Consumer models of store price perceptions and store choices

Lourenco, C.J.

Publication date:
2010

Document Version
Publisher's PDF, also known as Version of record

Consumer Models of Store Price Image Formation and Store Choice

Carlos J. S. Lourenço

Consumer Models of Store Price Image Formation and Store Choice

Proefschrift

ter verkrijging van de graad van doctor aan de Universiteit van Tilburg op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de aula van de Universiteit op woensdag 24 november 2010 om 14.15 uur door

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To my brother, Luís, and my parents, Felisbela and Jorge

Acknowledgements

Education and discipline make you successful...

This dissertation is the result of a research endeavor that started in Tilburg University in the summer of 2005, and I now take this opportunity to express my heartfelt gratitude to all of those who have contributed to it and to those who have helped me, one way or the other.

I start by thanking my promotor, Els Gijsbrechts. Els always let my enthusiasm blossom, and I always felt I had the freedom to choose my own path and make my own mistakes, which allowed me to grow as an independent scholar. Els knew better, of course, and wisely nudged me into the right direction with her generous, experienced, and sharp advice at all times. When I was doubtful and apparently stuck, Els always gave me courage and taught me how to look at problems to see a way out of them. Els, my gratitude is beyond words; from conceptualizing to writing, from modeling and coding to data cleaning and variable operationalizations, from presenting to making questions, and many, many other crucial 'hard' and 'soft' skills of a good researcher, the learning I got from you has been extraordinary. Thank you for helping me writing and for revising the dissertation text, and for having embarked me on this journey. I very much look forward to the revisions of our papers and the company of your intelligent humor and laughter.

I thank Richard Paap for believing in the store price image project and accepting to work with us, for sharing his immense knowledge about Bayesian Econometrics, and for revising my derivations of posteriors, MCMC samplers, and code. Richard's knowledge, kindness and willingness to help, make him a great co-author and an enjoyable and fun person to work with. Richard, I look forward to our revisions, and to hear your thoughts about the Rotterdam Film Festival, traveling, and everything else.

I also thank the members of my doctoral committee, Bart Bronnenberg, Inge Geyskens, Richard Paap, and Koen Pauwels. It is an honor to have such renowned and brilliant scholars in my doctoral committee, from whom I take great inspiration. Thank you for taking the time reading my dissertation and for your sound and detailed comments and advice on how to improve it and make it more relevant, hopefully on the way to publications. I thank Koen Pauwels in particular, for making the effort to come all the way from vibrant Istanbul to Tilburg.

I am also grateful to Rik Pieters, Marnik Dekimpe, and Harald van Heerde, who have lend us their invaluable comments on our research and papers, and guidance during my PhD. I am indebted to Bas Donkers, with whom I have fruitful discussions about my research and how to overcome the perils of estimation of structural models. Thank you for your genuine interest in our work and for your many detailed comments and explanations. I am thankful to Nuno Camacho, with whom I have many stimulating debates and conversations that deepen and broaden my knowledge about (behavioral) economics, and with whom I have discussed and learned a great deal about Bayesian estimation. I have also benefited from the insightful comments and the many discussions I had with Femke van Horen, Maciej Szymanowski, and Jaione Yabar; thank you for reading some of the chapters and for the many useful suggestions you gave me. I thank Sandra Maximiano (Marisa) for countless discussions about decision making and economics, and the sound advice that always improved the quality of my work.

I thank AiMark and GfK for providing us the rich data we work with, in particular Alfred Dijs, and Tom Beerens, who is always willing to help us gathering, preparing, and explaining the data. I also thank Mark Vroegrijk, Anne ter Braak, Barbara Deleersnyder, and Inge Geyskens for help with the data, and Maciej Szymanowski, Bart Bronnenberg, Robert Rooderkerk, and Berk Ataman for tips and for kindly answering to my questions about coding and Bayesian estimation when I started doing both.

I am thankful to Tammo Bijmolt and Peter Leeflang, for accepting me in Groningen while doing the MPhil in Tilburg, and later for understanding and accepting my decision to move to Tilburg. I thank Jan-Benedict Steenkamp for his inspiring words when I started the PhD, which I never forgot and worked as a propeller for all those years. I am also grateful to those at the Erasmus School of Economics, in particular, Stefan Stremersch, Benedict Dellaert, and Bas Donkers, for making me part of the wonderful marketing group there, which allowed me to start new research projects while having the time and the resources to finish my dissertation. I also shall not forget the help of those in Tilburg whose support made sure things ran smooth: Scarlett, Heidi, Ank, Ailsa, and Carla.

...and love and care make you happy.

Living in Amsterdam early in the PhD was a lot easier and enjoyable with the warm company of Marisa, Marcos, Carla, Miguel, Ana, Ernesto, Adam, Randolph, Seble, Massimo, and the almighty Chris, at UvA (I miss the eclectic musical selection and inviting atmosphere of Café Kriterion); Marlies and Holly; and Miriam, Eneas, César, and Silvia at Ceramplein. I thank Marisa for always being there, at any hour of the day or night. I am immensely thankful for the incentive you gave me to pursue an academic career, and for having sparked it. Agradeço-te por me saberes, entrares e levares dentro.

In Tilburg University, I thank Bauke and Sandra, for their warm heart and advice when I needed it. In the Marketing Department there I was fortunate to meet Erdinç and Nino during the Mphil programme, with whom I learned so much. I also had the privilege of receiving the advice from my 'older' fellow PhDs Maria, Fleur, Valentina, Ralf, and Martijn; the advice and kindness of Stefan and Inge; Anick's company outside in the campus; Davy, Roger, Hans, and Dirk's shared passion for indie music; Henk's good mood and jokes; Jan, Cedric, Petra, Maike, and Ellen's warmth; Vincent and Annemieke's experience and refreshing curiosity; Peter's perseverance and belief; and Marnik's encouragement every time down the corridor (and elsewhere). I also feel grateful for the joy of spending time in Tilburg with Berk, Man-Wai, Mark, Didi, Anne, Millie, and René; for Neomie's sweetness and laughter; for Rita's force of nature; for the running company of many, in particular Maciej, Harald, Rutger, Femke, and George; for Robert's fraternal understanding; for Rutger's efficiency tips (useful in Vancouver); and for the good moments and many laughs from hanging out with George.

Rik reverberates blossoming energy in every mind he touches, which he did in mine, and I thank him for showing me the lab and for the CB bug in me. Most of all, thank you for all the help you gave me, and for seeing through. I am thankful to Jia for her ability to put me in the right direction and for listening; thank you also for the welcoming postcard you left in Albertus Magnusstraat. I want also to express my gratitude to Femke, whose warmth captivated me from moment one, and who was so crucial in so many moments, lending me her sincere advice and friendship; thank you for listening and for taking care. I was very lucky to have Geraldo in the Finance department downstairs, and around the corner; thank you for always being there. I thank Jaione for giving me strength and motivation, and having reminded me the power of thoughts, to go for it, be foolish, and connect the dots. For everything, eskerrik asko.

I also thank others that I met along the way, some of whom became friends, and that made up for a rich social life: Pedro Bom (thank you for sharing your knowledge about music and so many things), Miguel Carvalho (one of the smartest people around), Pedro Raposo and Tânia, Thanh, Viorel Roscovan, Heejung, Joyce, Annekatherin, Kenan, Andrea, Marta Serra, Vasilis, Marta Szymanowska, Anna, Laura, Seza, Neil and Giselle, in Tilburg; Jenny, Adriana, Ernst, and Matilda, in Groningen; my AMA buddies, Francesca, Isabel, and Auke (my great mate in Arizona); and Maarten, in Leuven.

I thank those who made my move to Rotterdam so easy and enjoyable while I was finishing my dissertation, my colleagues and friends, Maciej, Jaione, Nicole, Berk, Nalan, Viorel, Eelco, Dimitris, Tülay, Cecilia, Paula, Bas, Benedict, Aurélie, Sarah, Isabel, Stefan, Gui, Jordana, Vijay, Stefano, Bram, Carlos, Ron, Sofie, Tim, Luit, and Nel, Sara, Franzi, Cathelijn, and Irina, and, in particular, the triptych made of Joana, Rui, and Nuno (our very special friendship is something I cannot describe in words). Thank you all for the patience and understanding during the last months.

I thank my paranymphs – Luís and Maciej – for being beside me up there and for helping me with the defense. Maciej, it impresses me and inspires me your dedication, quest for truth and integrity; I look forward to enjoy your warmth presence in Rotterdam for as long as possible. Luís, I admire you and your drive to live life, and I have counted with you all these years for your mature and pragmatic advice; I feel happy and honored that you have accepted to be part of this day.

I thank also those who helped me all the way from Portugal. Far away so close, my good friends, Celine, Bruno, Pedro, Rita, Rui, Nuno, and Baião. Also, Sandro Mendonça and Helena Carvalho at ISCTE, the Portuguese university of my heart, for their friendship and for believing. A toda a minha família, com quem partilho as raízes e valores, por todo o apoio. Em particular, à Inocência, pela cumplicidade, sempre, e à Cátia, Sara, Catarina, e ao Toni, pela ajuda, o carinho e a amizade. À Janete, à Cristina, à Carminha, e ao João, pela amizade em absoluto.

À minha mãe, Felisbela, e ao meu pai, Jorge. Sei da dificuldade que a distância dos que amamos cria, das muitas saudades. Agradeço-vos de coração o esforço que sei que fazem por me compreenderem e aceitarem como indivíduo, assim como às minhas escolhas. Agradeço o esforço que fizeram por me proporcionarem e ao Luís a melhor educação, um esforço do corpo e do suor, o melhor que sabíeis e podíeis. Conseguirei eu um dia fazer o mesmo, e ter-vos-ei feito jus. E a ti, Luís, pela amizade e o amor, independentemente do sangue que em nós corre. Obrigado pelo vosso apoio em todas as horas. Caminhais sempre comigo e por isso vos dedico esta tese.

Rotterdam, October 21, 2010

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> The potentially important role of perceptions, ranging from classical psychophysical perception of attributes, through psychological shaping of perceptions, to reduced dissonance, to mental accounting for times and costs, remains largely unexplored in empirical research on economic choice.
>
> *Nobel Prize Lecture, December 8, 2000*
> McFadden, Daniel L.

Chapter 1

Introduction

Store-level research in retail marketing has focused predominantly on 'hard variables' that may influence consumers' store choice, such as price, assortment, or location. Contrary to brands or product categories, however, comparison of alternative stores may be a daunting task for consumers: typical retail stores carry thousands of different products across a wide range of categories, and their prices fluctuate over time due to, for instance, frequent price promotions. When evaluating stores, consumers may, therefore, resort to their *perceptions* of relevant store dimensions. Holistic perceptions held about retail stores, in particular those regarding the retailer's expensiveness, are thus regarded among the most important drivers of consumers' choices (e.g. Bell, Ho, and Tang 1998, Simester 1995).

Recognizing this pivotal role of store (price) images in consumer decision-making, the retailers' battleground has been extended from the stores' shelves to the consumers' minds. France-based Carrefour, the largest hypermarket chain in the world, for instance, has invested more than half a billion dollars in its price image in 2009 alone (MarketWatch 2009). In the Netherlands, the market-leader Albert Heijn started a price war aiming at improving, among other measures, its unfavorable price image held by most Dutch consumers (van Heerde, Gijsbrechts, and Pauwels 2008). And in April 2010, the giant Wal-Mart cut the prices of 10,000 items, mostly food and other staples (CNBC 2010) in the U.S. market, with the goal of "polishing its discount image" (Wall Street Journal 2010).

Yet, despite the importance of store price images, and the large dollar sums involved in managing these images, research about the topic is sparse and, so far, has left retailers with little guidance to set their pricing and price image strategies. The present work hopes to contribute to filling this gap.

1.1 Background

Before introducing our work, it is instructive to set the stage, and briefly characterize the relevant literature related to store price image (SPI) research. This research has focused on two aspects: the integration of both actual and perceived prices into behavioral models of decision-making, and the antecedents and conceptualization of store price images.

1.1.1 Consumer use of actual and perceived overall prices

Behavioral models of consumer decision making typically accommodate two types of price information: objective prices, and subjective perceived prices or price images (see e.g. the conceptual models in Dickson and Sawyer 1990, Jacoby and Olson 1977, Zeithaml 1982, 1984). According to economic theory, prices influence choices because they are considered perfect, objective indicators of the monetary costs of purchasing (Monroe 2002). In addition to this classical perspective, psychology and marketing have long acknowledged the subjective nature of prices and have found support for the existence and effects of *perceived* prices (e.g. Zeithaml 1988, Monroe 1973), notably in the form of reference prices (see e.g. Winer 1986, Kalyanaram and Winer 1995, Briesch et al. 1997). Recently, this notion of a dual price construct has been extended to the level of the store, and consists of actual, objective basket prices and subjective holistic summaries of a store's overall expensiveness or store price images (see e.g. Mazumdar, Raj, and Sinha 2005, van Heerde et al. 2008).

1.1.2 Conceptualization of store price images

Store image has been defined as the way the store is perceived in the shopper's mind (Martineau 1958). The conceptualization of such a store image rests upon three main pillars (see Ailawadi and Keller 2004, for a recent review of retailer image research). First, store image is typically seen as a multidimensional construct, with price and quality (of the assortment) arising as its core dimensions (Mazursky and Jacoby 1986, Hildebrandt 1988). Second, as demonstrated by Alba et al. (1994, p.219), "[store price] perceptions are very malleable and may be shaped by forces under direct control of those who set prices." Specifically, the formation of a retailer's price (and quality) image is commonly described as an evolving, dynamic process (Mazursky and Jacoby 1986, Büyükkurt

1986, Nyström 1970, Feichtinger, Luhmer, and Sorger 1988) – perceptions being updated as new information comes in. Third, given the complexity of the store offer, consumers have only incomplete information and are uncertain about retail stores, thus resorting to available (intrinsic or extrinsic) perceptual cues when inferring the retailer's overall price (and quality) (Feichtinger et al. 1988, Mägi and Julander 2005, Alba et al. 1994).

Two types of cues can be distinguished for store price image formation: non-price cues and actual prices. Non-price cues may come from sources that stores have little or limited control upon, such as word-of-mouth (e.g. Herr, Kardes, and Kim 1991, Zeithaml, Berry, and Parasuraman 1993), or from in-store atmospherics (Grewal and Baker 1994, Baker, Parasuraman, Grewal, and Voss 2002), or store communication in which the retailer does not advertise any specific prices in a direct manner (see the SPI studies based on advertising signaling of e.g. Shin 2005, Srivastava and Lurie 2004, Simester 1995). While non-price cues may help consumers come up with an initial expectation of the store's overall price level, they may be inconsistent with or at best indicative of store prices. Hence, if actual prices become available, consumers are likely to resort to these more informative actual price cues (Alba et al. 1994). Support for this contention comes from evidence gathered mostly in lab experiments – namely, from the early studies of Büyükkurt (1986) and Nyström, Tamsons, and Thams (1975) and the more recent work of Alba and colleagues (1994, 1999) and that of Desai and Talukdar (2003). These studies have also suggested that consumers integrate product-specific price and promotion cues to form their store price perceptions.

While previous studies have underscored some important *antecedents* of store price images and the main features of their *formation process*, many questions remain largely unanswered.

1.2 Limitations and existing gaps in the literature

1.2.1 Methodological limitations and challenges

Store price images refer to aggregate perceptions assembled from multiple (price) cues. This makes the process of store price image formation more difficult to study compared to, for instance, the formation of price perceptions for single products or brands. To our knowledge, the conceptual and analytical models of SPI formation (Büyükkurt 1986, Nyström 1970, Feichtinger et al. 1988) have not been taken outside the lab. While lab studies provide some relevant insights under highly controlled conditions, they may not be fully apt to uncover the way price images are formed in real life settings – where consumers receive a myriad of signals, which are (or are not) integrated and/or forgotten over time. Hence, experimental studies may not paint the full picture when it comes to assessing the impact of various cues on consumers' price beliefs about stores.

The difficulty of addressing this issue lies essentially in the need to combine more than one type of data. Consumers' price perceptions of a retail store can be obtained through direct inquiry by means of questionnaires. These data can then be linked to 'hard' data on retail prices, as well as to information on consumer store visits (reflecting the extent to which these actual store prices were accessible to the consumer). As simple as it sounds, however, combining purchasing data with longitudinal survey data is not simple, and involves the non-trivial task of bringing them together in one model. At least three challenges arise when attempting to do so.

First, both types of data are available at different frequencies. Specifically, survey data on consumers' beliefs are seldom longitudinal in nature and, if so, are usually available at a frequency (much) lower than price or purchasing data. Second, the large number of cues that may intervene in the formation of store price images (namely the prices of many different products in a typical supermarket), requires a heavy modeling structure with a large number of parameters. A last challenge is the need to have both types of data (store perceptions as well as actual data on store visits and marketing mix) identified for the same consumers, over time.

Access to a unique data set, combined with state-of-the-art modeling approaches, will allow us to meet these challenges, and propose answers to a set of research questions we believe could not be addressed as effectively otherwise.

1.2.2 Unanswered research questions

Given the complexity of the topic, and the methodological difficulties involved, several SPI-related issues remain as of yet unexplored. These issues relate to two types of processes and associated outcome variables. On the one hand, more insights are needed into what drives the formation of store perceptions – with a particular focus on the role of retailer marketing actions, such as price and assortment decisions, therein. Here, the interest is in tracing the effect of 'hard' retailer instruments, on 'soft' consumer mindset metrics. On the other hand, as indicated by Srinivasan, Vanhuele, and Pauwels (2010), there is a need to empirically assess how – taken together – (retailer) marketing mix instruments and consumer (store) perceptions translate into 'hard' outcome metrics, over time. Our work aims to provide specific insights on both types of issues.

Concerning the formation of store perceptions, one remaining question that is particularly relevant for category managers (Grewal and Levy 2007), pertains to the relative importance of the *many* different category prices present in a typical supermarket for the formation of SPIs, and to the underlying category drivers. Also, we have little knowledge about how changes in the retail assortment composition, especially regarding the share of national brands (NBs) and private labels (PLs), impact consumers' overall impressions about stores. This is important because the two types of brands may enjoy different associations in consumers' minds, and generate different overall appreciations of the store. The question becomes particularly compelling for hard-discount retail chains such as Aldi and Lidl, whose limited assortments were originally private label-dominated, but who are now under pressure to expand the share of NBs. How would such changes impact the price and quality perceptions of these retailers?

Concerning the link between 'mindset metrics' and 'hard' performance measures (Srinivasan et al. 2010, Gupta and Zeithaml 2006), several gaps are to be addressed as well. What is the size of the impact of store price perceptions, vis-à-vis actual prices, on retail performance measures such as store traffic? Who are the consumers sensitive to one and/or the other type of information, and why? So far, and to our knowledge, the link between store price images and traffic has been addressed only in self-reported survey studies (Arnold, Oum, and Tigert 1983, Severin, Louviere, and Finn 2001, Finn and Louviere 1990, 1996, Cox and Cox 1990), which lacked actual marketing data, namely prices. The exception is van Heerde et al. (2008), who include both objective and perceived prices into their store choice and spending models. However, their work does not explicitly model SPI formation, and – given its different focus – does not explore consumer differences in response to actual prices versus price images – something we intend to address.

We give an overview of our approach to these questions next, and summarize each of the three essays in more detail afterwards.

1.3 Dissertation overview

To conduct our studies, we use a data set that combines scanner panel records on store choice and spending, with longitudinal measures of store price and quality images held by the same individual panel members. These data refer to a GfK panel of households that represent a stratified sample of The Netherlands and cover a period of four years, from January 2002 to December 2005 (the third essay makes use of data for 2006 as well).

Figure 1.1 clarifies the nature and focus of the three main chapters. As indicated in the columns of the figure, these chapters differ in the input variables used and their focal level of interest (store level, category differences or brand-type differences). The rows clarify the outcome variables studied in these chapters: store price images (SPIs) and store quality images (SQIs) of different stores, and observed store traffic. Two other dimensions cross all the levels of our data: individuals and time, allowing us to explore the dynamics of store images, and to specify models at the individual-level (and explore unobserved heterogeneity).

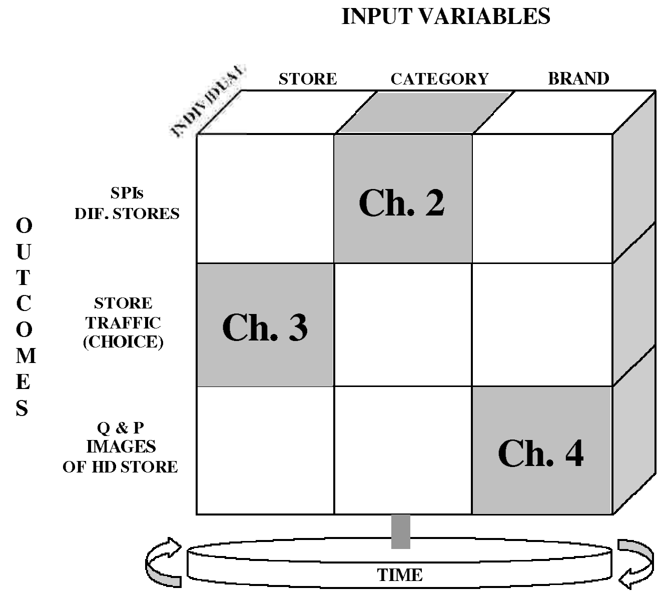

Figure 1.1: Overview of dissertation

In Chapter 2, we develop a dynamic individual-level model of store price perception formation. In this model, different product category prices are integrated into an overall measure of store expensiveness. The informativeness of a category price, in turn, is a function of that product category's intrinsic characteristics, over and above its economic share in the consumer typical shopping basket.

In Chapter 3, 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 aim at showing 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.

In Chapter 4, we investigate how different brand typologies and changes in a retailer's assortment composition affect consumers' perceptions about stores. To this end, we focus on hard discounter stores that have recently introduced national brands to their all-private-label assortments. Since national brands are regarded as having higher levels of differentiation and quality than their private label counterparts, and are, on average, more expensive, this shift in the store's assortment strategy is expected to affect store quality and price perceptions.

Methodologically, Chapter 2 combines Bayesian learning with an ordered probit specification to capture SPI formation. In Chapter 3, we combine this model of SPI formation, with a random-coefficients multinomial probit model for store choice. The models in these two chapters are estimated with state-of-the-art Bayesian approaches that make extensive use of stochastic simulation methods. In Chapter 4, we use a bivariate ordered probit that naturally accounts for the correlation between the price and quality images of the hard discounter.

1.4 Detailed chapter summaries

1.4.1 Chapter 2 – Store price image formation and category pricing

In this chapter, we address two related questions: which product categories are more influential in shaping SPIs, and what drives these effects? Regarding the first question, we propose a framework that integrates different sources of information, namely actual prices of different product categories, in a dynamic process of store price image formation. In a nutshell, prior to visiting a store, consumers hold uncertain beliefs about how cheap or how expensive the store is (Alba et al. 1994) – remaining quite unsure about the actual overall price level they will face in the store. Upon a store visit, consumers have access and are exposed to category prices, and by integrating and updating these incoming price signals, consumers learn about the store's overall price level (Büyükkurt 1986, Mägi and Julander 2005).

Regarding the second question, our research proposes characteristics typical of what we term *lighthouse categories*, i.e. product categories that signal low prices, and yet constitute only a small portion of spending. We conceptualize that the over-time impact of category prices on store price image formation is shaped along two dimensions. The first dimension is the monetary value of the category for the consumer, or share-of-wallet. Consumers expect higher present and future returns from being aware of prices in product categories that are monetarily more relevant for them (Wakefield and Inman 1993, Urbany, Dickson, and Kalapurakal 1996). The second dimension captures how informative the category prices are about the store's expensiveness. This 'informativeness' depends on the extent to which the category prices are (i) *accessible* for the consumer and (ii) perceived as *diagnostic* of the overall store price level (Herr et al. 1991, Feldman and Lynch 1988), and is linked to the characteristics of the product category. We discuss both dimensions in detail and offer testable hypotheses regarding their effect on SPI learning.

1.4.2 Chapter 3 – Consumer use of basket prices and store price images when choosing a store

Our questions in this chapter are threefold. 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 ('Eye-For-Detail' consumers) for store selection, also adjust their store patronage to (price-based) changes in SPI ('Big Picture' consumers)? 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 similar to Chapter 2. Taking the perspective that shopping activity is part of a household's production process (Becker 1965), we explore which consumer characteristics related to the cost of acquiring price information on the one hand, and the expected gains of this price search on the other, trigger the use of each type of price information. We propose that these costs and gains, and their antecedents, differ between the two types of price response, such that consumers may fall into four possible segments: (1) convenience, (2) eye-for-detail, (3) big picture, (4) and combined use.

'Convenience' shoppers 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, and Fox 2008), or by convenience-factors such as distance (Gauri, Sudhir, and Talukdar 2008). '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 implied monetary savings. '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. Finally, consumers may simultaneously exhibit both types of price-sensitivity, either to compensate for one another or due to situational factors that may make them rely more on one or the other type of price cues.

1.4.3 Chapter 4 – The impact of national brand introductions on price and quality images

Recently, Deleersnyder, Dekimpe, Steenkamp, and Koll (2007) have shown that NB introductions at hard discount stores may entail *short term* win-win implications for both retailers and manufacturers. Yet, an important and thus far unaddressed question is whether and how NB introductions – so directly at odds with the core positioning of the hard-discounter format – affect consumers' *long lasting* perceptions of these chains.

If carrying more NBs changes the hard discounters' price or quality image, this is likely to affect their performance in the long run.

