to be first trying new brands	0.0036	0.181	-0.0054*	-1.800	-0.0240	-1.616
Buy latest trends before friends approve	0.0111	0.546	0.0036	1.197	-0.0166	-1.101
Put extra effort to shop in favorite store	0.0047	0.252	0.0018	0.639	0.0159	1.128
NRC Handelsblad reading	0.0362*	1.766	-0.0042	-1.236	-0.0212	-1.396
Parool reading	-0.0103	-0.419	0.0078**	2.076	-0.0272	-1.498
R2	0.095		0.064		0.037	

[a]Weighted least squares with weights equal to the inverse of the posterior standard deviations. Mean imputation of missing values. *p< 0.1; **p< 0.05; ***p< 0.01.