This chapter aims to address that issue. Since national brands are typically regarded by consumers as having higher quality than their private label counterparts, but are, on average, more expensive (Kumar and Steenkamp 2007, Ailawadi, Pauwels, and Steenkamp 2008, Geyskens, Gielens, and Gijsbrechts 2010), the shift in the discounter stores' assortment strategy is expected to improve their quality image, to the detriment of their price image. As in Jacoby and Mazursky (1984), and consistent with information economics (Arrow 1963, Akerlof 1970, Spence 1973), we view (national) brands as cues used by consumers to infer both the overall quality and price levels. Brands are usually deemed informative about quality, as quality is by definition unobserved and therefore perceived with uncertainty (Zeithaml 1988, Richardson, Dick, and Jain 1994). In a store context, however, where prices vary over time and across products and price information is therefore complex and ambiguous, consumers may be uncertain about a store's overall expensiveness too (Alba et al. 1994). In such a setting, the presence of known brands may also prove helpful in the formation of overall price perceptions (Monroe, Grewal, and Compeau 1991, Biswas, Wilson, and Licata 1993). In Chapter 4, we empirically test for the significance and size of the effects of NB presence, on both the price and quality image of a hard discounter. One important aspect to consider in the context of this chapter, is that store price and quality perceptions may be correlated directly, which we accommodate explicitly in our methodology.

In Chapter 5 we summarize our main findings and discuss their implications, and set the directions for a future research agenda.

Chapter 2

Dynamic Store Price Image Formation and Category Pricing

2.1 Introduction[§]

Economic recession and the advent of hard discounters have increased consumers' sensitivity to prices in their shopping and store choice decisions. However, given the overwhelming number of items offered by a typical supermarket, reliance on detailed product-level prices can be prohibitive for consumers. Instead, consumers may use holistic constructs that summarize how cheap or expensive stores are – store price images – to guide their store choice and purchasing decisions (Arnold et al. 1983, Mazumdar et al. 2005). Defined as consumer perceptions or beliefs about the overall price level of stores (e.g. Nyström et al. 1975, Brown 1969), price images constitute a key dimension of the overall image of retailers (Ailawadi and Keller 2004). A recent Nielsen report indicates that "*Good Value for Money* is now the most important determinant of grocery store choice," and that "... of those consumers who rated 'good value for money' as very or quite important when deciding where to do their grocery shopping, 70% said it was important the store had a *reputation for being cheaper than competitors* – even if, in reality, this was not the case" (Nielsen 2008, p.4).

Given this 'power of perception', managing store price images has become a major concern in retail pricing practice (Levy et al. 2004). For instance, France-based Carrefour, the largest hypermarket chain in the world, has invested more than half a billion dollars in its price image in 2009 alone (MarketWatch 2009). As another example, in April 2010, the giant Wal-Mart cut the prices of 10,000 items in the U.S. market, with the goal of "polishing its discount image" (CNBC 2010, Wall Street Journal 2010). And, be-

[§]This chapter is based on joint work with Els Gijsbrechts (Tilburg University) and Richard Paap (Erasmus University Rotterdam), under 2nd round review in *Journal of Marketing*. We thank participants at Marketing Dynamics 2007 and Marketing Science 2008, and seminar participants at Erasmus School of Economics, Catholic University of Leuven, University of Groningen, and ISCTE-IUL (Lisbon).

tween 2003 and 2005, the leading Dutch supermarket chain Albert Heijn slashed prices in a wide range of categories so as to restore a more favorable price perception (van Heerde et al. 2008).

Dropping prices improves store price perceptions, as was shown for the case of Albert Heijn (van Heerde et al. 2008). At the same time, price reductions *across-the-board* are bound to be highly detrimental to profitability. Hence, with retail margins becoming increasingly tight, a critical question for retailers is *which* product categories are more salient in the consumer store price image formation process, and *why* (Grewal and Levy 2007). Such knowledge is crucial for the development of category-level pricing policies that create a favorable price perception of the store, while maximally preserving store revenue or margins. Unfortunately, despite its importance, store price image (SPI) research is sparse, and little is known about how perceptions of store expensiveness are influenced by in-store category prices (Bell and Lattin 1998). The present study takes one step towards addressing this gap.

The main contributions of this research are twofold. First, we propose a framework on which product categories are more influential in shaping SPIs, and what drives these effects. Specifically, we identify characteristics typical of what we term *lighthouse categories*, i.e. product categories that strongly signal low store prices, yet make up only a small portion of store spending (we will further characterize lighthouse categories in Section 2.2). Second, we empirically test this framework, by estimating a dynamic model of SPI formation including category prices, based on a unique data set. This dataset combines weekly store visit and purchase information from a representative panel of households, with semi-annual store price perceptions of these same households. The data cover all major retail chains in the Netherlands (close to twenty chains), contain information on purchases and weekly prices in these stores for nearly fifty major product categories, and cover a period of four years.

Our focus on category prices is justified by the presence of a wide array of product categories in a typical supermarket – the prices of which are not likely to be processed by consumers in the same way – and by earlier findings that category-specific factors are powerful drivers of price response (Bell, Chiang, and Padmanabhan 1999). It also fits into a category management perspective, and allows generating strategic guidelines that can readily be put into action by retailers. According to recent industry reports, 84% of retailers cite the opportunity to increase profitability as their motivation for using category management, which is becoming increasingly popular among grocers and other retailers alike (Grocer 2007, Nielsen 2004).

For academics, our framework offers an enhanced understanding of the store price image formation process and the role of different categories therein. In particular, we shed light on the category characteristics that drive the formation of store price perceptions. For managers, our findings provide guidance on how to develop a favorable price perception of the store, in a setting where margins are already dramatically under pressure. Specifically, our framework helps to identify which product categories create a favorable store price image while constituting only a small portion of the consumer share of wallet (SoW). This latter aspect is important because a drop in prices will allow consumers to pay less for the acquired items. If these items constitute an important share of their spending already allocated to the store anyway, the price drop will entail a lot of subsidization, and a sizeable revenue reduction for the retailer. In contrast, categories for which price reductions signal a favorable price image for the store overall, while representing only a small portion of actual sales, do not have this disadvantage.

The remainder of this chapter is organized as follows. In the next section, we briefly discuss relevant background literature, and develop our conceptual framework. In Section 2.3, we present the unique data set that will allow us to test this framework. Section 2.4 provides a description of the model. Estimation results are presented in Section 2.5. Finally, Section 2.6 provides conclusions and future research directions.

2.2 Background and conceptual framework

Consumers' overall judgment of store prices is considered to be stimulus-based (e.g. Alba et al. 1994, Büyükkurt 1986).[1] Hence, as a defining principle of our conceptual framework, we use insights from research on stimulus-based price judgments, which are largely influenced by product characteristics (see e.g. Briesch et al. 1997, Pauwels, Srinivasan, and Franses 2007). Below, we first discuss relevant background literature on price learning and SPI formation. Next, we present our conceptual framework on the impact of product category characteristics.

2.2.1 Background: SPI formation as a learning process

Several papers characterize store price image development as a learning process, in which consumers become knowledgeable about the overall price level of stores, based on actual in-store prices. Prior to visiting a store, consumers hold beliefs about how cheap or how expensive the store is. These prior beliefs, however, have uncertainty associated with them (Alba et al. 1994) – consumers remaining quite unsure about the actual overall price level they will face in the store. Upon a store visit, consumers are exposed to several sources of information that signal the overall price level of the store, namely category prices. By integrating and updating these incoming price signals, consumers learn about the store's price image (Büyükkurt 1986, Mägi and Julander 2005).

[1] When outside the store or in the absence of actual prices, consumers may rely on their memory of product prices to form their (memory-based) SPIs (see e.g. Ofir et al. 2008). We focus on a stimulus-based process only.

Consumer learning about the overall price level of a store occurs whenever new price information is encountered, and evaluated against previous knowledge or beliefs (e.g. Nyström 1970, Feichtinger et al. 1988). Even consumers who have a priori knowledge about the properties of a price distribution and/or have conducted price search in the past, do process new incoming price information (Urbany et al. 1996). Consumers feel a need to continuously update their store price knowledge, either intentionally or incidentally (Mazumdar and Monroe 1990), for at least three reasons. First, category price information is considered more diagnostic than prior beliefs based on non-price cues. Hence, consumers may cease using the latter in favor of price information to update previous knowledge (Alba et al. 1994). Second, even category prices are only noisy cues that do not perfectly signal the overall price level of a store. Additional signals, therefore, further contribute to SPI formation. Third, price information may become outdated, which further motivates consumers to process recent signals.

Taken together, several studies support that consumers (i) search for and pay attention to prices, (ii) accumulate price knowledge, (iii) learn over extended periods of time, and (iv) differ in their extent of learning from different product prices (e.g. Urbany et al. 1996, Urbany, Dickson, and Sawyer 2000, Vanhuele and Drèze 2002, Monroe and Lee 1999, Mazumdar and Monroe 1990, Briesch et al. 1997). Our model of store price image formation builds upon these insights. It postulates that it is the accumulated and updated price knowledge over time, integrated across several categories, that translates into an overall store price perception. Which product category prices exert a dominant role in store price image formation, and why, are key questions that we address next.

2.2.2 Conceptual framework: Category-pricing and store price image formation

Our key objective is to examine the role of different categories in the store price image formation process. More specifically, we aim to identify product category characteristics that shape how strongly prices of that category influence the overall 'expensiveness' perception of the store. We conceptualize that the over-time impact of category prices on store price image formation, is shaped along two dimensions. The first dimension is the monetary value of the category for the consumer. Consumers expect higher present and future returns from being aware of prices in product categories that are monetarily more relevant for them (Wakefield and Inman 1993, Urbany et al. 1996), i.e. that capture a higher share of their wallet. The second dimension captures how informative the category prices are about the store's expensiveness. This 'informativeness' depends on the extent to which the category prices are (i) *accessible* for the consumer and (ii) perceived as *diagnostic* of the overall store price level (Herr et al. 1991, Feldman and Lynch 1988). Each of these dimensions is linked to the characteristics of the product category. We combine the two dimensions in Figure 2.1.

Categories in the bottom-left cell have only weak signaling value about the store's overall price level. In addition, they have a high purchase share. Therefore, lower prices or price cuts in these categories may lead to important revenue losses for the store, without producing the desired SPI effect. Price cuts in this group of categories are thus to be avoided by the retailer interested in SPI management. Similarly, categories in the bottom-right cell are of little interest for the retailer who wants to convey a favorable store price image. Even though price reductions in these small-share categories are likely to entail limited revenue losses, their low 'informativeness' makes them less suited for SPI management. Conversely, categories in the top-left cell are deemed informative about the store's overall expensiveness, yet – because of their large share of wallet – represent a high risk of subsidization for the retailer.

MONETARY VALUE (w_c)

INFORMATIVENESS ($\sigma^2_{\eta_c}$)

	HIGH	LOW
HIGH	Subsidization	**LIGHTHOUSE CATEGORIES**
LOW	Avoid	Unattractive

Figure 2.1: Conceptual framework defining lighthouse categories in the context of SPI learning

In the top-right cell of Figure 2.1 are situated what we label 'Lighthouse Categories'. These product categories are particularly attractive for retailers interested in benefiting from favorable price perceptions. They have a high potential to shape store price image, while constituting only a small portion of the consumer share of wallet. Price reductions in these categories could attract consumers to the store, while entailing a low risk of subsidization. We now discuss both dimensions – monetary value and informativeness –, and offer directional hypotheses regarding their effect on SPI learning.

Monetary value

Consumers have more to gain from visiting stores that offer low prices in categories that constitute a large portion of their typical shopping basket (Wakefield and Inman 1993, Urbany et al. 1996). As a result, categories that represent a large chunk of the shopping budget of a given consumer – share of wallet – are expected to have a higher impact on the formation of store price perceptions for that consumer. Accordingly, we hypothesize that:

H 1 *Share of wallet increases the impact of category prices on SPI formation.*

Yet, while share of wallet captures the financial incentives to monitor category prices, different product categories have different characteristics that distinguish them in their ability to signal the overall price level of a store.

Informativeness

As already mentioned, the informativeness of a product category depends on its price *accessibility* – How salient and easy-to-process is price information from this category? – and *diagnosticity* – Is price information from this category indicative of a store's expensiveness? Table 2.1 lists a set of category-specific characteristics that may determine the accessibility and diagnosticity of category prices. These category factors are based on previous cross-category studies in the marketing literature (e.g. Narasimhan, Neslin, and Sen 1996, Pauwels et al. 2007, Fader and Lodish 1990, Macé and Neslin 2004), and are actionable for retailers. We organize our discussion around five main groups of product characteristics: those related to *price*, *promotions*, *shopping habits*, *assortment*, and *storability*.

Price
A category's *expensiveness* is expected to be an important driver of store price image learning from prices. Although related, a category's expensiveness is not to be confused with share of wallet. Share of wallet reflects the monetary importance of a product category relative to other product categories in a consumer's shopping budget, and is a consequence of the consumer's preferences and needs. A category's expensiveness, in turn, represents how much is payed on a typical purchase occasion, regardless of the distribution of category shares (Narasimhan et al. 1996). It serves as an intense psychophysical stimulus. More expensive categories attract more attention from consumers. This facilitates price recall from memory (Mazumdar and Papatla 2000), and, more importantly, increases price awareness and usage (e.g. Zeithaml 1988, Miyazaki, Sprott, and Manning 2000). We therefore postulate that:

H 2 *Category expensiveness increases the impact of category prices on SPI formation.*

A second price-related characteristic is the category's *price spread*, that is, the difference between the lowest and highest prices in the category. On the one hand, recent findings by Vanhuele and Drèze (2002) suggest that price spread has a negative impact on consumer price knowledge. If within-category price differences are high, the price information may be more diffuse, and consumers may find it harder to form an overall impression of store expensiveness based on these prices. On the other hand, based on arguments and findings in Briesch et al. (1997) and Pauwels et al. (2007), consumers pay more attention to prices in categories with a higher price spread. We therefore expect price spread to impact SPI learning from category prices, but without a clear hypothesis regarding the direction of its effect. Formally,

H 3 *Price spread affects the impact of category prices on SPI formation.*

Promotions

Apart from more stable price characteristics, the category's promotional strategy, in particular the *frequency* and *magnitude* of promotional price cuts (Alba et al. 1994, 1999, Lalwani and Monroe 2005), may affect its importance for SPI formation. From an accessibility point of view, *frequent* price promotions may increase price consciousness (Kopalle, Mela, and Marsh 1999, Mela, Jedidi, and Bowman 1998, Mela, Gupta, and Lehmann 1997). However, promotional activity also requires additional effort in processing prices, which may deter consumers from keeping track of prices in frequently promoted categories (Mazumdar and Papatla 2000). Moreover, from a diagnosticity perspective, frequent price promotions generate many mixed signals – regular prices and promoted prices – as to what price level consumers may expect in the store, thus weakening the signals' informativeness. Given these countervailing forces, we expect promotional frequency to impact SPI learning from category prices, but without a clear direction regarding its effect. Formally,

H 4 *Promotion frequency affects the impact of category prices on SPI formation.*

As far as promotion depth is concerned, *deeper* price cuts are more likely to exceed the threshold of noticeable differences (Monroe 2002, Luce and Edwards 2004). Hence, strong price reductions may become more accessible due to increased salience. In addition, deeper price cuts may produce a contrast effect, and thus become more diagnostic about the overall price level of a store (Hamilton and Chernev 2009). We therefore formulate the following hypothesis:

H 5 *Promotion depth increases the impact of category prices on SPI formation.*

Instruments that support price promotion activities in a category, such as in-store *display advertising*, are expected to have an impact on store price image learning. Display activity increases the likelihood that consumers notice (i.e. have access to) ongoing price promotions inside the store (e.g. Bolton 1989, Chevalier 1975). Hence, advertised (promotional) prices that enjoy enhanced exposure inside the store, are expected to facilitate SPI learning. Formally:

H 6 *Display activity increases the impact of category prices on SPI formation.*

Shopping habits

A category's *interpurchase time*, i.e. the time between two subsequent purchases from the category, is also likely to influence how category prices are used for SPI formation. Conventional wisdom suggests that memory deteriorates over time, a notion that is supported in consumer research (see e.g. Lynch and Srull 1982). Specifically, the precision with which constructs are recalled decreases with the time elapsed since the information was first encoded (Rubin and Wenzel 1996). Recent findings in behavioral pricing (Vanhuele and Drèze 2002) suggest that long-term price knowledge is even lower than the short-term price knowledge typically found in price recall studies (e.g.

Dickson and Sawyer 1990), and that longer interpurchase times make prices less readily available in memory and for use in price judgments (Briesch et al. 1997, Pauwels et al. 2007, Mazumdar and Papatla 2000). Therefore, consumers have a strong(er) reason to pay attention to prices of infrequently purchased categories. At the same time, however, prices of product categories bought less frequently may be less salient in consumers' minds, making them appear less important and be paid less attention to. Given these opposite expectations, we formulate an hypothesis without a clear direction regarding the effect of interpurchase time on SPI learning from prices:

H 7 *Interpurchase time affects the impact of category prices on SPI formation.*

Brand loyalty in a category produces a dual effect. On the one hand, tracking prices is facilitated in product categories enjoying high brand loyalty levels, as consumers closely follow only the price of the brand usually purchased (Biehal and Chakravarti 1983). On the other hand, in product categories where brand loyalty is high, prices may not be totally diagnostic, as prices of brands consumers are loyal to may not reflect the average price level of the store. Hence, we do not formulate a directional hypothesis:

H 8 *Brand loyalty affects the impact of category prices on SPI formation.*

Assortment

Another potential determinant of the informativeness of prices is *market concentration* in the product category. In low concentration markets, price-based competition is higher than in high concentration markets, and consumers switch more among product alternatives (Narasimhan et al. 1996). As a consequence, it is harder for consumers to keep track of all prices in the product category. Moreover, in a differentiated market with many brands, prices are likely to be non-diagnostic about the product category and therefore the store expensiveness. Conversely, highly concentrated markets not only make category prices more diagnostic, but also facilitate price tracking (Pauwels et al. 2007). Hence, we formulate the following hypothesis:

H 9 *Market concentration increases the impact of category prices on SPI formation.*

A category's *number of stock keeping units (SKUs)*, may also influence SPI learning. Recent findings by Ofir et al. (2008) show that the number of prices affects the formation of overall price perceptions. Basically, categories encompassing a large number of SKUs may confuse consumers due to the existence of many potentially different prices. In line with these observations, we expect price signals from these categories to entail a high cost of integration and encoding (low accessibility) and to be relatively uninformative regarding the store's overall expensiveness (low diagnosticity). Formally:

H 10 *The number of SKUs reduces the impact of category prices on SPI formation.*

Storability

All else equal, categories that are storable in nature are expected to exert a stronger influence on store price image formation. More easily stockpiled and storable categories often enjoy greater shelf space (Chiang and Wilcox 1997), making their prices more accessible. Moreover, consumers are more inclined to monitor prices and price cuts in storable categories, because of the larger potential savings from stockpiling these products (Narasimhan et al. 1996). Intentionally learned prices are in general more accessible than incidentally learned ones (Mazumdar and Monroe 1990), and storable products are typically less bought on impulse (Pauwels, Hanssens, and Siddarth 2002). We, therefore, hypothesize that:

H 11 *Storability increases the impact of category prices on SPI formation.*

The hypothesized effects of product category characteristics on store price image formation are summarized in Table 2.4. Before presenting our dynamic model of SPI formation used to empirically test these propositions, we discuss, in the next section, our unique data set and the operationalization of the variables.

2.3 Data and operationalizations

2.3.1 Price perceptions, category prices, and overall price levels

For our empirical analysis, we have detailed scanner panel data on store choice and spending, for a sample of $N = 497$ households, and for all $S = 18$ major grocery retail chains in The Netherlands. The data span a period of four years, from 2002 to 2005. Store price and promotion data are available on a weekly basis, for $C = 49$ product categories. To ensure comparability across categories, we transform observed category prices – which are expressed in different category-specific units, such as liters or kilograms – into price indices $PI_{c,st}$. Specifically, we calculate $PI_{c,st} = P_{c,st}/\overline{P}_{c,I_t}$, where $P_{c,st}$ is category c's actual price in store s in week t, itself a carefully constructed weighted average across brands within the category, and $\overline{P}_{c,I_t}$ is category c's average actual price across all stores during an initialization period I_t, which serves as a reference point (see van Heerde et al. 2008, for more details).

For the same individual panel members and in the same time period, we have information on perceptions of several store dimensions, including price. 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. These survey data were collected semiannually by GfK among their panel members, through store intercept interviews. Each of the 9 survey waves was conducted during one week, allowing households to judge the overall price level of more than one store and more than once, depending on how many stores they visited in that week and how often. Except for the wave that took place in week 5 in 2004, surveys were conducted in weeks 16 and 40 of every year. We note that the aggregate distribution of observed SPIs (across households, stores, and time periods) is bimodal (see first two columns of Table 2.2).

The evolution of aggregate price perceptions of some of the major chains is plotted in the left panel of Figure 2.2, next to their weekly overall price levels (right panel). The top lines refer to high priced (HiLo) stores such as Albert Heijn or Super de Boer,

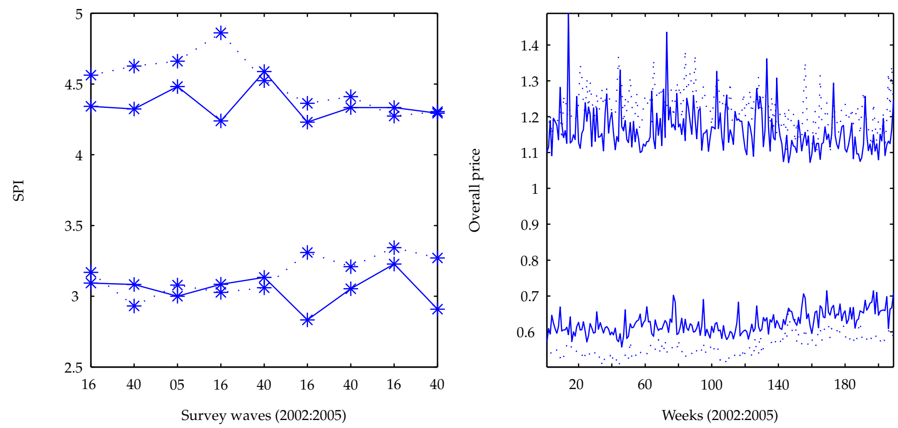

Figure 2.2: Evolution of aggregate SPI (left panel) and overall prices (right panel) in two HiLo (top lines) and two EDLP stores (bottom lines). HiLo stores plotted: Albert Heijn (top dotted lines) and Super de Boer (top solid lines). EDLP stores plotted: Aldi (bottom dotted lines), and Lidl (bottom solid lines).

the strategy of which is based more on service and quality than on price. Bottom lines refer to low priced (EDLP) stores or hard discounters such as Aldi or Lidl, whose strategy is focused on (low) price. Consider, for instance, the most (Albert Heijn) and the least expensive (Aldi) stores (top and bottom dotted lines, respectively). After a deterioration that lasted approximately until the end of 2003, the store perceived as most expensive enjoyed an improvement in its price image. During that same period, the store perceived as the least expensive saw its low price image deteriorate over time.

Figure 2.2 reveals three crucial insights in the data that support our conceptualization of a dynamic formation process of store price images. First, consumers perceive different stores differently with respect to prices or overall expensiveness. Second, price perceptions evolve over time. Third, actual store prices and store price images are clearly linked, both cross-sectionally and over time.

2.3.2 Category shares-of-wallet and category characteristics

We compute category shares for each household – shares-of-wallet – based on its purchases across all stores in the data. A list of all product categories, and the distribution of their average shares-of-wallet across households, is displayed in Table 2.3, together with the corresponding average prices (across stores and over time). *Meat* takes the highest proportion of the shopping budget, with an impressive average share-of-wallet of 10%, whereas pizzas is the smallest category, with an average share-of-wallet of only .2%. Out of all 49 product categories considered, the eight categories with highest share-of-wallet (*Meat*, *Alcoholic drinks*, *Vegetables*, *Fine meat*, *Fruit*, *Bread*, *Cheese*, and *Soft drinks*) comprise more than half of the budget spent on a typical shopping basket

Table 2.1: Operationalization and descriptive statistics of product category characteristics

Characteristic	**Operationalization**[a]	**Average (s.d.)**	**Min (product)**	**Max (product)**
Promotion frequency	Number of times price index is below .95 (e.g. Fok, Horvath, Paap, and Franses 2006, Raju 1992, Nijs, Dekimpe, Steenkamp, and Hanssens 2001)	.860 (.087)	.426 (cleaning products)	.951 (potatoes)
Promotion depth	Average promotional price cut (e.g. Fok et al. 2006, Raju 1992, Nijs et al. 2001)	.597 (.272)	.340 (cheese)	2.146 (personal care)
Display activity	Number of weeks product category was on display (Bolton 1989)	.319 (.189)	.008 (cheese)	.722 (soft drinks)
Expensiveness	Average euros spent per purchase occasion (e.g. Narasimhan et al. 1996, Fader and Lodish 1990, Pauwels et al. 2007)	3.153 (1.866)	.949 (bread substitutes)	11.038 (alcoholic drinks)
Interpurchase time	Average interpurchase time in weeks (e.g. Narasimhan et al. 1996, Fader and Lodish 1990, Pauwels et al. 2007)	5.375 (2.940)	1.240 (vegetables)	11.770 (personal care)
Market concentration	Sum of shares of top-3 brands (e.g. Pauwels et al. 2007, Raju 1992, Fok et al. 2006)	.645 (.143)	.272 (pastries)	.921 (soup)
Storability	Indicator of ability to stockpile (e.g. Narasimhan et al. 1996, Bell et al. 1999, Macé and Neslin 2004)	–	0	1
Price spread	Difference between maximum and minimum prices (e.g. Briesch et al. 1997, Pauwels et al. 2007, Vanhuele and Drèze 2002)	9.345 (15.784)	.458 (eggs)	88.256 (personal care)
Number of SKUs	Number of stock-keeping-units in the category (e.g. Chiang and Wilcox 1997, Bell et al. 1999, Macé and Neslin 2004, Pauwels et al. 2007)	1325.354 (1383.005)	101 (cleaning products)	6878 (vegetables)
Brand loyalty	Average brand loyalty in the category (e.g. Bell et al. 1999)	6.537 (3.682)	2.206 (cleaning products)	19.052 (milk and dairy drinks)

[a] The exact expressions can be obtained upon request to the authors.

(51%).

As discussed earlier, the 'informativeness' or SPI-signaling power of category prices will depend on intrinsic category characteristics. We follow previous cross-category studies in marketing to guide the operationalization of these variables. Table 2.1 lists all characteristics and their corresponding descriptive statistics. The last two columns display the extreme values (minimum and maximum), and the corresponding product categories. For instance, personal care products have the largest price spread and interpurchase time, alcoholic drinks are the most expensive products, and vegetables have the highest number of unique stock keeping units.

2.4 The model

2.4.1 Preliminaries

Building on previous conceptualizations (Büyükkurt 1986, Feichtinger et al. 1988), we model store price image formation as a process of adaptive learning over time. In line with recent marketing studies, we adopt a Bayesian framework to capture learning (e.g. Erdem and Keane 1996, Dixit and Chintagunta 2007). The Bayesian framework mimics the process of store price image formation suggested above and is an attractive way to model consumers' use of prices from memory (Erdem, Keane, and Sun 2008). We use the following notation: $i = 1, \ldots, N$ individual consumers, $s = 1, \ldots, S$ stores, $t = 1, \ldots, T$ time periods and $c = 1, \ldots, C$ product categories.

2.4.2 SPI formation over time

We assume that a consumer's beliefs $S\widetilde{P}I_{ist}$ about the overall price level of stores are unobserved; the researcher observes only stated price perceptions $MSPI_{ist}$. In our model, the latent variable $S\widetilde{P}I_{ist}$ gets mapped onto the measured $MSPI_{ist}$, which can take on values $\{j = 1, \ldots, J\}$ according to the following rule

$$MSPI_{ist} = \begin{cases} 1 & \text{if } \alpha_0 < S\widetilde{P}I_{ist} \leq \alpha_1 \\ 2 & \text{if } \alpha_1 < S\widetilde{P}I_{ist} \leq \alpha_2 \\ \vdots & \vdots \\ J & \text{if } \alpha_{J-1} < S\widetilde{P}I_{ist} \leq \alpha_J \end{cases} \tag{2.1}$$

where the α_j are threshold parameters to be estimated, and with higher values of $S\widetilde{P}I_{ist}$ linked to higher values of $MSPI_{ist}$. We further assume that unobserved store price images $S\widetilde{P}I_{ist}$ can be decomposed into an idiosyncratic component SPI^*_{ist} representing a consumer's price beliefs updated over time (see Mazursky and Jacoby 1986), and a disturbance term ε_{ist}, observed by the consumer but not the researcher. Formally,

$$S\widetilde{P}I_{ist} = SPI^*_{ist} + \varepsilon_{ist}, \quad \varepsilon_{ist} \sim N(0, \sigma^2_{S\widetilde{P}I}), \tag{2.2}$$

where the disturbance term ε_{ist} is assumed to follow a standard normal distribution, to be independent of the perceptual error variance (i.e. $\sigma^2_{SPI_{ist}}$, the variance of SPI^*_{ist}; see below) and to be independent of SPI^*_{ist}. For identification, we set the variance $\sigma^2_{\widetilde{SPI}} = 1$. This identification restriction together with (2.1) leads to the well-known ordered probit model, often applied to ratings data (Rossi and Allenby 2003).

SPI^*_{ist} is assumed to be updated over time in a Bayesian fashion. In the initial period, when consumer i has had no access to price information, his/her prior belief about the expensiveness of store s, SPI^*_{is0}, is assumed to be stochastic (also from the point of view of the researcher) and to be normally distributed, i.e.

$$SPI^*_{is0} \sim N(SPI_{s0}, \sigma^2_{SPI_{is0}}), \tag{2.3}$$

where the variance $\sigma^2_{SPI_{is0}}$ represents the consumer-specific initial uncertainty about the overall price level of store s. In other words, and similar to previous learning studies, we assume that when consumers have no other sources of information, their prior belief about the mean overall price level of store s is the same, yet each consumer is uncertain about the true overall price level of the store for his/her typical shopping basket.

Whenever a consumer visits a store (s)he is exposed to in-store price information in the form of category prices – observed by both the consumer and the researcher – that will be used as sources of information to update existing overall price level beliefs. We propose that category prices reflect, i.e. provide a signal for, stores' true SPIs, up to a term $\tau_{c,st}$. Formally:

$$PI_{c,st} = SPI_{st} + \tau_{c,st}, \quad \tau_{c,st} \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_{\tau_c}) \tag{2.4}$$

and thus $PI_{c,st} \sim N(SPI_{st}, \sigma^2_{\tau_c})$.

The model assumptions so far imply that, once inside the store, consumers can be influenced by all category prices. It does not mean, however, that consumers use all these prices to the same extent. Consumers are different in their motivation and/or ability to pay attention to observed prices, encode them, or retrieve them from memory. For instance, consumer motivation to learn prices may be either intentional or incidental thus resulting in different price information extracted (Mazumdar and Monroe 1990). To accommodate differences in the way price information signals the overall price level of the store, we specify individual-specific price signals as a combination of category prices $PI_{c,st}$ and an individual component $\eta_{c,ist}$, observed by the consumer but not the researcher. Formally, the category price signals that consumers receive in store s at time t, are assumed to be independently normally distributed around observed category prices in that store, with a constant variance $\sigma^2_{\eta_{c,i}}$ across stores and over time, i.e.

$$P^*_{c,ist} = PI_{c,st} + \eta_{c,ist}, \quad \eta_{c,ist} \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_{\eta_{c,i}}) \tag{2.5}$$

and thus $P^*_{c,ist} \sim N(PI_{c,st}, \sigma^2_{\eta_{c,i}})$. Substituting equation (2.4) into (2.5), it is clear that category price signals are also normally distributed around a store's true mean overall price level with variance $\sigma^2_{\delta_{c,i}} = \sigma^2_{\tau_c} + \sigma^2_{\eta_{c,i}}$, i.e.

$$P^*_{c,ist} = SPI_{st} + \delta_{c,ist}, \quad \delta_{c,ist} \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_{\delta_{c,i}}), \tag{2.6}$$

where $\delta_{c,ist} = \tau_{c,st} + \eta_{c,ist}$ and thus $P^*_{c,ist} \sim N(SPI_{st}, \sigma^2_{\delta_{c,i}})$. Note that the only component in the variance of category price signals unknown to the researcher is $\sigma^2_{\eta_{c,i}}$. The price signal variances play a crucial role in our learning model since they represent how noisy or how precise a category price signal is. Moreover, they are not only category-specific but also consumer-specific, i.e. they capture unobserved heterogeneity in learning from the different product categories (see Narayanan and Manchanda 2009).

Consumers are assumed to learn about a store's overall price level according to a Bayesian rule that combines (i) their prior expensiveness beliefs with (ii) the available price information in each period (summarized in IP_{ist}) into an updated or posterior belief. Since both the prior belief and all signals are normally distributed, consumer i's posterior belief about the overall expensiveness of store s at time t follows a normal distribution as well (see e.g. Gelman, Carlin, Stern, and Rubin 2004), i.e. $SPI^*_{ist}|IP_{ist} \sim N(SPI_{ist}, \sigma^2_{SPI_{ist}})$, with mean and variance, respectively,

$$SPI_{ist} = \sigma^2_{SPI_{ist}} \left(\frac{1}{\sigma^2_{SPI_{is,t-1}}} SPI_{is,t-1} + \sum_{c=1}^{C} \frac{1}{\sigma^2_{\eta_{c,i}}} P^*_{c,ist} \right) \tag{2.7}$$

and

$$\sigma^2_{SPI_{ist}} = \left(\frac{1}{\sigma^2_{SPI_{is,t-1}}} + \sum_{c=1}^{C} \frac{1}{\sigma^2_{\eta_{c,i}}} \right)^{-1}. \tag{2.8}$$

The posterior mean of the store price belief in (2.7) is a weighted average of the different sources of information available: the prior mean belief and the price signals from different product categories.[2] Similarly, the weights are proportional to the precision of each piece of information: the precision of the prior belief, i.e. $1/\sigma^2_{SPI_{is,t-1}}$, and, crucial to our study, the precision of each category price signal, i.e. $1/\sigma^2_{\eta_{c,i}}$ $(c = 1, \ldots, C)$.[3] In the next subsection we specify the link between the variances of category price signals and category characteristics.

[2]The posterior mean can also be written as the prior mean adjusted toward the price signals, i.e. $SPI_{ist} = SPI_{is,t-1} + \sum_{c=1}^{C} \gamma_{c,ist}(P^*_{c,ist} - SPI_{is,t-1})$, with $\gamma_{c,ist} = \sigma^2_{SPI_{ist}} / (\sigma^2_{SPI_{ist}} + \sigma^2_{\eta_{c,i}})$. The γs are the so-called Kalman gain coefficients (see e.g. Erdem and Keane 1996).

[3]The posterior variance of the store price belief in (2.8) has a similar interpretation, i.e. it combines the prior variance (precision) and the variance (precision) of the price signals. Over time, this posterior variance converges to zero. Conditional on the category price signal variances, not only is the posterior variance deterministic but also the posterior mean, as consumers observe the actual category prices.

2.4.3 Including category drivers of SPI learning

All else equal, a consumer i with a low value of $\sigma^2_{\eta_{c,i}}$ in a given product category c, learns faster from, and attaches higher weight to, the prices of that product than a consumer l with a high value of $\sigma^2_{\eta_{c,i}}$ $(\forall_{i \neq l})$ (see Narayanan and Manchanda 2009, for a similar interpretation). Aggregated across consumers, a product category c with a low $\sigma^2_{\eta_c}$ is considered more important than a product category d with a high $\sigma^2_{\eta_d}$ $(\forall_{c \neq d})$ for the formation of store price images. *Lighthouse categories* are thus those product categories with low average price signal variance (i.e. a high precision) across consumers, and yet have a low average share-of-wallet across consumers (see Figure 2.1).

In line with our conceptualization, we specify the category- and consumer-specific variances $\sigma^2_{\eta_{c,i}}$ as a function of two components. The first component is a category's monetary value $w_{c,i}$ for the consumer i, which is based on the consumer's share-of-wallet (SoW). For each consumer, the shares-of-wallet satisfy the sum constraint, i.e. $\sum_{c=1}^{C} w_{c,i} = 1$. The second component is the category's informativeness, which is based on $k = 1, \ldots, K$ category-intrinsic characteristics $m_{k,c}$ described in Section 2.2. Formally,

$$-\ln \sigma^2_{\eta_{c,i}} = \beta_0 + \beta_1 \ln w_{c,i} + \sum_{k=1}^{K} \beta_{k+1} \ln m_{k,c} + \xi_{c,i}, \tag{2.9}$$

with $\xi_{c,i} \sim N(0, \sigma^2_{\xi})$, and thus equation (2.9) corresponds to a normal linear regression model specification. Note that the double log specification guarantees the signal variances are positive, allows for interactions between all regressors, and makes the coefficients directly interpretable as elasticities.[4]

In summary, the full specification of the store price image model in (2.1)–(2.9) includes three components: (i) an ordered probit component dealing with the discreteness of our observed store price image measures, (ii) a Bayesian learning process linking observed price signals to store price image over time, and (iii) a normal linear regression specification relating the price signal variances to category characteristics. Instead of using a two-step estimation approach to assess the moderator effects of category characteristics, we estimate the parameters of our model jointly, thereby increasing the efficiency of the estimates (see e.g. Fok et al. 2006). For that purpose, we adopt a Bayesian estimation approach. The Appendix provides details on the estimation procedure.

2.5 Results

The estimation results are based on an MCMC chain of $S_1 = 110\,000$ draws, after discarding the first $S_0 = 95\,000$ draws as burn-in.Visual inspection of the evolution of the

[4]The original specification is a multiplicative model of the form $\sigma^2_{\eta_{c,i}} = e^{-\alpha} w_{c,i}^{-\beta_1} \prod_{k=1}^{K} m_{k,c}^{-\beta_{k+1}} e^{-\xi_{c,i}}$ (for any characteristic operationalized as a dummy we use $e^{\beta_{k+1} m_{k,c}}$). Hence, $\beta_0 = \ln \alpha$ in equation (2.9).

sampled values of the parameters of interest suggests that the simulation chain has converged. Posterior means of the ordered probit threshold parameters α are reported in Table 2.2. 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 of the ordered probit component of the model, α_0, α_1, and α_9 are set to $-\infty$, 0, and $+\infty$, respectively). The model correctly predicts about one third of all observed SPI scores (28.1%), a figure that favorably compares to random assignment (11.1%).[5] Below, we first report the estimated precisions of the category price signals. Next, we zoom in on the impact of underlying category drivers.

2.5.1 SPI learning parameters

The aggregated category price learning parameters across households (i.e. the precisions $1/\sigma^2_{\eta_c}$) are reported in Table 2.3, together with the corresponding average shares-of-wallet (across households) and average actual prices (across stores and over time). We also rank all product categories based on each of the three variables, from highest to lowest. Based on a median split of the categories' shares-of-wallet on the one hand, and the estimated precisions of price signals on the other, we classify the categories into four groups (see the framework in Figure 2.1): *Avoid* (low learning; high SoW), *Unattractive* (low learning; low SoW), *Subsidization* (high learning; high SoW), and *Lighthouse Categories* (high learning; low SoW).

Changes in the prices of product categories in the bottom-left quadrant are to be avoided for purposes of SPI management. Not only are the price signal precisions in these categories among the lowest (i.e. below the median), their weight in the typical consumer shopping basket is also quite high (above the median). This is the case for *Bread* or *Cheese*, for instance, which enjoy a high share-of-wallet (above 5%), but, according to our estimates, have a low ability to signal SPIs. In turn, both the estimated price signal precisions and the shares-of-wallet of categories in the bottom-right group, such as *Vinegar* or *Sugar*, are below the median, making them 'Unattractive' for purposes of SPI management. In contrast, product categories in the 'Subsidization' group have both above-median price signal precisions and shares-of-wallet. A drop in the prices of these categories favorably affects the store's price image, but could be costly in terms of revenue reduction. This is the case for *Alcoholic drinks* or *Meat*, for instance, which have a high ability to signal SPI but together take almost a fifth of consumers' shopping budget. Finally, product categories in the top-right quadrant also exhibit estimated price

[5] In 59% of the cases, the difference is less than 2 points. The non-parametric Spearman correlation is .30 and the mean absolute deviation (MAD) is 1.3(3). The highest variance inflation factor (VIF) is 8.058 and the lowest tolerance level 0.124, which together suggest absence of high multicollinearity among category characteristics.

Table 2.2: Posterior results for cutoff parameters

SPI	%	parameter	mean	s.d.	2.5	50	97.5
		α_0	-999	0	-999	-999	-999
1	1.7	α_1	0	0	0	0	0
2	13.1	α_2	0.3987	0.0135	0.3720	0.3986	0.4249
3	30.7	α_3	1.1147	0.0080	1.0997	1.1144	1.1278
4	17.3	α_4	1.5243	0.0105	1.5082	1.5233	1.5436
5	28.8	α_5	2.5888	0.0153	2.5570	2.5890	2.6195
6	6.9	α_6	3.4006	0.0433	3.3163	3.3977	3.4901
7	0.8	α_7	3.6924	0.0583	3.5849	3.6909	3.8048
8	0.5	α_8	4.1206	0.1026	3.9322	4.1168	4.3355
9	0.2	α_9	999	0	999	999	999

signal precisions above the median, but represent a below-median share in a typical shopping basket. These are the lighthouse categories, i.e. the product categories able to signal SPI while having a reduced risk of subsidization. A striking observation is that almost all product categories in this group are *Personal care* and *Cleaning products*. Below, we zoom in on the category characteristics driving this category grouping.

2.5.2 Product category moderators of SPI learning

Table 2.4 reports the posterior results regarding the impact of category characteristics on learning from category prices. Note that since the dependent variable is specified as the (ln)variance of price signals, not as a precision, a positive sign indicates a decrease in SPI learning, while a negative sign points to an enhanced effect of category prices on SPI. The 95% highest posterior density intervals of all parameters exclude zero.

As expected, the proportion of the shopping budget or *share-of-wallet* allocated to a category, works as an incentive to learn about the store's overall price level from that category's prices ($\overline{\beta}_1 = 0,047$). Similarly, both the category's *price spread* and overall *expensiveness* increase learning from category prices ($\overline{\beta}_9 = 0,032$ and $\overline{\beta}_5 = 0,205$, respectively). While these results confirm that consumers are likely to pay more attention to, and more closely track the prices of more expensive categories, the price spread effect is somewhat unexpected. In hindsight, consumers may have a stronger incentive to monitor prices in categories with a large price spread, just to make sure they do not overpay. This increased price attention may more than compensate for the lower 'diagnosticity' of category prices – explaining the positive impact on SPI learning.

In line with previous findings (Alba et al. 1994, 1999), we find that both promotional characteristics affect SPI learning, and are actually the strongest to do so. Whereas *promotional frequency* decreases learning from category prices ($\overline{\beta}_2 = -0,732$) – suggesting that prices become less easy to process because of their volatility – *promo-*

Table 2.3: List of product categories, precision, SoW, and actual prices

SUBSIDIZATION (High Learning - High SoW)

Product Category	Precision mean[a]	Precision max	Precision min	Categ. rank	SoW[a]	Categ. rank	Actual price index[b]	Categ. rank
Alcoholic drinks	0.954	1.544	0.369	3	7.3%	2	0.953	41
Paper towels & toilet paper	0.877	2.207	0.313	5	1.4%	22	1.060	14
Laundry detergents	0.801	2.088	0.146	7	1.3%	23	0.947	42
Hot drinks	0.778	1.136	0.523	9	3.3%	12	1.158	2
Soft drinks	0.747	2.458	0.124	10	4.8%	8	0.908	46
Pastries	0.732	2.787	0.212	11	1.7%	17	0.992	33
Meat	0.671	1.141	0.313	13	10.0%	1	1.048	18
Milk & diary drinks	0.658	2.025	0.129	16	3.7%	9	0.919	45
Fish	0.658	1.979	0.079	17	1.9%	16	1.033	22
Vegetables	0.601	0.837	0.235	23	6.2%	3	0.978	35
Fine Meat	0.601	2.330	0.000	24	6.1%	4	1.113	8
Fruit	0.603	1.584	0.270	22	5.8%	5	1.051	16
Poultry	0.610	1.280	0.217	21	2.6%	13	1.061	13
Cake	0.632	1.158	0.237	20	1.7%	19	1.047	19
Total	0.709[c]				57.6%[d]		1.019[c]	

LIGHTHOUSE CATEGORIES (High Learning - Low SoW)

Product Category	Precision mean[a]	Precision max	Precision min	Categ. rank	SoW[a]	Categ. rank	Actual price index[b]	Categ. rank
Personal care	1.016	3.850	0.185	1	0.4%	41	1.225	1
Cleaning products	0.961	2.007	0.392	2	0.2%	47	0.833	49
Cosmetics hair	0.839	2.188	0.136	6	0.7%	33	0.962	39
Cosmetics skin	0.931	1.313	0.373	4	1.1%	25	1.156	3
Diapers & female hygiene	0.779	1.849	0.169	8	0.7%	32	1.020	27
Dental care	0.730	1.222	0.267	12	0.4%	42	1.004	31
Dishwashing	0.665	1.339	0.265	14	0.4%	39	1.072	12
Mik replacements	0.661	1.125	0.239	15	0.7%	31	0.849	48
All purpose cleaners	0.643	1.061	0.304	18	0.3%	46	0.901	47
Bake & dessert	0.640	1.240	0.205	19	0.5%	36	0.927	44
Ice cream	0.598	0.869	0.226	25	0.8%	30	0.981	34
Total	0.769[c]				6.2%[d]		0.994[c]	

AVOID (Low Learning - High SoW)

Product Category	Precision mean[a]	Precision max	Precision min	Categ. rank	SoW[a]	Categ. rank	Actual price index[b]	Categ. rank
Bread	0.588	0.830	0.424	30	5.4%	6	1.140	5
Cheese	0.500	2.002	0.128	45	5.4%	7	1.022	26
Milk products	0.575	1.828	0.133	34	3.7%	10	0.996	32
Biscuits & cookies	0.570	1.452	0.199	35	3.5%	11	1.049	17
Salted snacks	0.592	1.061	0.248	26	2.4%	14	0.944	43
Oils & fats	0.578	1.066	0.253	33	2.2%	15	1.088	11
Potatoes	0.564	1.441	0.219	36	1.7%	18	1.140	4
Chocolate products	0.590	0.995	0.260	28	1.6%	20	1.029	23
Prepared meals	0.591	2.110	0.091	27	1.5%	21	0.971	36
Sandwich spread	0.533	1.776	0.168	40	1.1%	24	1.026	25
Total	0.568[c]				28.6%[d]		1.041[c]	

UNATTRACTIVE (Low Learning - Low SoW)

Product Category	Precision mean[a]	Precision max	Precision min	Categ. rank	SoW[a]	Categ. rank	Actual price index[b]	Categ. rank
Soup	0.513	0.727	0.254	44	1.1%	26	1.038	21
Meal componment decorating	0.581	1.307	0.269	32	1.0%	27	1.027	24
Salads	0.467	1.078	0.131	46	1.0%	28	1.046	20
Eggs	0.450	1.284	0.109	47	0.8%	29	1.115	7
Meal decorating products	0.532	1.371	0.165	41	0.7%	34	0.966	38
Rice & pasta	0.561	2.042	0.189	37	0.5%	35	1.054	15
Sugar	0.529	1.597	0.234	42	0.5%	37	1.101	9
Bread substitutes	0.432	1.948	0.110	48	0.4%	38	0.968	37
Specialty bread	0.558	1.550	0.146	38	0.4%	40	1.018	29
Air freshner	0.588	2.639	0.114	29	0.3%	43	1.019	28
Bakery	0.541	0.857	0.179	39	0.3%	44	0.960	40
Breakfast products	0.585	1.438	0.177	31	0.3%	45	1.011	30
Pizzas & snacks	0.522	1.670	0.128	43	0.2%	48	1.138	6
Vinegar	0.411	1.625	0.111	49	0.2%	49	1.090	10
Total	0.519[c]				7.6%[d]		1.039[c]	

[a] Average across households.

[b] Average across stores and over weeks.

[c] Average across all categories in the set.

[d] Sum of all categories in the set.

Table 2.4: Posterior results: effect of product category characteristics

	Hypothesis[a]	**Mean**	**S.d.**	**2,5%**	**50%**	**97,5%**
Intercept		-0.6937	0.1417	-0.4632	-0.6709	-0.9821
Share-of-wallet	(+)	0.0471	0.0014	0.0498	0.0471	0.0443
Promotion frequency	(?)	-0.7321	0.0583	-0.6219	-0.7300	-0.8489
Promotion depth	(+)	0.2240	0.0252	0.2727	0.2240	0.1745
Display activity	(+)	0.0540	0.0054	0.0643	0.0540	0.0434
Expensiveness	(+)	0.2050	0.0118	0.2282	0.2050	0.1816
Interpurchase time	(?)	0.1649	0.0207	0.2076	0.1637	0.1278
Market concentration	(+)	-0.0970	0.0305	-0.0371	-0.0969	-0.1558
Storability	(+)	0.1081	0.0114	0.1305	0.1080	0.0860
Price spread	(?)	0.0322	0.0073	0.0464	0.0323	0.0178
Number of SKUs	(−)	-0.0602	0.0132	-0.0332	-0.0611	-0.0840
Brand loyalty	(?)	0.1511	0.0228	0.1968	0.1500	0.1096
Error precision		3.7307	0.0351	3.6627	3.7307	3.8001

[a] Since the dependent variable is specified as the (ln)variance of price signals, not as a precision, the expected signs are the *reverse* of the hypothesized learning effects.

tional depth, as expected, enhances learning ($\overline{\beta}_3 = 0,224$). Similarly, and in line with expectations, *display activity* increases the impact of category prices on SPI formation ($\overline{\beta}_4 = 0,054$).

The estimated effect of *brand loyalty* is positive, with higher levels of brand loyalty increasing learning ($\overline{\beta}_{11} = 0,151$). *Interpurchase time*, also, has a significant negative effect on the variance of price signals ($\overline{\beta}_6 = 0,165$). That is, high interpurchase times encourage consumers to integrate category prices into their overall perceptions of store expensiveness.

Turning to the assortment-characteristics, we find that the *number of SKUs* in the category has a positive coefficient. This is as expected: categories with many items seem to impair rather than facilitate SPI learning ($\overline{\beta}_{10} = -0,060$). Similarly, but contrary to expectations, higher levels of *market concentration* appear to be associated with lower levels of SPI learning from category prices ($\overline{\beta}_7 = -0,097$). One explanation is that, because of the intense competition, price levels in these categories are not deemed to differ across stores, and hence considered less informative to evaluate store expensiveness. Finally, and as hypothesized, more easily *stockpiled* categories appear to be more informative for store price image formation ($\overline{\beta}_8 = 0,108$).

Given the double log specification, our estimates are directly interpretable as elasticities and thus as measures of the relative importance of product category characteristics on SPI learning. As already mentioned, the two promotional dimensions – frequency and magnitude – are the most important characteristics in the SPI formation process. Expensiveness, interpurchase time, and brand loyalty (in this order), come immediately after in the ranking, and only price spread ranks lower than share-of-wallet.

Table 2.5: Products categories ranking highest (lowest) on category characteristics that increase (decrease) SPI learning from category prices[a]

Characteristics that increase learning of SPI from category prices (highest 5 product categories)							
Characteristic	**Product Category**	**rank learn**	**rank SoW**	**Characteristic**	**Product Category**	**rank learn**	**rank SoW**
Promotion depth	*Personal care (LC)*	1	41	Interpurchase time	*Personal care (LC)*	1	41
	Paper towels & toilet paper (S)	5	22		*Cleaning products (LC)*	2	47
	Bake & dessert (LC)	19	36		*Dental care (LC)*	12	42
	Cosmetics skin (LC)	4	25		*Dishwashing (LC)*	14	39
	Cosmetics hair (LC)	6	33		*All-purpose cleaners (LC)*	18	46
Display activity	*Soft drinks (S)*	10	8	Price spread	*Personal care (LC)*	1	41
	Biscuits & cookies (A)	35	11		*Paper towels & toilet paper (S)*	5	22
	Milk products (A	34	10		*Meal component decorating (U)*	32	27
	Salted snacks (A)	26	14		*Bake & dessert (LC)*	19	36
	Hot drinks (S)	9	12		*Pastries (S)*	11	17
Expensiveness	*Alcoholic drinks (S)*	3	2	Brand loyalty	*Milk & dairy drinks (S)*	16	9
	Meat (S)	13	1		*Milk products (A)*	34	10
	Cheese (A)	45	7		*Bread (A)*	30	6
	Laundry detergents (S)	7	23		*Hot drinks (S)*	9	12
	Fine Meat (S)	24	4		*Oils & fats (A)*	33	15
Characteristics that decrease learning of SPI from category prices (lowest 5 product categories)							
Characteristic	**Product Category**	**rank learn**	**rank SoW**	**Characteristic**	**Product Category**	**rank learn**	**rank SoW**
Promotion frequency	*Personal care (LC)*	1	41	Number of SKUs	*Sugar (U)*	42	37
	Bakery (U)	39	44		*Air freshener (U)*	29	43
	Dental care (LC)	12	42		*Pizzas & snacks (U)*	43	48
	Specialty bread (U)	38	40		*Dishwashing (LC)*	14	39
	Cleaning products (LC)	2	47		*Cleaning products (LC)*	2	47
Market concentration	*Cheese (A)*	45	7				
	Cosmetics skin (LC)	4	25				
	Soft drinks (S)	10	8				
	Chocolate products (A)	28	20				
	Pastries (S)	11	17				

[a] *U = Unattractive, S = Subsidization, A = Avoid, LC = Lighthouse Categories.*

Table 2.5 combines the insights from our two sets of results. For each product characteristic with a positive impact on SPI learning, we list the five product categories with the highest score for that characteristic (top panel). Similarly, for each characteristic that reduces learning, we indicate the lowest scoring categories (bottom panel). We also report the categories' rankings in terms of the average effect on SPI learning, and their average SoW (given by $1/\sigma^2_{\eta_c}$ and w_c, respectively). All but three lighthouse categories identified earlier (*Diapers & female hygiene*, *Milk-replacements*, and *Ice cream*) figure among the product categories with either the highest or lowest values in most product characteristics. All these lighthouse categories share the fact that they are among the ones with highest values of promotion depth, price spread, and interpurchase times. At the same time, they exhibit the lowest values of promotion frequency, number of SKUs, and market concentration – results that have important managerial implications for retailers interested in managing SPI.

2.6 Conclusions, limitations and future research

2.6.1 Conclusions

In this chapter, we proposed a framework where actual prices of different product categories are integrated in a process of store price image formation. We argued that a product category's ability to signal SPI is determined not only by its share-of-wallet but also, and more importantly, by a number of category characteristics that drive the diagnosticity and accessibility of its category prices. Building on this framework, we developed a model of SPI formation over time in which category prices act as unbiased, noisy signals about stores' cheapness or expensiveness, and in which consumers update their overall price beliefs according to Bayesian updating rules. In addition, we specified the precision of the category price signals as a function of their underlying category-specific drivers. We estimated the model with a Bayesian approach. In so doing, we made use of a large and unique data set, combining weekly store visits and purchase data with semiannual store price perceptions, for a representative panel of households.

We highlight three main findings. First, we find that various product categories carried by the retailer play a substantially different role in the SPI formation process, with average price signal precisions ranging between 1.016 for *Personal care* to 0.411 for *Vinegar*. This difference in the categories' contribution to store price image suggests that, when managing SPIs through prices, careful thought must be given to which product categories best suit this purpose.

Second, higher share-of-wallet categories have a higher impact on SPI formation. However, the link is not very tight, as suggested by the low elasticity of share-of-wallet (compared to those of most product category characteristics). This further underscores the importance of a category-specific pricing approach for SPI improvement. It shows that retailers have the possibility to select categories that contribute favorably to SPI, yet in which price cuts do not overly hurt revenue. Successful SPI management should focus on lighthouse categories, which – though they constitute only a small portion of sales – exert a strong impact on the store's overall price beliefs. Our results identify such lighthouse categories – indicating that they are predominantly related with *Personal* and *Home care*.

We also identify categories that are *not* suitable to create a favorable price image. Product categories such as *Bread* or *Cheese*, for instance, are to be avoided when managing SPIs, as these categories have a high share-of-wallet (meaning that price reductions are bound to hurt revenue) yet a low signaling ability. *Alcoholic drinks* or *Meat*, in contrast, have a high ability to signal SPI, but they still entail a high risk of subsidization, as they represent almost a fifth of consumers' shopping budget. This casts doubt on the conventional wisdom that store price image improvement calls for price cuts in food categories – as practiced by Wal-Mart (CNBC 2010) – and especially in 'fresh' categories – as was done by Albert Heijn (van Heerde et al. 2008). While our results show that price drops in these categories, indeed, contribute to a favorable store price perception, they also cut into an important portion of overall store revenue and margin. Hence, retailers whose profitability is under pressure, may wish to revisit their choice of 'signaling' categories based on our findings.

Third, we identify which category characteristics drive the ability to signal low store prices. Our findings support the notion that category characteristics that increase the attention to prices, or for which there are strong (monetary) incentives to track prices – e.g. display activity, promotion depth, price spread – increase SPI learning. And while characteristics generating simpler price distributions – interpurchase time and brand loyalty – also increase SPI learning, characteristics likely to generate more complex distributions of category prices – e.g. promotion frequency and number of SKUs – decrease SPI learning. Retailers can use these insights to re-consider their pricing approaches across categories – reaping higher margins in these low signaling categories, while emitting a message of cheapness through low prices in others.

2.6.2 Limitations and future research

Clearly, this study has some limitations that open the way for new research questions. First, we focused on the impact of prices on store price image development. However, other variables may also have an impact on the formation of SPIs. For instance, press or advertising messages (see e.g. Shin 2005, Simester 1995, Srivastava and Lurie 2004), may signal the overall price level of stores and contribute to the formation of price beliefs in the mind of consumers. Also, other store characteristics such as atmospherics, lighting, or shelf arrangements and the use of outer-packs may generate an image of cheapness for the store. For lack of information, we could not analyze the effect of (changes in) such cues in our study. Interestingly, an emerging practice among retailers is to manage these cues by store aisle. Specifically, Carrefour Belgium, in an attempt to enhance the appeal of its hypermarkets, is now refurbishing its stores so as to create an image of cheapness in some aisles (product categories), while striving for a more 'luxurious' appearance in others. An interesting question is whether the categories that contribute to a favorable price image through low prices, are also those where non-price cues need to signal cheapness – and vice versa. Future research could pursue this issue.

Second, our study focuses on category prices as signals of SPI. This focus is consistent with a category management perspective, and with the observation that retailers often express their 'differential' advantage in terms of specific category offers. Yet, prices within a category may differ in their SPI signaling ability. On the one hand, consumers may be inclined to use the prices of leading national brands, which are available throughout different stores, as anchors to judge the stores' overall price levels relative to others. On the other hand, store wide private label prices may stand out in the formation of SPI. To our knowledge, the importance of national brand versus private label prices for SPI formation has not been addressed, and we hope that our study stimulates work in this area.

Third, we identified those lighthouse categories that better signal SPI and yet have a low share-of-wallet. This conceptualization allowed us to group categories, and provided an intuitive way to approximate the likely 'subsidization' of consumers if prices are dropped in the 'wrong' categories. However, changes in prices not only change SPI. They also have a more direct effect on category sales inside the store, which is not to be overlooked (see e.g. Bolton 1989, Hoch et al. 1995, Bell et al. 1999). For instance, while we find storability to be associated with enhanced SPI learning from prices, Bell et al. (1999) found it to be associated with increased elasticity of category demand. Hence, lowering prices in storable categories would lead to both stronger category demand increases and more favorable SPIs. The same authors, however, found size of the assortment and market concentration to be associated with higher demand elasticities, while we find the two product characteristics to be detrimental to SPI learning. Hence, for these category characteristics, it seems that retailers face a trade-off between higher immediate demand increases, yet lower SPI signaling value when dropping prices. Future studies should further document the net outcomes of price changes in different categories, by including the impact of category prices on both store traffic (through SPI) and category spending.

Finally, while we extensively documented the formation of store price beliefs, a next question is how changes in SPI translate into store traffic and spending – something we did not look into. Empirical studies that include SPI as a determinant of store selection are rare (see van Heerde et al. 2008, for an exception). Moreover, papers that do consider the impact of SPI typically ignore the fact that SPIs themselves are adjusted over time, based on actual price levels. Future research, therefore, should address the mediating role of SPIs for price-induced changes in store traffic and spending.

2.A Model estimation

Instead of using a two-step estimation approach to assess the moderator effects of category characteristics, we estimate the parameters of our model jointly, thereby increasing the efficiency of the estimates (Fok et al. 2006, see e.g.). For that purpose, we adopt a Bayesian estimation approach. Bayesian estimation is carried out by sampling random draws from the joint posterior distribution of all unknowns and parameters. We first explain our sampling procedure, and then describe the priors and starting values used to implement the model estimation. Next, we present the joint posterior and the full conditional distributions.

2.A.1 Bayesian MCMC estimation

Our set of parameters and latent variables consist of: the latent price beliefs $S\widetilde{P}I_{ist}$, the cutoff parameters α_j, the category- and consumer-specific price signal variances $\sigma^2_{\eta_{c,i}}$, the parameters β that describe the effects of category characteristics and share of wallet (and an intercept), and the linear regression error precision $h = 1/\sigma^2_{\xi}$. The *joint posterior distribution* of all unknowns and parameters in our model has an unknown form. Therefore, we use Markov Chain Monte Carlo (MCMC) simulation to obtain draws from the joint distribution.

We split up the vector of parameters in several blocks and use Gibbs sampling together with data augmentation (Tanner and Wong 1987), that is, we sequentially draw from the full conditional distributions of the parameters. This generates a Markov chain which converges under mild conditions (see Gelfand and Smith 1990, Tierney 1994). In particular, we use the Gibbs sampler developed by Albert and Chib (1993) for discrete ordered data. For parameters for which the full conditional posteriors do not belong to any known family of distributions we use an independence chain Metropolis Hastings (M-H) algorithm (Chib and Greenberg 1995).

2.A.2 Likelihood, priors, and joint posterior

For the sake of readability, we define the set of all unknowns $\Psi = \{\Theta, S\widetilde{P}I_{ist}\}$ and the subset of parameters $\Theta = \{\sigma^2_{\eta_{c,i}}, \beta, h, \alpha\}$. We use the following priors for the parameters: $\beta \sim N(\underline{\beta}, \Omega)$, $h \sim$ Gamma, and $p(\alpha) \propto c$ (a flat prior), where α is the vector of cutpoints or concentration parameters. The *joint posterior distribution* of all unknowns is proportional to the full data likelihood (i.e. it also includes the latent variables) times the prior distribution, i.e. (prices on the right side of the conditionality symbol are omitted for simplicity):

$$p(\Psi|MSPI_{ist}) \propto p(MSPI_{ist}, S\widetilde{P}I_{ist}|\Theta)p(\Theta). \tag{2.A-1}$$

Note that the likelihood function (the first term on the right side in 2.A-1) includes not only the observed $MSPI_{ist}$ but also the unobserved $S\widetilde{P}I_{ist}$. Making use of a simple property of conditional probabilities, the augmented likelihood becomes

$$p(MSPI_{ist}, S\widetilde{P}I_{ist}|\Theta) = p(MSPI_{ist}|S\widetilde{P}I_{ist}, \Theta) \times p(S\widetilde{P}I_{ist}|\Theta). \tag{2.A-2}$$

It is clear that the value of $MSPI_{ist}$ is known with certainty when conditioned on $S\widetilde{P}I_{ist}$ and α, and thus the first term in (2.A-2) can be simplified into

$$p(MSPI_{ist}|S\widetilde{P}I_{ist}, \Theta) = I(\alpha_{MSPI_{ist}-1} < S\widetilde{P}I_{ist} \leq \alpha_{MSPI_{ist}}), \tag{2.A-3}$$

with $MSPI_{ist} \in \{1, 2, \ldots, J\}$. Plugging (2.A-2) and (2.A-3) in (2.A-1), the joint posterior distribution becomes

$$p(\Theta, S\widetilde{P}I_{ist}|MSPI_{ist}) \propto p(S\widetilde{P}I_{ist}|\Theta)p(\Theta) \times I(\alpha_{MSPI_{ist}-1} < S\widetilde{P}I_{ist} \leq \alpha_{MSPI_{ist}}). \tag{2.A-4}$$

Let $y_{c,i} = \ln \sigma^2_{\eta_{c,i}}$, β a $M+1$-dimensional vector of coefficients, $\beta = (\beta_0, \ldots, \beta_M)'$, with $M = K + 1$, and $X_{c,i}$ the collection of X-values for the individual-category pair, and $x_{c,i} = (1 \;\; \ln w_{c,i} \;\; \ln m_{1,c} \ldots \ln m_{K,c})'$. Writing (2.A-4) with the probability distributions in use, we get the final expression of the joint posterior:

$$\begin{aligned} p(\Psi|MSPI_{ist}) \;\; \propto \;\; & \prod_{i=1}^{N} \left\{ \prod_{s=1}^{S} \prod_{t=1}^{T} \left[\frac{1}{\sqrt{\sigma^2_{SPI_{ist}}}} \exp\left(-\frac{1}{2} \frac{(S\widetilde{P}I_{ist} - SPI_{ist})^2}{\sigma^2_{SPI_{ist}} + 1} \right) \right] \right. \\ \times \;\; & \left. \prod_{c=1}^{C} \left[h^{1/2} \exp\left(-\frac{h}{2} (y_{c,i} - x'_{c,i}\beta)^2 \right) \right] \right\} \\ \times \;\; & |\Omega|^{-1/2} \exp((-1/2)(\beta - \underline{\beta})'\Omega^{-1}(\beta - \underline{\beta})) \\ \times \;\; & h^{\frac{\nu-2}{2}} \exp\left(-\frac{h\nu}{2\tau'^{-2}} \right) \\ \times \;\; & I(\alpha_{MSPI_{ist}-1} < S\widetilde{P}I_{ist} \leq \alpha_{MSPI_{ist}}). \end{aligned} \tag{2.A-5}$$

2.A.3 Complete conditional posteriors

Full conditional posterior for h

The terms of 2.A-5 that depend on h are the following (for simplicity, we do not repeat the conditional arguments in this section):

$$p(h| \quad) \propto \prod_{i=1}^{N} \left\{ \prod_{c=1}^{C} \left[h^{1/2} \exp\left(-\frac{h}{2} (y_{c,i} - x'_{c,i}\beta)^2 \right) \right] \right\} h^{\frac{\nu-2}{2}} \exp\left(-\frac{h\nu}{2\tau'^{-2}} \right). \tag{2.A-6}$$

Multiplying over c and i (and using matrix notation), we have

$$p(h| \quad) \propto h^{\frac{NC}{2}} \exp\left(-\frac{h}{2} \Big((y - X\beta)'(y - X\beta) \Big) \right) h^{\frac{\nu-2}{2}} \exp\left(-\frac{h\nu}{2\tau'^{-2}} \right). \tag{2.A-7}$$

Summing up the exponentials and rearranging terms, we have

$$p(h|\quad) \propto h^{\frac{NC+v-2}{2}} \exp\Big(-\frac{h}{2}\Big((y-X\beta)'(y-X\beta)+\nu\tau'^2\Big)\Big). \tag{2.A-8}$$

which is the kernel of a Gamma density. That is,[6]

$$h|\quad \sim G\big(\overline{\tau}^{-2},\overline{v}\big), \tag{2.A-9}$$

where

$$\overline{v} = NC + \nu, \tag{2.A-10}$$

and

$$\overline{\tau}^2 = \frac{(y-X\beta)'(y-X\beta)+\nu\tau^2}{\overline{v}}. \tag{2.A-11}$$

Full conditional posterior for β

The terms of 2.A-5 that depend on β are the following (overlined parameters refer to posterior parameters):

$$\begin{aligned} p(\beta|\quad) \quad &\propto \quad \prod_{i=1}^{N}\Big\{\prod_{c=1}^{C}\Big[\exp\Big(-\frac{h}{2}(y_{c,i}-x'_{c,i}\beta)^2\Big)\Big]\Big\} \\ &\times \quad \exp((-1/2)(\beta-\underline{\beta})'\Omega^{-1}(\beta-\underline{\beta})). \end{aligned} \tag{2.A-12}$$

Multiplying over c and i and summing up the exponentials, we can write

$$p(\beta|\quad)\exp\Big(-\frac{1}{2}\Big(h(y-X\beta)'(y-X\beta)+(\beta-\underline{\beta})'\Omega^{-1}(\beta-\underline{\beta})\Big)\Big). \tag{2.A-13}$$

And manipulating the matrices we can write the term inside the exponential as

$$(\beta-\overline{\beta})'\overline{\Omega}^{-1}(\beta-\overline{\beta})+H,$$

where

$$H = hy'y+\underline{\beta}'\Omega^{-1}\underline{\beta}-\overline{\beta}'\overline{\Omega}^{-1}\overline{\beta}$$

and

$$\overline{\Omega} = (\Omega^{-1}+hX'X)^{-1} \tag{2.A-14}$$

$$\overline{\beta} = \overline{\Omega}(\Omega^{-1}\underline{\beta}+hX'y) \tag{2.A-15}$$

Finally, substituting into 2.A-13 and dropping the terms that do not depend on β, we get:

$$p(\beta|\quad) \quad \propto \quad \exp\Big(-\frac{1}{2}(\beta-\overline{\beta})'\overline{\Omega}^{-1}(\beta-\overline{\beta})\Big), \tag{2.A-16}$$

which is the kernel of a Normal distribution. Hence,

$$\beta|\quad \sim N(\overline{\beta},\overline{\Omega}). \tag{2.A-17}$$

[6]Overlined parameters refer to posterior parameters.

Full conditional posterior for α_j

It is easier to draw from the components of α one at a time (see Koop 2003, p.220). Because we are conditioning on α_{-j} (i.e. all α with α_j removed), α_j must lie in the interval $[\alpha_{j-1}, \alpha_{j+1}]$. In addition, the fact that we are conditioning on both $MSPI$ and $S\widetilde{P}I$ allows us to know which values of the latent data correspond to which values for the actual data. Finally, the conditioning arguments provide no other information about α_j. Therefore, the posterior conditional for α_j is a Uniform distribution:

$$\alpha_j | \quad \sim U(\overline{\alpha}_{j-1}, \overline{\alpha}_{j+1}) \tag{2.A-18}$$

for $j = 2, \ldots, J-1$, where

$$\overline{\alpha}_{j-1} = \max\{\alpha_{j-1}, \max\{S\widetilde{P}I_{ist} : MSPI_{ist} = j\}\}$$

and

$$\overline{\alpha}_{j+1} = \min\{\alpha_{j+1}, \min\{S\widetilde{P}I_{ist} : MSPI_{ist} = j+1\}\}.$$

The notation $\max\{S\widetilde{P}I_{ist} : MSPI_{ist} = j\}$ ($\min\{S\widetilde{P}I_{ist} : MSPI_{ist} = j+1\}$) denotes the maximum (minimum) value of the latent data over all individuals who have chosen the rating level j.

Full conditional posterior for $S\widetilde{P}I_{ist}$

Each consumer is independent conditional on the information in X and each observation for a consumer is independent conditional on the vector of mean beliefs SPI_{ist}. This means that we can draw the latent $S\widetilde{P}I_{ist}$ for a particular consumer and a particular observation separately from all other observations (we condition $S\widetilde{P}I_{ist}$ on $S\widetilde{P}I_{-ist}$, i.e. all set of $S\widetilde{P}I$s with $S\widetilde{P}I_{ist}$ removed). The draws are sequentially obtained from a truncated normal distribution:

$$S\widetilde{P}I_{ist} | \quad \sim \text{Truncated N}_{(\alpha_{MSPI_{ist}-1}, \alpha_{MSPI_{ist}}]}(SPI_{ist}, \sigma^2_{SPI_{ist}} + 1). \tag{2.A-19}$$

Full conditional posterior for $\sigma^2_{\eta_{c,i}}$

The terms of the joint posterior that depend on $\sigma^2_{\eta_{c,i}}$ are the following (recall the expression of the mean price belief in Equation 2.7):

$$\begin{aligned} p(\sigma^2_{\eta_{c,i}} | \quad) \quad \propto \quad & \prod_{i=1}^{N} \Bigg\{ \prod_{s=1}^{S} \prod_{t=1}^{T} \Bigg[\frac{1}{\sqrt{\sigma^2_{SPI_{ist}}}} \exp\Bigg(-\frac{1}{2} \frac{(S\widetilde{P}I_{ist} - SPI_{ist})^2}{\sigma^2_{SPI_{ist}} + 1} \Bigg) \Bigg] \\ & \times \prod_{c=1}^{C} \Bigg[h^{1/2} \exp\Bigg(-\frac{h}{2} (y_{c,i} - x'_{c,i}\beta)^2 \Bigg) \Bigg] \Bigg\}. \end{aligned} \tag{2.A-20}$$

The complete posterior conditional for the individual level parameters $\sigma^2_{\eta_{c,i}}$ does not have a known form. We use an independence chain Metropolis-Hastings algorithm (Chib and Greenberg 1995) with a normal candidate generating density to make draws from the distribution in (2.A-20). The mean and variance of the candidate density are set equal to the mean and variance of the linear regression component of the model.

2.A.4 MCMC sampler

The MCMC sampling algorithm can be summarized in the following steps:

- Compute SPI_{ist} and $\sigma^2_{SPI_{ist}}$ from Bayesian learning equations;
- Sample $\widetilde{SPI}_{ist}|(\quad)$ from a Truncated Normal distribution;
- Sample $\alpha|(\quad)$ from a Uniform distribution;
- Sample $\beta|(\quad)$ from a Normal distribution;
- Sample $h|(\quad)$ from a Gamma distribution;
- Sample $\sigma^2_{\eta_{c,i}}|(\quad)$ using a Gaussian random-walk chain Metropolis-Hastings algorithm
  - Evaluate conditional posterior $\sigma^2_{\eta_{c,i}}|(\quad)$ on current draw and on candidate draw (computing again the Bayesian learning quantities)
  - Accept candidate draw depending on acceptance probability
- Repeat

To improve the rate of acceptance of candidate draws for the learning parameters, we do not sample all learning parameters at once but we sample them in a block per product category.

2.A.5 Model implementation

To start up the Gibbs sampler, we put the the initial values for the thresholds equal to $\alpha_j = j - 0.5$, with $j = 2, \ldots, J-1$ and $J = 9$. For the degrees of freedom and the mean of the (inverse-)gamma prior distribution, we use $v_0 = 1$ and $s_0^2 = 1\,500$, respectively. The starting value for the precision h in the linear regression is set equal to $1/s^2$, where s^2 is the OLS sum of squares using the initial values, divided by the number of degrees of freedom (number of observations minus the number of regressors). Finally, the mean prior hyperparameters for β are set equal to either 0, -0.5, or 0.5, depending on whether there is a clear expectation for the hypothesized effect and in which direction. The corresponding variances are set equal to 0.5 and all covariances are set equal to zero.

For the initial values of the Bayesian learning quantities – the mean price image perceptions SPI_{is0} and their variances $\sigma^2_{SPI_{is0}}$ – we use average values of the observed, self-reported price images from the first wave period (not used for estimation). Accordingly, for SPI_{is0}, we add an individual standard normal random value to the store-specific average prices in the first wave period. We use the first wave store-specific average variance values (computed across households) as the mean parameters of the inverse gamma-distributions from which we draw $\sigma^2_{SPI_{is0}}$. Finally, the C individual random starting values for $\sigma^2_{\eta_{c,i}}$ are drawn from the (absolute) values of a standard normal distribution. In Equation 2.9 we put $w_{c,i}$ equal to 1×10^{-9} to handle shopping basket weights equal to zero. The model was coded and estimated in MATLAB®.

Chapter 3

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

3.1 Introduction[§]

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. van Heerde et al. 2008, Mägi and Julander 2005). 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).

Despite its managerial relevance, surprisingly little is known about the effect of SPIs on observed store choices, let alone in combination with actual prices. For one, very few empirical studies include SPI as a determinant of store selection, an exception being van Heerde et al. (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, and 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

[§]This chapter is based on joint work with Els Gijsbrechts (Tilburg University). We thank participants at Marketing Science 2009 (Michigan, USA) and Marketing Dynamics 2010 (Istanbul, Turkey).

understand the over-time effect of price, relative to other store choice determinants like assortment or location (Briesch et al. 2008, Bell et al. 1998, Gauri et al. 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 that 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 chapter we address these pressing issues, and aim at reducing some of the existing gaps. Our questions are threefold. 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. The latter is consistent with earlier analytical work on SPI formation over time (e.g. Feichtinger et al. 1988, Büyükkurt 1986), and its parameters can be regarded as indicators of adaptive consumer learning. 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 then combine our household-level estimates of price sensitivity, with extensive background data, so as to explore which demographic and shopping characteristics trigger consumers to use one or the other type of price information (see e.g. Urbany et al. 1996, Hoch et al. 1995, for a similar approach).

Our empirical 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 cue (either actual weekly prices or SPI). Third, we find that households that attend to actual weekly 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 insights are relevant not only from an academic perspective, they also empower retailers with important knowledge to set prices while maintaining profitability (Levy et al. 2004, Grewal and Levy 2007).

The remainder of the chapter is organized as follows. In the next section, we briefly present our conceptual framework. Section 3.3 sheds light on the unique features of the data set, and presents the models. Estimation results are summarized in Section 3.4. In Section 3.5, we explore the profiles of price and SPI-sensitive consumers. Section 3.6 highlights implications, by simulating the over-time impact of a price change among consumers with different types of price sensitivity. Finally, we offer conclusions and discuss opportunities for future research in Section 3.7.

3.2 Conceptual framework

3.2.1 Background literature on prices and store choice

According to economic theory, prices influence choices because they constitute objective indicators of the monetary costs of purchasing (Monroe 2002).[1] 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 et al. 1998, Bell and Lattin 1998). Similarly, the prevailing *industry wisdom* is that (promotional) price changes drive store traffic (Urbany et al. 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 et al. 1998, Briesch et al. 2008). Similarly, individual-level analyses have revealed the segment of consumers who cross-shop to benefit from weekly price changes, to be very small (Gauri et al. 2008). This discrepancy has led some researchers to conclude that the impact of price has been over-estimated (Urbany et al. 2000).

However, it is not because one fails to uncover strong (immediate) effects, that actual prices are unimportant for store choice. For one, 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 their overall image 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 et al. 1975). Considered a distinct retail price dimension (Mägi and Julander 2005), several studies – indeed –

[1] For a recent model in economics with imperfect consumer price knowledge, see Carvalho (2009).

have found consumers' self-reported store price images one of the most important determinants of store patronage (Nielsen 2008, Arnold et al. 1983, Severin et al. 2001, Finn and Louviere 1990, 1996, 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 et al. (1988) and Büyükkurt (1986), 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 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 (Desai and Talukdar 2003, Büyükkurt 1986), but not the ensuing store choice effect. Others consider the impact of price image (Mazumdar et al. 2005, Mägi and Julander 2005), or of both actual prices and price image (van Heerde et al. 2008), but treat SPI 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 will be empirically investigated in subsequent sections. We note upfront that our emphasis is on store choice (or store traffic) as the dependent variable, and not on promotion-induced shifts in spending once the consumer is inside the store. Given that "store traffic is essential to retailer profitability" (Fox et al. 2009, p.709) and that stealing traffic from competitors is the primary reason for retailers to engage in temporary price cuts (Urbany et al. 2000), this perspective seems worthwhile.

3.2.2 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. 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 (Urbany et al. 1996, Gauri et al. 2008). 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 3.1: (1) convenience, (2) eye-for-detail, (3) big picture, (4) and combined use.

Store price images

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

Figure 3.1: Groups of price sensitive consumers based on use of basket prices and store price images.

'Convenience' shoppers correspond to the typical non-price sensitive grocery shoppers, whose store choice is driven by non-price marketing mix variables such as assortment (Briesch et al. 2008), or by convenience-factors such as distance (Gauri et al. 2008). Though these consumers may, as indicated by Gauri et al. (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 bother with 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 implied 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 temporal prices, or by splitting their purchases – 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 et al. (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. This process of price encoding need not be effortful or time consuming, and can even take place unconsciously (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 time costs, 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, outlined below, 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 SPI impact and formation (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.

3.3 Data and models

Since our approach benefits from the availability of a unique data set, we start with a brief description of these data. The models, and their estimation approach, are presented next.

3.3.1 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 variables, 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, 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 3.1 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 terms of 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.

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 3.2, 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

Table 3.1: 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 (m^2) 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.

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.

To illustrate the evolution of average price images, we zoom in on the HiLo market leader Albert Heijn and the EDLP chain Aldi. Table 3.3 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 3.2 and 3.3 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 conceptualization of SPI learning. In the next section, we propose a model of individual store choice that incorporates this learning mechanism.

3.3.2 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. After his visit to a store, the consumer will update his beliefs about the expensiveness of that store based on the prices encountered inside. Below, we first explain the store choice model, followed by our model of store price image updating.

Store choice

We model store choice through a random coefficients multinomial probit (MNP) model. On each shopping trip t, we observe consumer i's multinomial discrete store choice $y_{it} = s$ among S mutually exclusive stores (for $s = 1, \ldots, S$).[2] 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 choice, 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

[2] Throughout the paper we use store and retail chain, as well as shopping trip and time period, interchangeably. We consider only single-store shopping trips. See Vroegrijk, Gijsbrechts, and Campo (2010) for a recent study of multiple-store shopping trip behavior.

Table 3.2: 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).

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 $k = 1, \ldots, K$) and a normally distributed stochastic component ν_{its} representing the effect of unobservables. Formally,

$$u^*_{its} = w'_{its}\beta_i + \nu_{its}, \quad \nu_{its} \sim N(0, \Omega), \tag{3.1}$$

where Ω is a symmetric matrix, with non-zero off-diagonal elements. To solve the location identification problem present in (3.1) we use differences in utilities.[3] Specifically, we subtract the utility equation of an arbitrarily chosen store – the market leader – from each of the remaining $S - 1$ equations. The differenced utility equations can be written as follows

$$u_{its} = x'_{its}\beta_i + \varepsilon_{its}, \quad \varepsilon_{its} \sim N(0, \Sigma), \tag{3.2}$$

[3] The model in (3.1) has two identification problems. In particular, there is a locational and a scale indeterminacy, 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 in the case of an unrestricted Ω (see e.g. McCulloch and Rossi 1994). Note that there is no location identification problem if Ω is restricted to be diagonal. In that case, adding a scalar variable will change the covariance structure by adding correlation between choice alternatives and the elements of the diagonal of Ω are identified (Rossi, Allenby, and McCulloch 2005). Further restricting Ω to an identity matrix solves both identification problems. 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.

Table 3.3: Evolution of weekly prices and SPI within pricing formats

Period[a]	HiLo (Albert Heijn)		EDLP (Aldi)	
	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.

where each $u_{its} = u^*_{its} - u^*_{itS}$ denotes the differences with respect to the base alternative S and ε_{its} is a differenced error term. The vector x_{its} contains $S-1$ store-specific dummy variables for the store intercepts and K differenced marketing-mix variables for the sth store. Stacking together the $S-1$ equations of individual i in shopping trip t results in the following system of equations

$$u_{it} = X_{it}\beta_i + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \Sigma), \tag{3.3}$$

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

$$\beta_i \sim N(\mu_\beta, V_\beta). \tag{3.4}$$

Note that with a full Ω the model in (3.3) 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.[4] The model in (3.3), together with (3.4), is thus a multino-

[4]Our estimation results reveal the existence of non-zero, but negligible covariances in Ω.

mial probit (MNP) model with random coefficients.

The focal price variables are week-to-week prices, P_{its}, and 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 et al. (1998). While the price variables capture the variable cost of shopping (Bell et al. 1998), 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 visits ($y_{i,t-1,s}$). Given the set of selected variables, the utility function of a consumer i on shopping trip t at store s can be written as follows (recall that all values enter the utility function in differences),

$$\begin{aligned} u_{its} &= \beta_{0i}^{s} D_s + \beta_{1i} Dist_{is} + \beta_{2i} Assort_{is} + \beta_{3i} Loyal_{is} + \\ &+ \beta_{4i} P_{its} + \beta_{5i} MSPI_{i,t-1,s} + \beta_{6i} Feat_{its} + \beta_{7i} y_{i,t-1,s} + \varepsilon_{its}, \end{aligned} \tag{3.5}$$

where D_s is a dummy for store s and, as before, $\varepsilon_{its} \sim N(0, \Sigma)$. Further details on the variable operationalizations are given below. Equation (3.5) 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 (Leenheer, van Heerde, Bijmolt, and Smidts 2007, Gijsbrechts et al. 2008). Hence, the model already captures a rich pattern of choice dynamics based on consumer inertia and varied 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 (3.5) measure the same-period effect of prices on store choice, the dynamic effect of prices is captured through the formation of store price images – a process that we specify below.

SPI formation

We assume that consumers hold beliefs about the overall price level for each available store s. While the actual beliefs $\widetilde{SPI}_{its}$ are unobserved, the researcher does observe the (survey-based) categorical price perceptions $MSPI_{its}$. The latent variables $\widetilde{SPI}_{its}$ are mapped onto $MSPI_{its} = j$ if

$$\alpha_{j-1} < \widetilde{SPI}_{its} \leq \alpha_J, \quad j = 1, \ldots, J, \tag{3.6}$$

where α_j are cutoff points to be estimated, and with higher values of $\widetilde{SPI}_{its}$ linked to higher values of $MSPI_{its}$. It is further assumed that unobserved store price images $\widetilde{SPI}_{its}$ can be decomposed into (i) an idiosyncratic component SPI^*_{its}, representing consumers' price beliefs updated over time in a Bayesian fashion, as suggested by Feichtinger et al. (1988), and (ii) a disturbance term ξ_{its}, unobserved to the researcher but known to the consumer. Formally,

$$\widetilde{SPI}_{its} = SPI^*_{its} + \xi_{its}, \quad \xi_{its} \sim N(0, \sigma^2_{\widetilde{SPI}}), \tag{3.7}$$

where the disturbance term ξ_{its} is assumed to follow a standard normal distribution and to be independent of SPI^*_{its}. For identification, we set the variance $\sigma^2_{\widetilde{SPI}} = 1$. Together, (3.7) and (3.6) lead to the well-known ordered probit model.

Whenever a consumer visits a store, (s)he is exposed to in-store price information, which will be used to update current overall price level beliefs. To accommodate differences in the way price information signals the overall price level of the store, we specify individual-specific price signals, which are obtained as weighted averages. Formally, the price signals that consumers extract from or receive in store s in period t, are assumed to be normally distributed around observed prices in that store, with a constant variance $\sigma^2_{\eta_i}$ across stores and over time, i.e.

$$P^*_{its} = P_{its} + \eta_{its}, \quad \eta_{its} \overset{\text{i.i.d.}}{\sim} N(0, \sigma^2_{\eta_i}) \tag{3.8}$$

and thus $P^*_{its} \sim N(P_{its}, \sigma^2_{\eta_i})$. The stochastic term η_{its} is observed by the consumer but not by the researcher.

Consumers are assumed to learn about a store's overall price level according to a Bayesian rule that combines (i) their prior expensiveness beliefs, with (ii) the available price information in each period, into an updated or posterior belief. With prior beliefs and price signals normally distributed, consumer i's posterior belief about the overall expensiveness of store s at time t also follows a normal distribution (see e.g. Gelman et al. 2004), i.e. $SPI^*_{its}|(.) \sim N(SPI_{its}, \sigma^2_{SPI_{its}})$,[5] with mean and variance, respectively,

$$SPI_{its} = \sigma^2_{SPI_{its}} \left(\frac{1}{\sigma^2_{SPI_{i,t-1,s}}} SPI_{i,t-1,s} + \frac{1}{\sigma^2_{\eta_i}} P^*_{its} \right) \tag{3.9}$$

[5] To keep notation simple, we use (.) to summarize all price information available in each period.

and[6]

$$\sigma^2_{SPI_{its}} = \left(\frac{1}{\sigma^2_{SPI_{i,t-1,s}}} + \frac{1}{\sigma^2_{\eta_i}}\right)^{-1}. \tag{3.10}$$

The posterior mean of the store price belief in (3.9) is a weighted average of the prior mean belief and the overall price signal. Similarly, the weights are proportional to the precision of the prior belief and the precision of the overall price signal, respectively $1/\sigma^2_{SPI_{i,t-1,s}}$ and $1/\sigma^2_{\eta_i}$. The individual-specific overall price signal variances $\sigma^2_{\eta_i}$ are model parameters to be estimated, and their reciprocals (i.e. the precisions $1/\sigma^2_{\eta_i}$) represent the consumer price learning rates or, stated differently, how much prices affect the formation of consumers' price perceptions. Together with Equations (3.1) to (3.8), the Bayesian updating equations (3.9) and (3.10) complete the specification of our dynamic store choice model with store price image formation over time.

3.3.3 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 (see Gelfand and Smith 1990) to draw from the full conditional posteriors of the parameters. As mentioned above, a scale identification problem remains in the MNP model in (3.3). This Bayesian approach 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 then 'margin down' or 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 et al. 2005)[7]

$$\tilde{\beta} = \frac{\beta}{\sqrt{\sigma_{11}}}, \qquad \tilde{\Sigma} = \frac{\Sigma}{\sigma_{11}}. \tag{3.11}$$

The advantage of this approach is the simplicity of the sampler needed and its good mixing properties (Rossi et al. 2005), as all draws are sampled from familiar distributions (e.g. with $\sigma_{11} = 1$ imposed in the prior, the posterior of the precision matrix would no longer have a standard Wishart distribution). The exact expressions of the full conditional posterior distributions of the unknowns in the random coefficients MNP component are derived in 3.A.

[6] We adopt the usual assumption that the perceptual error variance $\sigma^2_{SPI_{its}}$ is independent of the disturbance terms ξ_{its}.

[7] 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). Another approach, described in McCulloch, Polson, and Rossi (2000) and Imai and van Dyk (2005), is to put a prior directly on the set of identified parameters, which requires a prior on the set of covariance matrices with the first element equal to 1.

As indicated above, a unique feature of our data set is that we have 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 estimate the SPI formation model in Equations (3.6) to (3.10) we again rely on Bayesian estimation procedures. The complete conditional posterior distribution of the beliefs $S\widetilde{P}I_{its}$ follows a truncated normal with the threshold parameters in Equation (3.6) as truncation points. These threshold parameters, in turn, are drawn from a uniform distribution. Finally, the M-H algorithm is used to estimate the learning parameters $\sigma^2_{\eta_i}$ with a candidate normal density (for details and the complete derivation of these posteriors, see Chapter 2).

3.4 Variable operationalization and estimation results

3.4.1 Variable operationalization

We use data on the households' shopping histories to generate the dependent variable for the store choice model, 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 et al. (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.[8] 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, $MSPI_{its}$, is based on the 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 et al. (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

[8] 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 van Heerde et al. 2008, Fox et al. 2004, 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 et al. 2008).

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 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.

3.4.2 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.[9] 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 3.4). Visual inspection suggests convergence of both the individual and the mean parameters (Fig. 3.2 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.

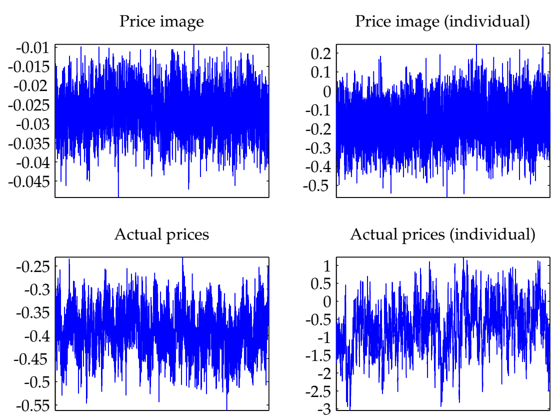

Figure 3.2: Gibbs sampler draws for the mean parameter (right panel) for price images (top panel) and actual prices (bottom panel), after discarding first 10000 draws for burn-in. For illustrative purposes, the left panel plots draws for the two types of price information of one particular household.

Table 3.4 reports the identified quantities $\tilde{\beta} = \beta/\sqrt{\sigma_{11}}$ and $\tilde{\Sigma} = \Sigma/\sigma_{11}$ (see Equation (3.11)) 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 3.4). Only for Dekamarkt

[9]The details about the priors used and initial values can be found in Appendix 3.A.

the 95% highest posterior density (HIPD) of the intercept includes zero.[10] 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 3.4 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 has a positive effect on store patronage: stores with bigger assortments (as measured by store floor space) having 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 outlets. 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. Furthermore, its effect may be taken up by price changes.

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 3.3. These histograms point to quite some dispersion (see also Table 3.4) – 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.

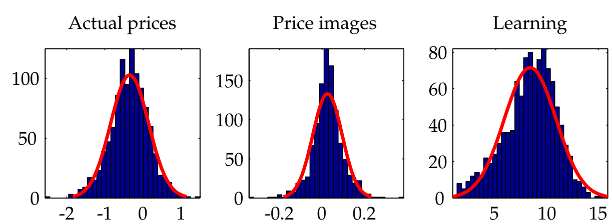

Figure 3.3: Histograms (with normal curve) of households' posterior means for SPI, actual prices, and price learning parameters (discarding burn-in draws).

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

Table 3.4: Posterior results for the MNP model and SPI thresholds

	Mean	S.d.	2,5%	50%	97,5%	diag(Σ)
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	

[a] For identification, α_0, α_1, and α_9 are set equal to $-\infty$, 0, and $+\infty$, respectively.

SPI formation

The estimates for the threshold parameters that allow mapping unobserved beliefs $\widetilde{SPI}_{its}$ into the observed, discrete $MSPI_{its}$ (see Equation (6)) are summarized in the third panel of Table 3.4. 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, and α_9 are set to $-\infty$, 0, and $+\infty$, respectively).[11] 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%).[12] The distribution of the price learning parameters across all households is depicted in the right panel of Figure 3.3.

[11] We used the estimated category- and individual-specific learning parameters from the model specified in Chapter 2. Hence, for the purposes of the current chapter, where the SPI formation model is based on one overall price signal $\sum_c w_{c,i} P^*_{cst}$, the individual-specific learning parameters are obtained by making

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.

3.5 Profiling price and price-image sensitive households

To this end, 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 3.5 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 3.6 lists the regression results. Note that a negative (positive) sign represents an increase (decrease) in the sensitivity towards the two types of price information and a decrease in learning (which is regressed directly as $1/\sigma^2_{\eta_i}$; see Equation 3.9). 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 image, or the strength with which these are updated based on price signals – corroborating that different households react to the different price cues. For clarity of exposition, we discuss the effects by type of variable, and describe only those effects that are significant.

3.5.1 Attitude towards prices and price cuts

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 purchases 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

$\sigma^2_{\eta_i} = \sum_c w^2_{c,i}\sigma^2_{\eta_{c,i}}$.

[12]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.

Table 3.5: 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.

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' ($\gamma = .0277; p < .05$).

3.5.2 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 3.6 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.

3.5.3 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 ($\gamma = .1654; p < .05$), buy smaller baskets ($\gamma = .0043; p < .05$), buy more private labels ($\gamma = -.0143; p < .05$), and are less brand-loyal ($\gamma = .0338; p < .05$); observations that do not hold for SPI-sensitive households. Also, weekly-price sensitive shoppers buy more brands that others will adopt ($\gamma = -.0535; p < .01$), while SPI-sensitive shoppers tend to try less new brands($\gamma = .0054; p < .01$). Households that never visited the high-price high-service chain leader in the market, are significantly more sensitive to weekly prices ($\gamma = -.3040; p < .01$) and to SPI ($\gamma = -.0140; p < .01$) 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 ($\gamma = -.0362; p < .1$), whereas higher SPI sensitivity is associated with Het Parool ($\gamma = -.0078; p < .05$), a newspaper associated with more liberal views.

Table 3.6: 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. *$p< 0.1$; **$p< 0.05$; ***$p< 0.01$. Complete results are reported in the Appendix.

3.6 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 cue? 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.

3.6.1 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 responsive to the price cue) or not (non-responsive). 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.

Store price images

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

Figure 3.4: Distribution of price sensitive consumers based on use of basket prices and store price images.

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 3.4). 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.

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 et al. 2000). At the same time, several authors suggest that far fewer consumers *actually* cross-shop to benefit from price deals (e.g. Urbany et al. 2000, Bodapati and Srinivasan 2001, Urbany, Dickson, and Key 1991). 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 3.7, 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, Pauwels, Hanssens, and Dekimpe 2004).

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 3.7, 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 3.7), 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.

3.6.2 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

Table 3.7: 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[b]						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).

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 3.8, 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 et al. 2009) – and amounts to approximately .70.

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 that does not account for the dynamic formation of store perceptions, clearly underestimates the impact of a price cut, and disproportionately so among specific consumer 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.

3.7 Conclusions, limitations and future research

3.7.1 Conclusions

In this chapter, 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 overshad-

Table 3.8: Effects of permanent price changes on store traffic across segments (HiLo format)[a]

	Δ in price	SPI ↑ trips	SPI % total	Price ↑ trips	Price % total	Both ↑ trips	Both % total	Sum of 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.

owed 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 these price-sensitive consumers keep track of actual weekly prices and use those to adjust their weekly store patronage. The other half tailor their store selection to overall beliefs about the store's 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 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 et al. (2009). While those authors already documented the presence of lagged price effects, we offer a structural 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. Hoch et al. 1995, Gauri et al. 2008), 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 that, 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 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.

3.7.2 Limitations and future research

Clearly, our study exhibits a number of limitations, that set the stage for future research. For one, 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 also appear in other categories such as apparel or consumer durables – an issue that 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 advertising or 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 retail instrument.

3.A Complete conditional posteriors

Priors

$$\Sigma^{-1} \sim W(\nu_0, H_0) \tag{3.A-1}$$

with $\nu_0 = 100$ and $H_0 = I_{S-1}$.

$$\beta_i \sim N(\mu_\beta, V_\beta) \tag{3.A-2}$$

Second stage:

$$\mu_\beta \sim N(\mu_{\beta 0}, \Sigma_{\beta 0}) \tag{3.A-3}$$

with $\mu_{\beta 0} = \mathbf{0}_{(S-1)\times K}$ and $\Sigma_{\beta 0} = 500 \cdot I_{(S-1)\times K}$. And

$$V_\beta^{-1} \sim W(\nu_{\beta 0}, V_{\beta 0}^{-1}) \tag{3.A-4}$$

with $\nu_{\beta 0} = (S-1) \times K + 4$ and $V_{\beta 0} = \nu_{\beta 0} \cdot I_{(S-1)\times K}$.

Gibbs sampler

For the latent utilities:

$$u_{its} | u_{it,-s}, \Sigma^{-1}, \beta, \mu_\beta, V_\beta \sim N(m_{its}, \tau_{ss}^2), \tag{3.A-5}$$

where

$$m_{its} = x'_{its}\beta_i + F'(u_{it,-s} - X_{it,-s}\beta_i), \quad F = -\sigma^{ss}\gamma_{s,-s}, \quad \text{and} \quad \tau_{ss}^2 = 1/\sigma^{ss}, \tag{3.A-6}$$

where σ^{js} denotes the (js)th element of Σ^{-1} and $\gamma_{s,-s}$ refers to the sth 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:

$$\beta_i | u, \Sigma^{-1}, \mu_\beta, V_\beta \sim N(\beta_{i1}, V_{i1}), \tag{3.A-7}$$

where

$$V_{i1} = \left(\sum_{t=1}^{T_i} X'_{it}\Sigma^{-1}X_{it} + V_\beta^{-1} \right)^{-1} \quad \text{and} \quad \beta_{i1} = V_{i1}\left(\sum_{t=1}^{T_i} X'_{it}\Sigma^{-1}u_{it} + V_\beta^{-1}\mu_\beta \right). \tag{3.A-8}$$

For the mean of the parameters:

$$\mu_\beta | u, \Sigma^{-1}, \beta, V_\beta \sim N(\mu_{\beta 1}, \Sigma_{\beta 1}), \tag{3.A-9}$$

where

$$\Sigma_{\beta 1} = \left(\Sigma_{\beta 0}^{-1} + NV_{\beta 1}^{-1} \right)^{-1} \quad \text{and} \quad \mu_{\beta 1} = \Sigma_{\beta 1}\left(\Sigma_{\beta 0}^{-1}\mu_{\beta 0} + V_{\beta 1}^{-1} \sum_{i=1}^{N} \beta_i \right). \tag{3.A-10}$$

For the variance of the parameters:

$$V_\beta^{-1}|u, \Sigma^{-1}, \beta, \mu_\beta \sim W(\nu_{\beta 1}, V_{\beta 1}^{-1}), \tag{3.A-11}$$

where

$$\nu_{\beta 1} = \nu_{\beta 0} + N \quad \text{and} \quad V_{\beta 1}^{-1} = \left[(V_{\beta 0}^{-1})^{-1} + \sum_{i=1}^{N} (\beta_i - \mu_\beta)(\beta_i - \mu_\beta)' \right]^{-1}. \tag{3.A-12}$$

For the variance of the utilities:

$$\Sigma^{-1}|u, \beta, \mu_\beta, V_\beta \sim W(\nu_1, H_1), \tag{3.A-13}$$

where

$$\nu_1 = \nu_0 + \sum_{i=1}^{N} T_i \quad \text{and} \quad H_1 = \left[H_0^{-1} + \sum_{i=1}^{N} \sum_{t=1}^{T_i} (u_{it} - X_{it}\beta_i)(u_{it} - X_{it}\beta_i)' \right]^{-1}. \tag{3.A-14}$$

Starting values:
$\Sigma^{-1} = I_{S-1}$, $\beta_i = \mathbf{1}_{(S-1)\times K}$ (for all i), $\mu_{\beta 1} = \mathbf{1}_{(S-1)\times K}$, $V_{\beta 1}^{-1} = I_{(S-1)\times K}$, and $u = \mathbf{0}_{\sum_{i=1}^{N} T_i \times 1}$.
The model was coded and estimated in Matlab.

3.B Profiling price and SPI-sensitive consumers: Full results

Table 3.9: Explaining SPI and basket price sensitivities, and learning[a]

	PRICE		PRICE IMAGE		LEARNING	
	$\widehat{b}$	t-stat	$\widehat{b}$	t-stat	$\widehat{b}$	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
R^2	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. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Chapter 4

The Impact of National Brand Introductions on Price and Quality Images of Discounters: An Exploratory Analysis

4.1 Introduction[§]

Sales of the top 10 discounters in the world are expected to grow by 50% in the next five years (Planet Retail 2010). By then, the German-based retailers Aldi and Lidl, pioneers of the hard discount concept and ranking number one and two on the top-10 discounter chart, are both expected to hit the $U.S. 100 billion mark (Planet Retail 2010). This remarkable success of hard discount retailers is rooted in their ability to practice low prices – 15 to 20% lower than those of large discounters like Wal-Mart (Wall Street Journal 2010). Compared to traditional retailers, hard discount stores focus on minimal assortments (between 1,000 and 1,500 SKUs, compared to 30,000 for an average U.S. supermarket), rely heavily on own brands, and use a simplified 'no-frills' store format with little promotional and merchandizing activity; strategic options that translate into cost efficiencies in the supply-chain. Not surprisingly, these hard discounters have acquired a substantial share of grocery sales at the expense of mainstream retailers in Western Europe, and are consistently growing in the U.S. (Steenkamp and Kumar 2009, Cleeren, Verboven, Dekimpe, and Gielens 2009, Planet Retail 2010).

Nonetheless, hard discount chains have realized that growth strategies based on prices are not without limits, and that an overreliance on price-based competition

[§]This chapter is based on joint work with Els Gijsbrechts (Tilburg University), under 2nd round review in *International Journal of Research in Marketing*.

makes them vulnerable to incoming discounters. Partly due to this realization, hard discounters are increasingly introducing national brands (NBs) into their merchandizing offer. At Lidl, 30% of the assortment is now composed of NBs, roughly the same percentage as their contribution to total sales (Steenkamp and Kumar 2009). Aldi, which not long ago had only private labels in its assortment, now lists well-known manufacturer brands in several product categories and markets, such as PepsiCo's Quaker oat, Kraft's Oscar Mayer hot-dogs or Dole's fresh fruit in the U.S. – to name just a few. For manufacturers, presence on the hard discounters' shelves is an opportunity to alleviate their dependency on mainstream retailers, who have extensively developed their own private label lines (Ailawadi et al. 2008), and have put increased pressure on national brand margins to compete with the discounters' success (Bloom and Perry 2001).

Despite its strategic importance for both manufacturers and retailers (ter Braak, Deleersnyder, Geyskens, and Dekimpe 2010), little is known about the impact of NB introductions at hard discount stores. In an interesting recent study, Deleersnyder et al. (2007) show that such introductions may entail win-win implications: enabling NBs to grow their share relative to competing brands, and hard discounters to gain share in the product category. However, the focus of that study is on *short term sales effects*. An important, yet unaddressed question is whether and how NB introductions – so directly at odds with the core positioning of the hard-discounter format – affect consumers' *long lasting* perceptions of these chains. If carrying more NBs changes the hard discounters' price or quality image, this is likely to affect their performance in the long run. Indeed, consumer perceptions are enduring (Gijsbrechts 1993), and are shown to be key drivers of store choice and spending (e.g. Cox and Cox 1990, Srivastava and Lurie 2004, van Heerde et al. 2008). Moreover, our findings in Chapter 3 suggest that this is particularly true for hard-discounter shoppers. If, as advocated in a recent Nielsen report, "Good Value is a Matter of the Mind" (Nielsen 2008, p.6), then hard discounters have an interest in tracing the effect of higher NB presence, on their price and quality image.

This paper aims to address that issue. Since national brands (i) are typically regarded by consumers as having higher quality than their private label counterparts, but (ii) are, on average, more expensive (Kumar and Steenkamp 2007, Ailawadi et al. 2008, Geyskens et al. 2010), the shift in the discounter stores' assortment strategy is expected to improve their quality image, to the detriment of their price image. We empirically test for the presence and size of these effects, using a unique data set that combines longitudinal information on a hard discounter's price and quality perceptions, with that chain's assortment composition over time. In so doing, we control for the potential correlation between the two types of perceptions.

The remainder of the paper is organized as follows. In the next section, we briefly review the relevant literature, and develop the conceptual framework. Section 3 describes the methodology. Data and variable operationalizations are discussed in Section 4, while the empirical results are presented in Section 5. Section 6 discusses the findings and limitations, together with suggestions for future research.

4.2 Conceptual framework

4.2.1 Literature background

Store image plays a pivotal role in retailers' strategies. Since at least Martineau's (1958) seminal work, a plethora of studies has demonstrated the importance of store image for retailer segmentation (Steenkamp and Wedel 1991) and positioning (Pessemier 1980), as well as its influence on consumer store choice and spending (e.g. Nielsen 2008, van Heerde et al. 2008).

Defined as the way the store is perceived in the shopper's mind (Martineau 1958), the conceptualization of store image rests upon three important aspects (see Ailawadi and Keller 2004, for a recent review of retailer image research). First, store image is typically seen as a multidimensional construct, with price and quality (of the assortment) as its core dimensions (Mazursky and Jacoby 1986, Hildebrandt 1988). Second, the formation of a retailer's (price and quality) image is commonly described as an evolving, dynamic process (Mazursky and Jacoby 1986, Büyükkurt 1986, Nyström et al. 1975) – perceptions being updated as new information comes in. Finally, given the complexity of the store offer, consumers have only incomplete information and are uncertain about retail stores, thus resorting to available (intrinsic or extrinsic) perceptual cues when inferring the retailer's overall price and quality (Feichtinger et al. 1988, Mägi and Julander 2005).

In this regard, manufacturer brands are seen as particularly important *extrinsic* cues for retailers (Ailawadi and Keller 2004). Compared to intrinsic cues (e.g. smell, taste and texture), extrinsic product cues, namely *brands* and *prices*, have repeatedly been found to explain a larger variance in perceptions of consumer packaged goods (Grewal, Krishnan, Baker, and Borin (1998), Dawar and Parker (1994), Allison and Uhl (1964); c.f. Collins-Dodd and Lindley (2003)). Brands are often referred to as one of the most important cues for consumers in contexts of uncertainty (e.g. Erdem, Swait, and Valenzuela 2006, Erdem and Swait 1998), as they communicate an array of complex information generated by their characteristics and by advertising and word-of-mouth (Stokes 1985).

Brands are usually deemed informative about quality, as quality is often perceived with uncertainty (Zeithaml 1988, Richardson et al. 1994). In a store context, however, where prices vary over time and across products and price information is therefore complex and ambiguous, consumers may be uncertain about a store's overall expensiveness too (Alba et al. 1994). In such a setting, the presence of known brands may also prove helpful in the formation of price perceptions (Monroe et al. 1991, Biswas et al. 1993). Consistent with these insights from cue utilization theory and rooted in information economics (Arrow 1963, Akerlof 1970, Spence 1973), (national) brands and the products they identify may be used to inform consumers about the overall price and quality of a discounter.[1]

4.2.2 Conceptual framework

Having more national brands in its assortment influences the hard discounter's price and quality perceptions in several ways, as schematically outlined in Figure 1. First, unless they simply replace previously offered own labels, national brand introductions may enlarge the hard discounter's assortment – adding more SKUs to the retailer's offer. Such an increase in assortment size could enhance the consumer's overall perception of quality offered by the store (Oppewala and Koelemeijer 2005)('+' effect in Figure 4.1). It could also influence its perceived cost of operation, leading to higher expected prices (or: a less favorable price image and hence a '–' effect in Figure 4.1).

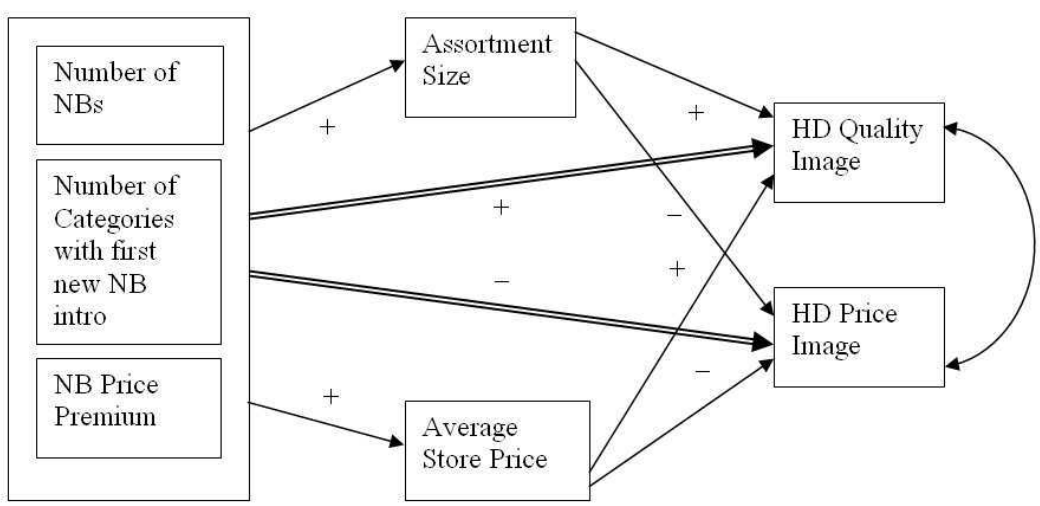

Figure 4.1: Conceptual framework and hypothesized effects of NB introductions on Hard Discounters.

Second, national brands are typically more expensive than private labels, with price premiums in U.S. supermarkets of approximately 25-30% (Ailawadi et al. 2001, Hoch and Lodish 2001). Hence, these NB introductions will lead to an increase in the store's *average actual price*. This, in turn, will negatively affect its overall price im-

[1] Aldi's US website features a set of questions – "Does ALDI carry brand names?" and "If you don't have the brands I know, how can I be sure of the quality?," – that reflects precisely these issues of uncertainty and consumer perceptions and the use of national brands' names as informative cues (Aldi 2010).

age (Mägi and Julander 2005)('–' impact in Figure 4.1), and may act as a quality signal ('+' impact on quality image in Figure 1). Thus, adding national brands may entail changes in the hard discounter's assortment size and average price level that lead consumers to update their quality and price perceptions of the store. However, we expect a greater presence of NBs on the hard discounter's shelves to affect its quality and price image over and above these two mechanisms.

Third, NBs – in contrast with the own labels carried by hard discounters – invest heavily in their 'aura of uniqueness and high quality' (Geyskens et al. 2010), and are typically perceived to have higher quality than private labels (Kumar and Steenkamp 2007). Being such 'beacons of quality', they are likely to enhance the perceived quality of the hard discounter's offer, over and above the mere effect of assortment size. Hence, we expect that as the *number of NBs in the assortment* goes up, so will the hard discounter's quality image ('+' effect in Figure 4.1). At the same time, consumers are aware that NBs come at a price premium. Hence, even shoppers who do not inspect actual store prices, and whose store price image is thus not affected by the increase in the average price of the store, may use the stronger presence of national brands as a cue for higher expensiveness ('–' impact on price image, in Figure 4.1).

Fourth, while a stronger presence of NBs in the hard discounter's assortment may produce an enduring shift in its quality and price perceptions, extra – yet temporary – shifts may come about *at the time* of the NB introduction. Such 'pulse' effects may arise because the introduction shakes consumers out of their inertia, leading them to revise their quality and price images of the store. At the same time, the impact may be temporary either because consumers over-react to the NB introduction initially – readjusting their beliefs as more information comes in – or because, after taking in the new brand information at first, 'forget' about their signaling value, and partly revert to their previous quality and price perceptions (see e.g. Mehta, Rajiv, and Srinivasan 2004, for evidence of consumer learning and forgetting). Such (temporary) shocks are expected to be particularly likely if the NB introduction is more 'disruptive' (van Heerde, Mela, and Manchanda 2004), i.e. if it is the first NB in its category. Hence, we expect NB introductions that increase the *number of categories with NB presence*, to have a more positive (negative) effect on store quality (price) image, at the time of introduction ('+' and '–' arrows in Figure 4.1, respectively).

Finally, the size of the quality and price perception adjustment may further depend on the magnitude of the *price premium charged by the NB* (Deleersnyder et al. 2007). Consumers' response to price changes may be nonlinear (Monroe 1973, Pauwels et al. 2007), in that large price differentials may generate disproportionate reactions. Large price premiums are more likely to be spotted, and – hence – may further enhance the signal of quality and expensiveness ('+' impact on quality image, '–' impact of price image, in Figure 4.1). The latter impact may be dampened, however, by a contrast effect (see e.g. Pauwels et al. 2007): to the extent that the price premium of newly introduced NBs over their category PL counterparts becomes higher, this may shift the hard discounter shoppers' reference price upward and make private label prices appear even lower than before. Especially for shoppers with a primary interest in private labels, this may offset the negative effect of NB price premiums on the overall store price image.

Figure 4.1 summarizes the hypothesized effects of these explanatory factors. It also indicates that store price and quality perceptions may be correlated directly, over and above the joint effect of these factors. On the one hand, more expensive (less favorable) price image perceptions may trigger perceptions of high quality at the store (in our framework, this would result in negatively correlated price and quality images). Evidence of such correlations has been found in the (cross-sectional) store image studies of e.g. Baker et al. (2002), Grewal et al. (1998). On the other hand, favorable attitudes towards a store may result in a 'halo' effect (Thorndike 1920, Holbrook 1983). Based on that mechanism, a positive correlation could result: consumers holding a high quality image of the HD chain, also associating it with a favorable (low) price image (in our framework, this would result in positively correlated price and quality images). In the methodology outlined below, we will acknowledge such possible price-quality image correlations.

4.3 Methodology

To investigate the effects of NB introductions on a discounter's price and quality images simultaneously, we use a bivariate ordered probit (BIOPROBIT) model, which naturally accommodates a possible correlation between two dependent variables. The model is particularly suited for our purposes, as it allows for the simultaneous analysis of two discrete and ordered dependent variables, like the price and quality perception ratings obtained from our surveys. Before applying this model to our data, we explain its features and estimation below.[2]

[2] Alternatively, we could consider a structural learning model, in which consumers use national brand signals for store price and quality image formation. However, such a model would be quite complicated. For one, it would involve simultaneous updating for two ordinal, correlated, dependent variables. In addition, next to the observed price signals, there would be a multitude of brand signals related with the introduction and/or the consumption of NBs and private labels. Given the nature of our data, it is unlikely that we would be able to obtain stable estimates for such a complex dynamic model. Hence, we opt for a more exploratory approach, based on aggregate store price and assortment characteristics over time.

4.3.1 Model specification

Let $MSPI_{ist}$ denote consumer i's self-reported overall *price* image about store s in period t, which can take on values $j = 1, \ldots, J$, and $MSQI_{ist}$ denote the same consumer's self-reported overall *quality* image about the same store and in the same period, which can take on values $k = 1, \ldots, K$.[3] We assume that self-reported images are the result of latent, unobserved price and quality perceptions in consumers' minds. We denote these, respectively, by $S\widetilde{P}I_{ist}$ and $S\widetilde{Q}I_{ist}$. The latent variables get mapped onto the self-reported overall perceptions according to the following scheme

$$MSPI_{ist} = \begin{cases} 1 & \text{if } S\widetilde{P}I_{ist} \leq \alpha_{p,1} \\ 2 & \text{if } \alpha_{p,1} < S\widetilde{P}I_{ist} \leq \alpha_{p,2} \\ \vdots & \\ J & \text{if } \alpha_{p,J-1} < S\widetilde{P}I_{ist} \end{cases} \tag{4.1}$$

and

$$MSQI_{ist} = \begin{cases} 1 & \text{if } S\widetilde{Q}I_{ist} \leq \alpha_{q,1} \\ 2 & \text{if } \alpha_{q,1} < S\widetilde{Q}I_{ist} \leq \alpha_{q,2} \\ \vdots & \\ K & \text{if } \alpha_{q,K-1} < S\widetilde{Q}I_{ist} \end{cases} \tag{4.2}$$

where $\alpha_{p,j}$ and $\alpha_{q,k}$ are unknown cutoff or threshold parameters for the price and quality perceptions, respectively (for all j and k), that satisfy the conditions $\alpha_{p,1} < \alpha_{p,2} < \ldots < \alpha_{p,J-1}$ and $\alpha_{q,1} < \alpha_{q,2} < \ldots < \alpha_{q,K-1}$. For identification, purposes $\alpha_{p,0} = \alpha_{q,0} = -\infty$ and $\alpha_{p,J} = \alpha_{q,K} = \infty$. We specify the equations of the unobserved store price and quality perceptions as follows

$$\begin{array}{rcl} S\widetilde{P}I_{ist} & = & \beta_p x_{p,ist} + \epsilon_{p,ist} \\ S\widetilde{Q}I_{ist} & = & \beta_q x_{q,ist} + \epsilon_{q,ist} \end{array}, \tag{4.3}$$

where β_p and β_q are the vectors of parameters governing the effect of the explanatory variables in the vectors $x_{p,ist}$ and $x_{q,ist}$ on $S\widetilde{P}I_{ist}$ and $S\widetilde{Q}I_{ist}$, and $\epsilon_{p,it}$ and $\epsilon_{q,ist}$ are the error terms of the price and quality equations, respectively. The error terms are supposed to be independent of the vectors of exogenous explanatory variables and are assumed to follow a standard bivariate normal distribution, i.e. (with variances set to one for identification):

$$\begin{pmatrix} \epsilon_{p,ist} \\ \epsilon_{q,ist} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right]. \tag{4.4}$$

The correlation ρ between $\epsilon_{p,ist}$ and $\epsilon_{q,ist}$ is unknown and is therefore a parameter to be estimated. The different combinations of the perceptual values are determined by

[3] Note that the response values of both measures need not to be the same. In our case, however, both price and quality perceptions were measured with a Likert scale from 1 to 9.

using the threshold values that define the areas of the bivariate normal density associated with each particular combination (Selezneva 2008). Given that the thresholds are not fixed *a priori*, such 'discrete' distribution is thus able to accommodate a variety of shapes, skewed or multi-modal, commonly found in discrete ordinal data.[4] The probability of a combination of perceptual levels $\{j,k\}(j = 1, 1, \ldots, J; k = 1, 2, \ldots, K)$ for a particular consumer i and store s in period t is then (see e.g. Greene and Hensher 2009):

$$\begin{aligned} Pr(MSPI_{ist} = j, MSQI_{ist} = k) &= Pr(\alpha_{p,j-1} < S\widetilde{P}I_{ist} \leq \alpha_{p,j}, \alpha_{q,k-1} < S\widetilde{Q}I_{ist} \leq \alpha_{q,k}) \\ &= Pr(S\widetilde{P}I_{ist} \leq \alpha_{p,j}, S\widetilde{Q}I_{ist} \leq \alpha_{q,k}) \\ &- Pr(S\widetilde{P}I_{ist} \leq \alpha_{p,j-1}, S\widetilde{Q}I_{ist} \leq \alpha_{q,k}) \\ &- Pr(S\widetilde{P}I_{ist} \leq \alpha_{p,j}, S\widetilde{Q}I_{ist} \leq \alpha_{q,k-1}) \\ &+ Pr(S\widetilde{P}I_{ist} \leq \alpha_{p,j-1}, S\widetilde{Q}I_{ist} \leq \alpha_{q,k-1}). \end{aligned} \tag{4.5}$$

In terms of the standard bivariate normal probability density $\phi_2(\cdot)$ and cumulative $\Phi_2(\cdot)$ distribution functions, and using the specified perceptual equations in (4.3), the joint probability can be written as follows (see e.g. Greene and Hensher 2009):

$$\begin{aligned} Pr(MSPI_{ist} = j, MSQI_{ist} = k) &= Pr(\alpha_{p,j-1} < S\widetilde{P}I_{ist} \leq \alpha_{p,j}, \alpha_{q,k-1} < S\widetilde{Q}I_{ist} \leq \alpha_{q,k}) \\ &= \int_{\alpha_{q,k-1}-\beta_q x_{q,ist}}^{\alpha_{q,k}-\beta_q x_{q,ist}} \int_{\alpha_{p,j-1}-\beta_p x_{p,ist}}^{\alpha_{p,j}-\beta_p x_{p,ist}} \phi_2(\epsilon_{p,ist}, \epsilon_{q,ist}, \rho) d\epsilon_{p,ist} d\epsilon_{q,ist} \\ &= \Phi_2(\alpha_{p,j} - \beta_p x_{p,ist}, \alpha_{q,k} - \beta_q x_{q,ist}, \rho) \\ &- \Phi_2(\alpha_{p,j-1} - \beta_p x_{p,ist}, \alpha_{q,k} - \beta_q x_{q,ist}, \rho) \\ &- \Phi_2(\alpha_{p,j} - \beta_p x_{p,ist}, \alpha_{q,k-1} - \beta_q x_{q,ist}, \rho) \\ &+ \Phi_2(\alpha_{p,j-1} - \beta_p x_{p,ist}, \alpha_{q,k-1} - \beta_q x_{q,ist}, \rho). \end{aligned} \tag{4.6}$$

Hence, the log-likelihood function to be maximized is given by:

$$\ln L = \sum_{t=1}^{T_i} \sum_{i=1}^{N} \sum_{j=1}^{J-1} \sum_{k}^{K-1} I(MSPI_{ist} = j, MSQI_{ist} = k) \ln Pr(MSPI_{ist} = j, MSQI_{ist} = k), \tag{4.7}$$

where $I(\cdot,\cdot)$ is an indicator function, N is the number of consumers, and T_i is the number of observations for consumer i. The parameters to be estimated are the $J + K - 2$ cutoffs α, the β's of both equations in (4.3), and the correlation ρ. In our empirical analysis, the vectors $x_{p,ist}$ and $x_{q,ist}$ include the same set of variables – as discussed next.

4.3.2 Data and operationalizations

Our empirical analysis focuses on one of the most successful hard discounters in the world, the German-based Lidl, part of the Schwarz Group. Lidl's group is the fifth

[4] In our case, the distribution of quality perceptions is bi-modal.

largest food retailer worldwide after Carrefour, Metro Group (Germany), Tesco and Wal-Mart, and ranks second on the chart of discounters (Planet Retail 2010). A family-run business, Lidl opened its first discount store in 1973, copying the concept of its main competitor, Aldi, also born in Germany. Lidl has been growing ever since and, in the last 15 years, opened new stores at the rate of one per day (Nielsen 2008). Operating approximately 8000 stores in over 20 countries worldwide, Lidl reached more than $U.S. 69 billion dollars in sales in 2007 (Delloite 2009) and is expected to soon hit the $U.S. 100 billion mark (Planet Retail 2010). Industry experts forecast the entry of Lidl stores in the U.S. and/or Canada in 2012.

We use data from Lidl's operations in The Netherlands, which despite its small size, is the country with the fifth most Lidl stores. With a consistent growth over the last few years, Lidl's share in the Dutch market has reached about 4%. Especially after the long price war among Dutch retail chains that started in 2003, discounters have occupied a space traditionally reserved for mainstream retailers, and consumers have adjusted their overall perceptions of incumbent supermarkets (van Heerde et al. 2008). Against this backdrop, it seems particularly relevant to explore how (if at all) carrying national brands affects consumers' price and quality perceptions about the discounter.

Dependent variables: Price and quality perceptions

We have information on consumer perceptions of store price and quality, measured on an ordinal scale from 1 (= least favorable) to 9 (= most favorable).[5] These survey data refer to a GfK panel of 4400 households that represent a stratified sample of The Netherlands. The data cover a period of five years, from January 2002 to December 2006. They were collected semiannually by GfK, based on store intercept interviews. Each of the 11 survey waves was conducted during one week, allowing households to judge the overall price level and perceived quality of more than one store and more than once – depending on how many stores were visited in that week, and how often. Except for the wave that took place in week 5 in 2004, surveys were conducted in weeks 16 and 40 of every year.

Table 4.1 (see the first four inner columns) and Figure 4.2 show the evolution of the price and quality perceptions about Lidl ($PriceImage_{ist}$, $QualityImage_{ist}$), averaged across households . Although more heterogeneous, average price perceptions are more favorable than their quality counterpart over the entire period of analysis – consistent with the prevalent perceived positioning of hard discounters. The price-quality gap was smallest in the beginning of 2003, when the actual overall price was at its highest but, also, many NB introductions were taking place, increasing both the number of NB SKUs and product categories with NB presence (see columns labeled *NBCum* and

[5] Note that the SPI scale was reversed in the previous chapters.

Table 4.1: Descriptive statistics

	Price image		Quality image		NBCum	NewNBCat	NBPremium	Assortment	ActualPrice
	mean	s.d.	mean	s.d.			mean	mean	mean
wave 1 (2002:16)	6.69	1.26	6.28	1.22	49	38	0.09	8.62	0.99
wave 2 (2002:40)	6.78	1.16	6.44	1.09	89	17	0.06	11.10	1.20
wave 3 (2003:05)	6.62	1.24	6.32	1.14	127	11	0.00	11.21	1.80
wave 4 (2003:16)	6.82	1.22	6.36	1.10	157	6	0.24	11.40	0.64
wave 5 (2003:40)	6.82	1.13	6.37	1.11	170	2	0.38	11.34	0.76
wave 6 (2004:16)	6.75	1.27	6.28	1.18	180	0	0.24	10.20	0.84
wave 7 (2004:40)	6.69	1.19	6.39	1.07	191	3	0.20	11.59	0.76
wave 8 (2005:16)	6.70	1.17	6.29	1.08	204	4	0.24	12.11	0.72
wave 9 (2005:40)	6.75	1.11	6.35	1.03	213	1	0.26	14.34	0.76
wave 10 (2006:16)	6.75	1.18	6.42	1.10	216	1	0.16	15.24	0.68
wave 11 (2006:40)	6.77	1.11	6.44	1.05	222	2	0.15	15.42	0.84

NewNBCat of Table 4.1 and Figure 4.3).

Operationalization of explanatory variables

For the same individual panel members and the same time period, we have scanner data on individual shopping trips and purchase histories at all Dutch grocery retailers. We use data at Lidl stores to compute our set of independent variables. The observations are recorded at the level of the household, noting the time of the day the shopping trip took place (morning, afternoon, evening), and which (and how many) SKUs were purchased. For each SKU, we know its brand name and price, as well as the product category it belongs to (out of a set of 59 product categories defined by GfK).

We use these data to operationalize our explanatory variables as follows. The large and representative sample allows us to operationalize assortment size at time t ($Assortment_{st}$) by judging which SKUs were available (i.e. for which at least one purchase was recorded in the entire panel) at Lidl between two subsequent survey periods (including the SKUs in the current period). The chain's actual overall price level at time t ($ActualPrice_{st}$) is computed as a weighted average of all SKU unit prices in that period, where the weights represent the SKUs' relative contribution to the retailer's revenue. To allow for meaningful comparison across categories, we first transform SKU unit prices within a category into indices. We do so by dividing the SKU's observed price per volume unit (e.g. liter, kilogram), by the average unit price in the category, across all stores in an initialization period (see van Heerde et al. 2008, for a similar procedure).

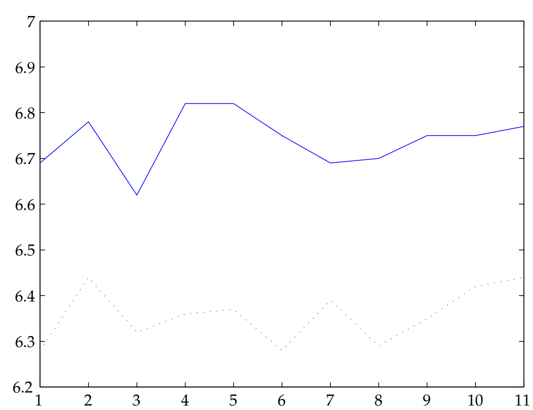

Figure 4.2: Evolution of aggregate SPI (top solid line) and SQI (bottom dotted line) in Lidl stores from 2002 week 16 to 2006 week 40.

To operationalize the variables related with NB introductions, we first classify the SKUs sold at Lidl into national brands and private labels. Given the large number of differently-named private labels at that chain, this is not an obvious task. We therefore use data across all mainstream supermarket chains to identify 'leading' NBs in each product category, i.e. the top 5 selling brands in that product category, after excluding the own brands of the mainstream supermarket chains. Next, we record which of the NBs are available at Lidl, in which categories, and since when. Given that NBs accepted by hard discounters are typically among the leading brands in their category (Aggarwal (2003); c.f. Deleersnyder et al. (2007)), this procedure is likely to capture all NB introductions at Lidl.

To quantify the total number of NBs in Lidl's assortment at a given point in time ($NBCum_{st}$), we first identify the introduction week of each brand, as the week in which an SKU purchase of that brand was first recorded in the panel. The number of NBs in each (survey) week, then equals the number of all NB SKUs available in (introduced no later than) that week. Similarly, we identify, in each product category, the first week a NB was available. We then use this information to operationalize the number of product categories where a NB is introduced for the first time since the last survey week ($NewNBCat_{st}$). Finally, the NB price premium ($NBPremium_{st}$) is obtained by (i) calculating, in each category where a NB is available, the percentage price difference between NBs and PLs (i.e. difference in average unit price between NB SKUs and PL SKUs in the category, divided by the average unit price of PL SKUs in the category), and then (ii) calculating a weighted average across categories – using category share of wallet at the chain as weights.

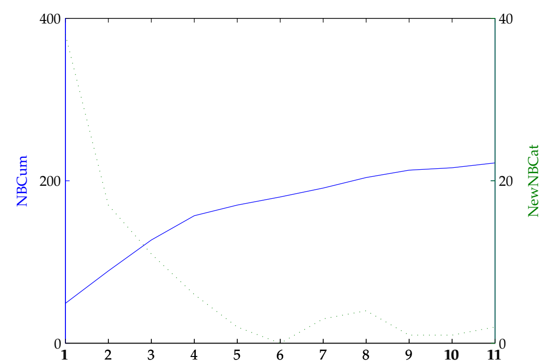

Figure 4.3: Evolution of NB introductions at Lidl stores from 2002 week 16 to 2006 week 40.

Table 4.1 provides descriptive statistics for the key explanatory variables (see five rightmost columns). The number of SKUs has increased over time, and although a great deal of the activity concerning NB introductions takes place in the beginning of our data period, NB introductions were observed up to the end of 2006. Despite the lower overall price levels by the time the last waves were conducted, the price gap between NBs and PLs reached its highest values in these periods.

Household characteristics

The impact of NB introductions on the HD's quality and price image may well differ across households. Moreover, since our data stem from store-intercept surveys, we need to account for possible selection bias: households visiting the HD chain as more NBs become available, possibly differing from those patronizing it early on. To accommodate household differences, and avoid confounding changes in HD price image with changes in the composition of the sample, we add household characteristics deemed to affect HD image and response to NB availability as controls (see Ailawadi et al. 2008, for a similar approach). In so doing, we allow not only for main effects of these household features, but also explore possible interactions with our focal variables – those related with the discounter's NBs.

Specifically, we expect consumers' HD image, and their response to increased NB availability, to be linked to two important shopping characteristics. First, different consumers sample (i.e. purchase and consume) different proportions of store brands and national brands (Tellis and Wernerfelt 1987) – according to their preferences. This may affect not only their reference prices and quality (Gijsbrechts 1993), but also their pre-disposition towards HD stores, and towards availability of NBs at these stores. Second, consumers patronizing relatively more discounters than mainstream supermarkets may be more acquainted with the discounters' format, and/or exhibit a different attitude towards this format. Again, these households' price and quality perceptions of the discounter store may be differently influenced by increases in the availability of NBs. We operationalize a household's private label propensity ($PLPropensity_i$) as the household's expenditure on private labels divided by the household's total expenditures, in an initialization period. Similarly, a household's discounter share ($DiscPropensity_i$) is given by the its number of trips to discounters (Aldi and Lidl in our data set) divided by its total number of shopping trips. For ease of interpretation, we mean-center these variables prior to inclusion in the models. In total, we have 3510 observations for model estimation (corresponding to 1583 different households), over a period of five years.

4.4 Empirical results

We estimate our models in Stata, using the bivariate ordered probit module – *bioprobit* – by Sajaia (2008). The standard errors are adjusted to account for repeated observations by household. Table 4.2 provides information on the model fit and the estimated correlation between the price and quality image random components, for five models: (i) model M1, including the assortment, actual store price and NB-related variables, but without household-controls, (ii) model M2, adding main effects for the household characteristics, (iii-iv) models M3 and M4, adding interactions with households' PL propensity and discounter propensity, respectively, and (v) a full model, M5, which includes interactions between the NB-related variables and both household-controls.[6]

The likelihood-ratio test of independence of equations ($\rho = 0$) is strongly rejected in all models, supporting the adequacy of a bivariate specification instead of a univariate one. The correlation between the two error terms is positive in all models, and approximately equal to 0.73 – capturing a halo effect. Comparing M2 with M1, we observe that adding main effects for the household characteristics substantially increases the likelihood, and leads to an improvement (lower values) of both the AIC and the BIC measures. Including interactions between Discounter proneness and NB presence (as in model M4); or especially between Private Label proneness and NB presence (as in model M3) entails an additional likelihood increase, and a further improvement in AIC. However, having both types of household interactions in the model (model M5) creates collinearity problems, and deteriorates the AIC and BIC measures. Based on these fit measures, and given its richer specification, model M3 appears to be the best choice (the lowest AIC value is that of M3). Below, we present the parameter estimates of this model, along with those of the simpler benchmarks M1 and M2 (the lowest BIC value is that of M2). We discuss the Price Image and Quality Image effects in turn.

4.4.1 Effects on price images

The parameter estimates in Table 4.3 reveal that while total assortment size does not significantly affect Lidl's price image ($p > .10$), higher actual store prices – as expected – do lead to a less favorable price perception of the store (Model M3: $\beta_{ActualPrice} = -0.1265; p < .1$; one-tailed). Shoppers with a higher propensity to visit hard discounters in general, do not hold more favorable price perceptions of Lidl ($p > .10$). This suggests that differences in the preference for low prices, rather than household heterogeneity in HD price perceptions, drives discounter patronage. Similarly, households with a strong focus on PLs do not perceive Lidl as more or less expensive than those with a NB orientation ($p > .10$).

Our key interest, however, is in the variables explicitly reflecting NB availability. The results clearly reveal that stronger NB presence affects Lidl's price image over and above its impact through objective price changes. For the average household, a higher number of NBs in the Lidl assortment, goes along with a more expensive store image ($\beta_{NBCum} = -0.0022; p < .05$; one-tailed). Thus, the more NBs are added to the discounter's assortment, the more negatively consumers will judge the discounter's overall price level. Note that, like the actual store price effect, this finding is consistent across the three specifications (M1, M2 and M3). Moreover, as can be seen from the in-

[6]The limited number of time observations per household precluded us from estimating random coefficients and hence incorporating unobserved heterogeneity in the model.

Table 4.2: Summary results BIOPROBIT models[a]

	M1	M2	M3	M4	M5
Log likelihood	-9334.4	-9310.0	-9302.3	-9307.6	-9302.2
Wald $p > \chi^2$(d.f.)	7.2	7.5	18.8	9.5	21.2
d.f.	5	7.00	9	9.00	11
AIC	18678.9	18634.0	18624.5	18633.1	18626.4
BIC	18709.7	18677.1	18680.0	18688.6	18694.2
ρ	0.727	0.730	0.730	0.731	0.731
Intercept	0.922***	0.930***	0.930***	0.931***	0.930***
s.e.	0.032	0.032	0.032	0.032	0.032

[a] In all models: observations = 3510 per equation, households = 1583. M1 is the baseline model without household-level variables. M2 is the baseline model with main household effects but without interactions. M3 includes interactions between the household's propensity to buy PLs, on the one hand, and *NBCum* and *NewNBCats* on the other. M4 includes interactions between the household's propensity to shop at a hard discounter on the one hand, and *NBCum* and *NewNBCats* on the other. M5 includes interactions between both household characteristics (propensity to buy PLs, and propensity to shop at a hard discounter) on the one hand, and *NBCum* and *NewNBCats* on the other.

significant interaction parameters in model M3, this effect is no different for shoppers who spend larger portions of their wallet on PLs.

Based on model M3, NBs with higher-than-average price premiums over private labels do not result in a more unfavorable price image – suggesting that the price effect is properly accounted for through the actual price variable. National brand introductions in categories where the discounter did not have any before, do not yield any additional effects on store price image for the average household either ($p > .10$). We do, however, find a significant interaction between household private label focus, and first NB entrants in a Lidl category. The effect is positive ($\beta_{NewNBCat \text{x} PLPropensity} = .0784$; $p < .05$), suggesting that NB entry in a category that exclusively held PLs so far, makes the store temporarily appear less expensive to PL prone consumers. As indicated above, this may be due to a contrast effect. Combining the (negative) main and (positive) interaction effects as in Jaccard and Turrisi (2003) shows, however, that the (net) impact of first NB entrants in a category is significantly positive only for households with a PL purchase share above 42%.

In sum, our results suggest that adding NBs to the discounter's assortment leads to a less favorable price image, over and above the effect of the actual store price increase. First NB entrants in a category may temporarily enhance the discounter's price

Table 4.3: Parameter estimates price image[a]

	M1	**M2**	**M3**	**M4**	**M5**
Main effects					
NBCum[b]	−0.0026∗∗	−0.0026∗∗	−0.0022∗∗	−0.0026∗∗	−0.0021
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0018)
NewNBCat[b]	−0.0072	−0.0073	−0.0031	−0.0079	−0.0020
	(0.0055)	(0.0055)	(0.0057)	(0.0056)	(0.0060)
Assortment[b]	0.0266	0.0271	0.0265	0.0276	0.0250
	(0.0165)	(0.0165)	(0.0164)	(0.0165)	(0.0165)
ActualPrice[b]	−0.1203∗	−0.1212∗	−0.1265∗	−0.1208∗	−0.1267∗
	(0.0931)	(0.0933)	(0.0934)	(0.0932)	(0.0933)
NBPremium[b]	0.1813	0.1753	0.2068	0.1684	0.2288
	(0.3058)	(0.3063)	(0.3071)	(0.3065)	(0.3076)
PLPropensity		−0.1177	−1.8269	−0.1019	−3.0149∗
		(0.2851)	(1.2260)	(0.2847)	(1.6740)
DiscPropensity		0.0081	0.0262	0.0933	1.3486
		(0.2315)	(0.2325)	(0.8828)	(1.1922)
Interactions					
NBCumxPLPropensity			0.0070		0.0128
			(0.0056)		(0.0079)
NewNBCatxPLPropensity			0.0784∗∗		0.1072∗∗∗
			(0.0307)		(0.0394)
NBCumxDiscPropensity				−0.0009	−0.0064
				(0.0040)	(0.0056)
NewNBCatxDiscPropensity				0.0109	0.0334
				(0.0222)	(0.0278)

[a] *$p<0.1$; **$p<0.05$; ***$p<0.01$. Standard errors in parenthesis.

[b] Given our directional hypothesis, we use one-tailed sign tests.

image, but this only holds for households with a large share of wallet spent on PLs.

4.4.2 Effects on quality images

Table 4.4 summarizes the results for the quality image equation. As expected, having more SKUs in the assortment enhances the store's quality image (model M3: $\beta_{Assortment} = .0328; p < .05$; one-tailed). In contrast, the discounter's actual price level has no significant effect on consumer perceptions of his merchandize quality ($p > .10$). The national brand price premium also fails to reach statistical significance ($p > .10$). Hence, prices do not seem to be directly informative for the formation of store quality perceptions of the discounter.

As for the main effects of household characteristics, we find that consumers with a high share of trips to discounters have significantly higher perceptions of Lidl's overall merchandize quality ($\beta_{DiscPropensity} = .4343; p < .10$). Private label propensity, though, is not significantly linked to Lidl's quality image ($p > .10$), possibly because PL-prone consumers focus more on price, and can also purchase PLs at mainstream supermarkets.

Focusing on the effect of increased NB presence, we obtain some interesting findings. First, against expectations, an increased number of NBs does not enhance Lidl's quality image. The negative but insignificant ($p > .10$) main effect is moderated by consumers' PL propensity, the interaction parameter being positive and marginally significant ($\beta_{NBCum\text{x}PLPropensity} = .0091; p = 0.12$). Applying Jaccard and Turrisi's (2003) approach to evaluate the joint influence of these parameters, we obtain a marginally significant negative impact only for households with zero PL shares (which are not observed in our sample), and insignificant effects elsewhere. Thus, a higher number of NBs in the discounter's assortment does not enhance its quality image.

A similar pattern is observed for the number of new product categories in which NBs are introduced. Except for PL shares lower than 8% (less than 10 households in our sample), the negative (but insignificant, $p > .10$) main effect is nullified by the positive and significant interaction with households' PL propensity ($\beta_{NewNBCat\text{x}PLPropensity} = .0604; p < 0.1$). Hence, making NBs available in more categories does not make a difference in terms of quality image, even in the introduction period.

4.4.3 Robustness checks

To ensure the validity of our findings, we conduct several robustness checks. First, we re-estimate the models using the number of new NB introductions, instead of number of new categories where a NB is introduced, as an explanatory (pulse) variable. Again, we find no significant effect for this variable. Alternatively, we replace the number of NBs in the assortment, by the total number of categories with a NB present. Again,

Table 4.4: Parameter estimates quality image[a]

	M1	M2	M3	M4	M5
Main effects					
NBCum[b]	−0.0021	−0.0022	−0.0020	−0.0023	−0.0019∗
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
NewNBCat[b]	−0.0063	−0.0073	−0.0051	−0.0076	−0.0044
	(0.0056)	(0.0057)	(0.0062)	(0.0056)	(0.0062)
Assortment[b]	0.0367∗∗∗	0.0346∗∗∗	0.0328∗∗	0.0346∗∗∗	0.0325∗∗
	(0.0166)	(0.0167)	(0.0166)	(0.0167)	(0.0167)
ActualPrice[b]	−0.0865	−0.0927	−0.0925	−0.0917	−0.0934
	(0.0951)	(0.0952)	(0.0953)	(0.0953)	(0.0953)
NBPremium[b]	−0.1653	−0.1690	−0.1408	−0.1733	−0.1340
	(0.3098)	(0.3105)	(0.3124)	(0.3105)	(0.3131)
PLPropensity		0.0189	−1.9637	0.0135	−2.1772
		(0.2865)	(1.3203)	(0.2865)	(1.8264)
DiscPropensity		0.4264∗	0.4343∗	−0.2944	0.6960
		(0.2325)	(0.2344)	(0.9327)	(1.2952)
Interactions					
NBCumxPLPropensity			0.0091		0.0101
			(0.0059)		(0.0084)
NewNBCatxPLPropensity			0.0604∗		0.0686
			(0.0366)		(0.0438)
NBCumxDiscPropensity				0.0035	−0.0011
				(0.0042)	(0.0060)
NewNBCatxDiscPropensity				0.0191	−0.0106
				(0.0250)	(0.0302)

[a] *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Standard errors in parenthesis.
[b] Given our directional hypothesis, we use one-tailed sign tests.

while this variable exerts a negative effect on Lidl's price image, we find no positive quality impact. Third, to further alleviate concerns about changes in sample composition, we re-estimate the model including only households that have patronized Lidl before the last two survey waves (i.e. before 2006). We find the results to remain substantively the same. Finally, we examined an inverted U-shape effect for number of NBs, by adding its square as an explanatory variable. This added variable did not increase model fit.

Overall, our results suggest that introducing NBs only affects the discounter's quality image to the extent that it widens the assortment. However, it does not generate a more positive effect than adding PLs to the line. This observation, combined with the result that NB presence deteriorates the discounter's overall price image beyond the actual price increase, constitutes a surprising finding that entails strong implications for hard discounter chains. We discuss these implications next.

4.5 Discussion

Being positioned as lean, cheap and strongly private-label focused originally, hard discounters have started to accept more NBs in their assortment, and are expected to continue going down that road (Planet Retail 2010). In so doing, they count on getting even better inroads into the mainstream supermarkets' customer segments. The results of our study, however, cast some doubt on the appeal of such an approach. Even though offering NBs may increase the discounter's category sales share in the short run (Deleersnyder et al. 2007), the long run implications appear less rosy. On the one hand, increased NB presence on the hard discounter's shelves deteriorates its favorable price image – cutting into its core competitive advantage. On the other hand, unfortunately, having more NBs does not seem to enhance the overall quality perception of its offer. Because of this asymmetric influence, the net outcome in terms of positioning in the consumers' mind does not seem all that favorable. We discuss some academic and managerial implications below.

4.5.1 Academic implications

Our study offers empirical evidence for the effect of assortment composition, i.e. the share of national brands in the hard discounter's offer, on two key dimensions of store image: price and quality. While the fact that price image is hurt makes intuitive sense, an intriguing question is why quality perceptions are not enhanced by having more NBs. As indicated by Jacoby and Mazursky, common wisdom suggests that "a retailer with a relatively low image might be able to improve this image by associating it with a more favorably evaluated brand or manufacturer image" (Jacoby and Mazursky 1984, p.121). Why, then, do we not observe such an effect? We see three possible reasons why increased NB presence does not enhance the HD's quality image.

A first explanation is that, by placing increased focus on NBs, hard discounters start to 'play in a different league'. Given that their reference set becomes that of mainstream retailers and soft discounters, they now need to measure up against different standards (Haans 2007). A somewhat related explanation comes from social psychology consistency theories (Heider 1944, 1946, 1958, Osgood, Suci, and Tannenbaum 1957). Encountering more (and higher priced) NBs may confuse consumers, and disrupt the discounter's perception of having a lean and cheap assortment, where quality is based on intrinsic product characteristics, rather than on costly, advertising-based brand image. Differently stated, a (more dominant) NB presence may be incongruent with the hard discounter's original selling point, and therefore fail to produce the expected positive perception changes among its customers.

A second explanation is that the perceived quality superiority of the NBs is simply too small to induce a meaningful shift in the HD's quality image. Like many

Western-European countries, the Dutch market is a 'PL-mature' country, and consumers in such countries (because they do not strongly believe that some categories are difficult to produce, or because they think PLs are often produced by NB manufacturers) attribute smaller quality gaps to NBs (Steenkamp, van Heerde, and Geyskens 2010). Brand-level perception data would be needed to verify whether such small perceived quality differences also apply to the hard discounter's private label compared to the specific NBs introduced on its shelves – thereby accounting for the lack of store image improvement.

A third reason may be that, given the limited size and space of hard discounter stores, having NBs on the shelves – the intrinsic features of which overlap with those of the PL brands – prevents the hard discounter from offering a deeper assortment, with variety in terms of product flavors and types rather than brands. Previous studies have shown, indeed, that assortment variety along attributes other than brand may strongly influence consumer perceptions and liking (van Herpen and Pieters 2002, Boatwright and Nunes 2001). Unfortunately, our data set did not contain SKU attribute information other than brand name. Future research could net out the effect of NB introductions from those of changes in assortment composition along other dimensions.

4.5.2 Managerial implications

If, as suggested by Nielsen (2008), "It's all in the mind", then hard discounters have an interest in revisiting the appropriateness of becoming more NB-oriented, and weigh the immediate sales effects against a possible deterioration of their positioning. Our study documents that NB introductions exert an unfavorable price image effect that is non-negligible. For instance, given our estimated coefficients, an increase of NB share from 14.4% to 17.8%, would — ceteris paribus – entail a one point change in the current mode of price image ratings. This is an important effect in view of the observed distribution of price image ratings, and given that these ratings have been shown to influence store patronage (van Heerde et al. 2008).

Given that enhanced NB presence does not seem to produce the desired image effects, hard discounters need to be careful not to jeopardize long term profit for short term gains. Rather than reducing their PL focus, they may need to opt for other strategies more in line with their core positioning. For one, our study underscores that changes in assortment size *do* have the potential to favorably affect the HD's quality image. Even though there are limits to this approach (given the small size of the HD store, and their need to keep the cost of their operations low), HDs may investigate possibilities to enhance the variety of their offer within the limits of available shelf space. They could do so by reducing the number of facings per SKU, adopting different packs, or use more 'efficient' ways of displaying the products. Alternatively, they could opt for higher SKU rotation – an option successfully adopted by some retail firms (Mantrala et al. 2009) that may also prove beneficial for hard discounters.

At the same time, if hard discounters feel that NB introductions are the way to go, they could strive to contain or eliminate the negative price image implications. Like Deleersnyder et al. (2007), we observe that the NB prices charged by the HD in our study are very close to those of the mainstream retailers, especially after the third survey wave. We find that, for first category introductions, this triggers a positive contrast effect on the HD price image, among consumers with a high PL propensity. However, this effect is temporary, and appears among shoppers that are not the primary target of the NB introductions in the first place – the remaining households holding more negative price perceptions after the NB introductions. A more appealing strategy may be to offer these NBs at *lower* prices than mainstream supermarkets. This will entail a dual effect. For one, it will entail a smaller increase in actual store price and, hence, a smaller decline in price image. Moreover, for NB shoppers focusing on cross-store NB price comparisons, this may strengthen the belief that these lean hard discounter stores can afford to be cheaper (which may actually improve their price image), without giving in on quality. Hence, our findings corroborate Deleersnyder et al.'s (2007) observation that "discounters may be missing an opportunity here" (p.315).

Clearly, this study has a number of limitations that trigger the need for further research. First, in exploring the impact of NB introductions on household perceptions, we are limited by the nature of our data. The fact that we do not observe positive quality image effects, does not prove those effects are not there – only that they are not apparent from our survey data. It is possible, for instance, that the impact of NB presence on quality image follows a nonlinear shape (e.g. an S-shape), and that our data cover a range where this curve is flat. Still, the fact that we do find significant price image effects, and that there is quite some (over time) variation in the quality image ratings as well as the NB presence, adds weight to our findings, and makes them warrant retailer attention.

Second, while we did have individual-level data, we typically had only few subsequent survey observations on store price and quality image per household. Even though we controlled for key household differences, this made it difficult to reliably account for unobserved heterogeneity between households. Future studies using longitudinal and more frequent price and quality image ratings by household could try to better tease out reaction heterogeneity.

Third, we used simple measures of NB presence, based on SKU counts, and ignoring category differences. As indicated by Steenkamp et al. (2010), the quality perception of NB versus PLs, and consumers' willingness to pay for NBs, differs across categories. Moreover, categories differ in their signaling value for store image. Future research may tap into the type of categories where NB introductions enhance the overall quality perception of the HD offer. In a similar vein, we did not look into the effects of specific NBs. As indicated by Deleersnyder et al. (2007), the success of NBs at hard discounters depends on brand characteristics such as their innovativeness, intrinsic strength, and outer-case design. Our data did not allow to investigate the store image effects of NB introductions differing on these dimensions – something we leave for future study.

4.A Cutoff estimates

Table 4.5: Cutoff estimates for price and quality images

	M1	M2	M3	M4	M5
Price Image					
$\alpha_{p,1}$	−3.6598	−3.6980	−3.6028	−3.7035	−3.6318
	(0.354)	(0.3561)	(0.3642)	(0.3672)	(0.3557)
$\alpha_{p,2}$	−3.1308	−3.1644	−3.0665	−3.1668	−3.0941
	(0.3074)	(0.3109)	(0.319)	(0.323)	(0.3091)
$\alpha_{p,3}$	−2.7621	−2.7958	−2.6967	−2.7971	−2.7244
	(0.302)	(0.3061)	(0.3134)	(0.3189)	(0.3036)
$\alpha_{p,4}$	−1.4705	−1.5049	−1.4057	−1.5060	−1.4331
	(0.3015)	(0.3056)	(0.3115)	(0.3202)	(0.3037)
$\alpha_{p,5}$	−0.8850	−0.9184	−0.8185	−0.9198	−0.8460
	(0.3017)	(0.3056)	(0.3118)	(0.3201)	(0.3039)
$\alpha_{p,6}$	0.0162	−0.0163	0.0849	−0.0175	0.0577
	(0.3011)	(0.305)	(0.3113)	(0.3196)	(0.3035)
$\alpha_{p,7}$	1.1262	1.0911	1.1954	1.0913	1.1687
	(0.3043)	(0.3087)	(0.3135)	(0.3238)	(0.3065)
Quality Image					
$\alpha_{q,1}$	−2.8931	−2.8071	−2.8016	−2.9478	−2.9494
	(0.3432)	(0.3511)	(0.3474)	(0.3658)	(0.3426)
$\alpha_{q,2}$	−2.6463	−2.5650	−2.5575	−2.7043	−2.7051
	(0.32)	(0.3295)	(0.3265)	(0.3461)	(0.322)
$\alpha_{q,3}$	−2.0612	−1.9810	−1.9719	−2.1195	−2.1195
	(0.3095)	(0.3181)	(0.3183)	(0.3333)	(0.3112)
$\alpha_{q,4}$	−0.4296	−0.3445	−0.3332	−0.4829	−0.4812
	(0.3097)	(0.3195)	(0.3169)	(0.3359)	(0.3113)
$\alpha_{q,5}$	0.1145	0.2007	0.2122	0.0626	0.0644
	(0.31)	(0.3196)	(0.3174)	(0.336)	(0.3117)
$\alpha_{q,6}$	1.1952	1.2855	1.2974	1.1475	1.1497
	(0.31)	(0.3196)	(0.3173)	(0.3361)	(0.3117)
$\alpha_{q,7}$	2.4550	2.5529	2.5658	2.4142	2.4174
	(0.3213)	(0.3304)	(0.3307)	(0.3444)	(0.3233)

Chapter 5

Concluding Remarks and Future Research Agenda

Where to shop is a key buying decision that arguably precedes and certainly is involved in decisions about whether, what and how much to buy. Evaluation of store alternatives, however, is far from trivial for consumers. Apart perhaps from unequivocal attributes like distance, judging and building a perception of other store dimensions, such as the store's overall price level or 'store price image (SPI)', involves many informational cues. Compared to the SKU- and brand-level, store-level prices vary not only over time. They also pertain to widely different product categories, from meat to personal care or from cereals to paper towels – categories that differ widely in aspects that are relevant to characterize buying behavior, and the prices of which are not likely to be processed by consumers in the same way. An important question in this regard is, therefore, which product categories are more important in the formation of store price images, and why – issues that remained largely unaddressed in the literature to date.

Knowledge of how category prices shape SPIs, while of great interest in itself to retail managers, raises additional, compelling questions. For one, if the retailer manages to steer consumers' price perceptions of his store, how will this translate into increased store traffic? And, if store price images are so closely related to actual prices, what is the relative importance of both types of price information in consumers' decisions about where to shop? Despite the recent work of Bell and colleagues (1998, 2001) that has renewed the interest in store patronage research within academia (e.g. Vroegrijk et al. 2010, Briesch et al. 2008, Gijsbrechts et al. 2008, Ailawadi et al. 2008, Dellaert et al. 1998), an enthusiasm shared by the retailing industry (e.g. Nielsen 2008), no prior study explicitly takes into account both actual and perceived store-level prices as well as their interrelationship.

In addition to product categories and prices, changes in the assortment composition of retail stores may also 'cue' consumers, not only about the overall expensiveness of stores, but also about their overall quality. In a setting where the power balance between retailers and manufacturers continues to shift, changes in the relative presence of national brands vs. private labels on the retailer shelves are bound to occur, the question remaining how they will influence consumers' store perceptions.

In this thesis, we presented three essays that aimed at addressing some of these questions. In the present chapter, we summarize our findings, discuss their main implications for managers and marketing scholars, and offer suggestions for future research.

5.1 Summary of main findings

In the first essay of this thesis, we proposed a framework where actual prices of different product categories are integrated in a process of store price image formation. We argued that a product category's ability to signal SPI is determined not only by its share-of-wallet but also, and more importantly, by a number of category characteristics that drive the diagnosticity and accessibility of its category prices. Building on this framework, we developed a model of SPI formation over time, in which category prices act as unbiased, noisy signals about stores' cheapness or expensiveness, and in which consumers update their overall price beliefs according to Bayesian updating rules.

In the second essay, we advocated 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 considered 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 complemented this choice model with a model of SPI formation over time, using a Bayesian learning framework. We used 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.

In the final essay, we empirically tested for the presence and size of the effects of NB introductions on a hard discounter's price and quality image. Since national brands are typically regarded by consumers as having higher quality than their private label counterparts, but are, on average, more expensive (Kumar and Steenkamp 2007, Ailawadi et al. 2008, Geyskens et al. 2010), the shift in the discounter stores' assortment strategy was expected to improve their quality image, to the detriment of their price image. Using a bivariate ordered probit model, we simultaneously assessed the effect of stronger NB presence – along with a number of control variables – on the hard discounter's quality and price image, thereby accounting for the link between both image dimensions.

In the three essays, we made use of a large and unique data set, combining weekly store visits and purchase data (and chains' prices and assortment composition over time), with semiannual store price and quality perceptions for a representative panel of households. We summarize our findings under two main overarching subheadings: those regarding store price (and quality) perception formation and the role of different product categories and brand types in that process, and those regarding the effects of store price perception on store choice and consumer dual price sensitivity.

5.1.1 Store price (and quality) perception formation and the role of different product categories and brand types

In this regard, we found that:

- Various product categories carried by the retailer play a substantially different role in the SPI formation process, with average price signal precisions ranging between 1.016 for *Personal care* to 0.411 for *Vinegar*.

- Higher share-of-wallet categories have a higher impact on SPI formation. However, the link is not very tight, as suggested by the low elasticity of share-of-wallet (compared to those of most product category characteristics).

- Product categories such as *Bread* or *Cheese*, for instance, are to be avoided when managing SPIs, as these categories have a high share-of-wallet (meaning that price reductions are bound to hurt revenue) yet a low signaling ability. *Alcoholic drinks* or *Meat*, in contrast, have a high ability to signal SPI, but they still entail a high risk of subsidization, as they represent almost a fifth of consumers' shopping budget. SPI management is best achieved by adjusting prices in lighthouse categories, i.e. categories that constitute only a small portion of sales and yet exert a strong impact on the store's overall price beliefs. We find these categories to be predominantly related with *Personal care* and *Cleaning*.

- SPI learning is enhanced by category characteristics that increase the attention to prices, or for which consumers have strong (monetary) incentives to track prices – share of wallet, expensiveness, display activity, storability, promotion depth, and price spread. While characteristics generating simpler price distributions – interpurchase time and brand loyalty – also increase SPI learning, characteristics likely to generate more complex distributions of category prices – promotion frequency, number of SKUs, and market concentration – decrease SPI learning.

- There is an asymmetric influence of NB introductions on a hard discounter's assortment. On the one hand, increased NB presence deteriorates the hard discounter's favorable price image, over and above the actual price increase from having more NBs – cutting into its core competitive advantage. On the other hand, unfortunately, having more NBs does not seem to enhance the overall quality perception of the HD offer.

5.1.2 Effects of store price perception on store choice, and consumers' dual price sensitivity

In this regard, we found that:

- Accounting for the effect mediated by SPI learning increases the over-time impact of actual price changes by approximately 15%, enhancing the importance of pricing as a strategic instrument for retailers. While Fox et al. (2009) already documented the presence of lagged price effects in the context of store traffic, we offer a structural explanation for these effects through SPI formation.

- Approximately one third of consumers use some type of price information (vis-à-vis two thirds using only non-price or convenience cues) to guide their over-time store selection.

- Only half of the price-sensitive consumers keep track of actual weekly prices and use those to adjust their weekly store patronage. The other half tailor their store selection to overall beliefs about the store's expensiveness.

- 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.

- Eye-for-detail consumers, i.e. who are more sensitive to weekly prices, report using store price information to direct *specific* brand purchases, are tenants rather than home owners, exhibit lower education levels, and belong to lower social classes. In addition, they are less store or brand loyal, buy more private labels, and have smaller purchase baskets – corresponding to the profile of cherry picking consumers.

- Big picture consumers, i.e. who are more responsive to stores' overall price images, report paying 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. SPI-sensitivity is also more prevalent among tenants rather than house owners, and is found in all social classes and education levels. Larger households exhibit stronger SPI updating.

- 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.

While many of our expectations are confirmed, we note that a number of our findings bring surprising new insights to the table. We find that, against conventional wisdom, the categories with a higher ability to signal a favorable SPI are in general not food and staples, but are instead linked to home and personal care. In addition, we find that when choosing where to shop, one third of consumers is sensitive to price information, either in the form of actual prices, store price perceptions, or both, thus challenging the monopolized attention given to distance. Finally, and against expectations, we find that the introduction of national brands on the shelves of a hard discounter does not improve its perceived overall quality, while hurting one of its main competitive advantages, i.e. its favorable (cheap) price image.

5.2 Implications

Apart from generating new substantive insights, our findings have a number of implications for marketing practice that we discuss next in the form of managerial guidelines.

5.2.1 To signal or not to signal: Rely on lighthouse categories to 'sail' your SPI

We found in Chapter 2 that after accounting for their share in the shopping budget of a typical consumer, the categories better suited to signal a favorable SPI are linked to home and personal care. Managers have typically put a lot of emphasis on food and staples,[1] possibly because these categories rank high in the consumer share-of-wallet and consumers have therefore a high incentive to pay attention to their prices. But, as we showed, the link between SPI learning and SOW is not as strong as with other product characteristics, demonstrating that retailers have the possibility to select categories that contribute favorably to SPI, yet in which price cuts do not overly hurt revenue. Retailers can thus use these insights to re-consider their pricing approaches across categories – reaping higher margins in these low signaling categories, while emitting a

[1]With the goal of "polishing its discount image" (Wall Street Journal 2010), the giant Wal-Mart announced recently a cut in the prices of 10,000 items, mostly food and other staples (CNBC 2010).

message of cheapness through low prices in others. This finding corroborates earlier results by Nijs, Srinivasan, and Pauwels (2007) that retailers who pay more attention to category management in setting prices, achieve higher levels of profitability.

5.2.2 It takes two to tango: Mind actual and perceived prices when stimulating store traffic

Considering a comprehensive dual price effect as we did in Chapter 3, 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. The economic relevance of one-third of consumers who are price- and/or SPI-sensitive is clearly demonstrated by the fact that their grocery shopping trips comprise nearly fifty percent of the total spending in the market. Moreover, visits from SPI-sensitive consumers are also expected to be economically more important, as these consumers typically shift their entire shopping basket when changing stores.

Our findings also offer a better understanding of who are the price-sensitive consumers, thus enabling effective segmentation and targeting strategies. Due to their distinct characteristics, retailers may wish to think of separately target consumers identified to have an 'eye-for-detail' as opposed to a 'big picture' of store prices.

For marketing researchers, our findings also emphasize the need to link 'hard' outcomes to mindset metrics, and the need to explicitly specify, to some extent at least, the dynamics of such 'soft' metrics. As indicated by Srinivasan et al. (2010), mind metrics have larger 'wear-in' periods than most 'hard' marketing mix instruments, that is, it takes longer for their effect to fully materialize in the firms' outcome measures. As such, they can serve as early warning signals or 'lead indicators' of problems to come. While Srinivasan et al. (2010) studied awareness, consideration, and liking, the mindset metrics adopted in our studies pertained to stores' price and quality images. Consistent with Srinivasan et al. (2010), our findings in Chapter 3 underscore that some of the actual price effect translates into store traffic only with a delay, through changes in consumers' adjusted price beliefs. Hence, store price images can act as a warning signal, and monitoring these SPIs can help retailers anticipate future changes in store traffic.

5.2.3 You don't change a winning team: How national brand introductions leave quality images untouched and hurt price images of hard discounters

The asymmetric influence of introducing NBs on the price and quality images of a hard discounter found in Chapter 4, cast some doubt on the appeal of this strategy to get into customer segments of mainstream supermarkets. If, as suggested by Nielsen

(2008), 'It's all in the mind', then hard discounters have an interest in revisiting the appropriateness of becoming more NB-oriented, and weigh the immediate sales effects against a possible deterioration of their positioning.

Given that enhanced NB presence does not seem to produce the desired image effects, hard discounters should be careful not to jeopardize long term profit for short term gains. Rather than reducing their PL focus, they may need to opt for other strategies more in line with their core positioning. For one, our study underscores that changes in assortment size *do* have the potential to favorably affect the HD's quality image. Even though there are limits to this approach (given the small size of the HD store, and their need to keep the cost of their operations low), HDs may investigate possibilities to enhance the variety of their offer within the limits of available shelf space. They could do so by reducing the number of facings per SKU, adopting different packs, or using more 'efficient' ways of displaying the products. Or, they could opt for higher SKU rotation – an approach successfully adopted by some retail firms (Mantrala et al. 2009) that may also prove beneficial for hard discounters.

Overall, our findings and their implications meet Levy et al.'s (2004) assertion that "being able to take price image into consideration is a significant improvement over traditional pricing techniques, because price image explicitly incorporates the relationship between actual price and perceived prices, as well as external competitive factors (p. xviii)."

5.3 Future research agenda

5.3.1 Cues intervening in and the dynamics of SPI formation

Although actual prices, encountered inside a store upon a store visit, are expected to be the main drivers of SPI, other price-related cues may intervene in the process. For instance, prices and price cues are usually accompanied by supporting advertising, such as out-of-store features and/or in-store displays. Hence, it would be interesting to assess the relative value of these informational cues on the formation of overall price perceptions, vis-à-vis that of actual prices. Conceptually, this is similar to the typical learning models used in marketing (see e.g. Erdem and Keane 1996, Narayanan and Manchanda 2009), where experience with and advertising of a brand (feedback and detailing in the context of pharmaceutical drugs) inform consumers about unobserved quality. Knowing which sources of price information are better able to signal the overall expensiveness of the store – features, displays, or shelf prices – is important for the development of effective pricing strategies – something we leave for future study.

Also, we found that promotion frequency and promotion depth are the two most important product category characteristics associated with consumer SPI learning, a result consistent with previous findings of Alba et al. (1994, 1999). A remaining question, then, is whether different promotion types or framing will affect SPI in the same way. Specifically, does a quantity discount of the same monetary value as a nominal price cut lead to the same store price perception? To the extent that quantity discounts are less directly linked with the concept of price, their impact on beliefs about store expensiveness is expected to be less prominent – making them less appropriate tools for SPI management. Future research, however, should test this proposition. A related question would be: does it make a difference whether the promoted price is presented in isolation or as a reduction off the reference price? And: should the discount be expressed in absolute terms or as a percentage price cut? An extensive body of literature on brand promotion effectiveness, has shown promotion framing to affect consumers' valuation of and response to the brand deal (Chen, Monroe, and Lou 1998, DelVecchio, Krishnan, and Smith 2007, Della Bitta, Monroe, and McGinnis 1981, Gupta and Cooper 1992). Using similar arguments, one might expect such framing to also influence the role of promotional price cuts for store price image formation – an issue worth further investigation.

In Chapter 2, we identified lighthouse categories as products that better signal SPI and yet have a low share-of-wallet. This conceptualization allowed us to group categories, and provided an intuitive way to approximate the likely 'subsidization' of consumers if prices are dropped in the 'wrong' categories. However, changes in prices not only change SPI. They also have a more direct effect on category sales inside the store, which is not to be overlooked (see e.g. Bolton 1989, Hoch et al. 1995, Bell et al. 1999). For instance, while we find storability to be associated with enhanced SPI learning from prices, Bell et al. (1999) found it to be associated with increased elasticity of category demand. Hence, lowering prices in storable categories would lead to both higher demand increases and favorable SPIs. The same authors, however, found size of the assortment and market concentration to be associated with higher demand elasticities, while we find the two product characteristics to be detrimental to SPI learning. Similarly, purchase frequency is associated with increased SPI learning, yet goes along with lower elasticity of demand (Bell et al. 1999). Hence, for these category characteristics, it seems that retailers face a trade-off between higher immediate demand increases, yet lower SPI signaling value when dropping prices. Future studies should further document the net outcomes of price changes in different categories, by including the impact of category prices on both store traffic (through SPI) and category spending.

In our study, building on previous literature describing the SPI formation process, we modeled consumers as 'Bayesian updaters' of SPI. However, we did not test whether, and cannot rule out that, consumers use other mental accounting or heuristic rules when judging store price levels. While Bayesian updating is considered to be the optimal updating rule, it has been shown that consumers often fail to behave as pure Bayesians (e.g. Camacho, Donkers, and Stremersch 2010, Boulding, Kalra, and Staelin 1999, Mehta, Chen, and Narasimhan 2008, Mehta et al. 2004). In the context of SPI formation, the question thus remains: do consumers use other rules, such as the well-known peak-end rule (Fredrickson and Kahneman 1993), when evaluating store prices? That is, do they combine only the last and the highest prices paid when forming an overall impression of the expensiveness of the store? Similarly, we used weighted averages of brand prices within a category to operationalize category price signals. However, building on the previous reasoning, do consumers not consider only the most expensive brand within a product category; or only the most expensive and the cheapest one, as category price signals for the formation of store price images? These questions are highly relevant for retailers aiming to fine tune their SPI management, and are in need of further investigation.

Regarding brands, in Chapter 4 we looked at the effect of introductions of national brands on the price and quality perceptions of a hard discounter. A similar and fascinating question pertains to the effects of different private-label tiers. Mainstream supermarkets have recently introduced elaborate private-label tier programs, with a very different price and quality positioning, and targeting different customer segments (see e.g. Geyskens et al. 2010). Do these private labels different in their ability to signal SPI and SQI? If so, which ones are more effective, and for which image dimension? Does their signaling value differ across customers, in particular, among those they are supposed to target? Or do these complex private-label programs confuse consumers, and jeopardize the formation of favorable price and quality images? For retailers interested in assessing the long-term consequences of their multi-tiered private label programs, these are important issues to be addressed.

Other non-price variables may also have an impact on the formation of SPIs. For instance, press or advertising messages (see e.g. Shin 2005, Simester 1995, Srivastava and Lurie 2004), may signal the overall price level of stores and contribute to the formation of price beliefs in the mind of consumers. Also, other store characteristics such as atmospherics, lighting, or shelf arrangements and the use of outer-packs may generate an image of cheapness for the store. For lack of information, we could not analyze the effect of (changes in) such cues in our study. A fascinating question is whether the categories that contribute to a favorable price image through low prices, are also those where non-price cues need to signal cheapness – and vice versa. Future research could pursue this issue.

5.3.2 Store choice and store perceptions

Regarding the research topic conducted in Chapter 3, 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 countries other than the Netherlands, and in other settings. While we considered the grocery setting, the dual price impact may also appear in other categories such as apparel or consumer durables – an issue that we leave for future study.

Moreover, 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.

Perceptions about store dimensions other than price, may also be helpful to enrich store choice models. For instance, Popkowski-Leszczyc, Sinha, and Sahgal (2004) use perceived metrics to measure intrinsic store preferences or store equity, through a 'factor analytic ' choice model of multi-purpose shopping. Another possibility involves the conceptualization of store patronage decisions as a two-step process, where store consideration and choice are modeled as subsequent stages, with different variables intervening in both stages (e.g. Fotheringham 1988, Finn and Louviere 1990, 1996). Our expectation is that while actual marketing mix instruments or 'hard' attributes, such as prices and assortment size/composition, will drive the selection of a store given the consideration set, perceived attributes or mind metrics are more likely to govern the initial screening or consideration-set formation stage. To our knowledge, this hypothesis has not been subject to empirical validation, perhaps because the operationalization and estimation of a choice model with a consideration set stage poses serious challenges. However, considerable progress in the area of consideration-set modeling (e.g. Bronnenberg and Vanhonacker 1996, Wu and Rangaswamy 2003, van Nierop et al. 2010, Vroomen, Franses, and van Nierop 2004, Chiang, Chib, and Narasimhan 1999, Paap et al. 2005), combined with the availability of richer data sets including hard and soft metrics, make this a promising area for future study.

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Breve sumário em português[§]

O tema central da presente dissertação parte da observação de que os indivíduos não decidem exclusivamente com base em informação objectiva. Em particular, e no contexto de escolhas quanto ao retalhista onde adquirir as categorias de produtos tipicamente encontradas num cabaz de bens de consumo não-duradouros, o facto de os consumidores tomarem em linha de conta não apenas aspectos objectivos como o nível de preços ou a distância, mas também, por exemplo, a percepção que detêm sobre os preços (e a qualidade) do retalhista – isto é, a imagem-preço (e imagem-qualidade) detida. Uma das razões principais pela qual os consumidores consideram as suas percepções relativamente aos preços e à qualidade de um retalhista nas suas escolhas, é a dificuldade em comparar objectivamente diferentes retalhistas. Por exemplo, as lojas de retalho oferecem tipicamente uma vasta selecção de produtos em múltiplas categorias, e o preço de cada produto varia ao longo do tempo, frequentemente devido a promoções.

Não constitui portanto uma surpresa que estas percepções holísticas detidas pelos consumidores em relação às lojas onde adquirem os seus bens, sejam vistas pelos retalhistas como um dos factores mais importantes a influenciar as decisões dos consumidores (Bell et al. 1998, Simester 1995). Reconhecendo este papel pivôt das imagens-preço e -qualidade no processo de tomada de decisão do consumidor, a batalha entre os retalhistas extendeu-se além das prateleiras das superfícies comerciais para a mente dos consumidores. A título de exemplo, a cadeia de hipermercados francesa Carrefour (a maior do mundo), investiu só em 2009 mais de mil milhões de dólares na sua imagem-preço (MarketWatch 2009). Na Holanda, o líder de mercado Albert Heijn, iniciou uma guerra de preços com vista a melhorar, entre outros aspectos, a imagem-preço desfavorável que detinha junto da maior parte dos consumidores (van Heerde et al. 2008). E em Abril de 2010, o gigante Wal-Mart reduziu o preço de 10,000 produtos, na sua maioria produtos alimentares e outros de consumo frequente, no mercado norte americano (CNBC 2010), com o objectivo de "polir a sua imagem-preço" (Wall Street Journal 2010)

Ainda assim, apesar da importância das imagens-preço e das avultadas quantias

[§] Não conforme o Acordo Ortográfico de 2009, por opção livre do autor.

envolvidas na sua gestão, a investigação sobre o tema é escassa e, até agora, deixou os retalhistas com poucas orientações em relação a como definir as suas estratégias de preço e de imagem-preço (e -qualidade). O presente trabalho pretende contribuir para colmatar esta falta na literatura económica.

No primeiro estudo, propomos um quadro de análise no qual os preços de diferentes categorias de produtos são integrados no processo de formação de imagens-preço. Argumentamos que a habilidade de uma categoria de produtos de sinalizar a imagem-preço da loja (IPL) é determinada não só pelo seu peso no orçamento do consumidor, mas também, e sobretudo, por um número de características que guiam a diagnosticidade e acessibilidade dos seus preços. Com base nesta perspectiva, desenvolvemos um modelo de formação da IPL ao longo do tempo, no qual os preços das categorias de produtos actuam como sinais imperfeitos, mas não enviesados, do nível geral de preços de um determinado retalhista. A formação de IPLs é definida como um processo de aprendizagem Bayesiano, o qual, em conjunto com a restante especificação do modelo para dar resposta à questão relativa às características de produtos mais relevantes nesse processo de formação, coloca sérios desafios de estimação econométrica.

No segundo estudo, defendemos que os preços podem afectar o número de visitas a um retalhista por duas vias: *directamente*, ao incentivar os consumidores a comprar nas lojas com preços mais baixos numa dada semana, e *indirectamente*, ao afectarem a percepção do nível geral de preços das lojas visitadas, e, assim, a propensão de estas serem visitadas novamente em futuras deslocações de compra por parte dos consumidores. Para testar empiricamente este efeito dual dos preços, especificámos um modelo de escolha de loja ao nível individual, que inclui quer os preços semanais quer as imagens-preço da loja. Para acomodar o facto de que as imagens-preço são afectadas pelos preços do cabaz de compras, complementamos este modelo de escolha com um modelo de formação das imagens-preço ao longo do tempo, usando uma perspectiva de aprendizagem Bayesiana, à semelhança do primeiro estudo. Usamos este modelo dual para ilustrar como uma alteração do nível de preços numa determinada semana pode afectar o tráfego de uma loja, não só através de um efeito directo contemporâneo dos preços, mas também nas semanas seguintes, devido ao efeito das imagens-preço revistas pelos consumidores ao longo do tempo.

No estudo final, testamos empiricamente a presença e a magnitude do efeito de introdução de marcas A na imagem-preço e na imagem-qualidade de um retalhista 'discount'. Como as marcas A são tipicamente consideradas pelos consumidores como tendo maior qualidade que as marcas brancas equivalentes, mas são, em média, mais caras (Kumar e Steenkamp 2007, Ailawadi et al. 2008, Geyskens et al. 2010), espera-se que a alteração na estratégia do retalhista quanto à selecção de produtos oferecidos, melhore a imagem-qualidade e deteriore a imagem-preço. Usando um modelo bivariado 'ordered probit', analisamos o efeito de uma maior presença de marcas A – controlando para diversas outras variáveis –, simultaneamente, na imagem-qualidade e na imagem-preço do retalhista, tendo assim em linha de conta a ligação existente entre as duas percepções.

Nos três estudos, fazemos uso de bases de dados únicas e de grande dimensão, que combinam dados de visitas semanais e de compra (e preços dos retalhistas e composição da selecção de produtos ao longo do tempo), com percepções sobre a qualidade e o nível geral de preços dos mesmos retalhistas, para um painel representativo de famílias na Holanda. Em termos de metodologia, notamos o uso de métodos de estimação econométrica Bayesianos avançados (nos dois primeiros estudos). Em cada estudo, discutimos os resultados encontrados e a sua relevância em termos teóricos, bem como as suas implicações para a gestão de unidades de retalho.

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