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Priscilla Yung Medeiros

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ABSTRACT

Essays in Empirical Analysis of Consumer Behavior and its Impact on Retailer's Optimal Strategies

Priscilla Yung Medeiros

I examine how consumers' purchase' decisions and intentions of purchases are affected by uncertainty about future deals (temporary price cuts or sales) for a product and how these results affect retailers' optimal pricing and marketing strategies. First I look at the effects of uncertainty about the timing of deals (i.e. temporary price cuts or sales) on consumer behavior in a dynamic inventory model of consumer choice. I derive implications for purchase behavior and test them empirically, using two years of scanner data for soft drinks. I find that loyal consumers buy a higher fraction of their overall purchases during deals as the uncertainty decreases. This effect increases with an increase in the product's share of a given consumer's purchase in the same category or if the consumer stockpiles (i.e., is a shopper). During a particular deal, loyal shoppers increase the quantity they purchase the more time that has passed since the previous deal, and the higher the uncertainty about the deals' timing. For the non-loyal consumers these effects are not significant. These results hold for products that are frequently purchased, like soft-drinks and yogurt, but do not hold for less frequently purchased products, such as laundry detergents. In the second chapter I analyze how the uncertainty about future deals affects consumers' intended

purchases during the Christmas period for four product categories: CDs/DVDs, clothing, cosmetics/fragrances and electronics. Using a method to elicit and measure revisions to subjective expectations, I conduct an e-mail survey and present to the respondents different scenarios where the degree of uncertainty on whether there will be certain types of deals in the next Christmas seasonal period varies. I find substantial heterogeneity in the revision of expectations. The empirical findings suggest that there are hidden costs of advertisement, such as consumers who spend less when they become more aware of future deals. In the third chapter I discuss manufacturers and retailers optimal pricing strategies incorporating the effects of deals' timing on consumer behavior. I also discuss situations where firms can profit from unpredictability such as using it as a source of increasing overall consumption of the brand.

Acknowledgements

I found amazing when I first came to United States from Brazil the amount of deals (temporary price cuts or sales) offered in this country and the habit American consumers have of searching for deals. I immediately started to also search for deals, and think how other consumers form their expectations about deals and how they also make their purchase decisions. Later, in my second year at Kellogg, I was sitting at Professors Igal Hendel and Aviv Nevo class of Advanced Topics in Industrial Organization, and they were teaching structural estimation of models of consumer behavior, when I finally linked my curiosity about deals with the material I was learning in class. That is how the idea for my main paper, "The Effects of Uncertainty about the Timing of Deals on Consumer Behavior", was born. At the same year, I was attending Professor Charles Manski course on Measuring Expectations when I also started writing my second paper, "Purchasing Intentions: The Effects of Uncertainty about Christmas Deals", as a requirement for the course. The next step was to start talking with Professors Igal Hendel and Scott Stern about my research ideas. Ever since they helped me countless number of times and gave me great guidance and insightful comments in my research.

Since my research has a marketing flavor, I also started interacting with Professor Eric Anderson, who was always very supportive of my progress, providing me with some extremely helpful marketing perspective of the problems I was interested. I also counted with the support and guidance of Professor David Besanko.

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CHAPTER 1

Introduction

In my dissertation I study how consumers' purchase' decisions and intentions of purchases are affected by uncertainty about future deals (temporary price cuts or sales) for a product and how these results affect retailers' optimal pricing and marketing strategies. In the first chapter, The Effects of Uncertainty about the Timing of Deals on Consumer Behavior, I examine the effects of uncertainty about the timing of deals (i.e. temporary price cuts or sales) on consumer behavior in a dynamic inventory model of consumer choice. I derive implications for purchase behavior and test them empirically, using two years of scanner data for soft drinks. I find that loyal consumers' decisions, both about the allocation of their purchases over time and the quantity to be purchased in a particular deal, are affected by the uncertainty about the timing of the deal for the product. Loyal consumers buy a higher fraction of their overall purchases during deals as the uncertainty decreases. This effect increases with an increase in the product's share of a given consumer's purchase in the same category or if the consumer stockpiles (i.e., is a shopper). During a particular deal, loyal shoppers increase the quantity they purchase the more time that has passed since the previous deal, and the higher the uncertainty about the deals' timing. For the non-loyal consumers these effects are not significant. These results hold for products that are frequently purchased, like soft-drinks and yogurt, but do not hold for less frequently purchased products, such as laundry detergents. The findings suggest that

manufacturers and retailers should incorporate the effects of deals' timing on consumers' purchase' decisions when deriving optimal pricing strategies.

The second chapter, Purchasing Intentions: The Effect of Uncertainty about Christmas Deals, I focus on intended purchases instead of actual purchases. The amount stores decide to spend on marketing their future deals affects first consumers' intended purchases. Acquiring information about deals is costly for consumers. Releasing information about deals is also costly for stores. The more stores spend on advertising their future deals, the more precise is the information acquired by consumers about future deals. This chapter analyzes how the level of uncertainty on the information released about future deals affects consumers' intended purchases. I focus on Christmas' deals and look at four product categories: CDs/DVDs, clothing, cosmetics/fragrances and electronics. Using a method to elicit and measure revisions to subjective expectations, I conduct an e-mail survey using new wording I called *belief in a predetermined uncertainty scenario*. First, I elicit respondents' prior beliefs about the probability that a sale anywhere from 20% to 35% or a sale over 35% will occur during the next Christmas period in each of four product categories. I also elicit the amount the respondents expect to spend in each of the four product categories. Next, I present five different uncertainty scenarios to the respondents, where the probability that no deals or a deal from 20% to 35% will occur during the Christmas season is predetermined in the question. Then I asked the respondents again how much they expect to spend in each of the four product categories, given the five predetermined probabilities of occurrence of a sale from 20% to 35%. In this way I elicit the posterior beliefs for the five different uncertainty scenarios. I find substantial heterogeneity in the way respondents revise their expectations. This finding emphasizes the need to consider flexible updating processes when modeling expectations of future purchases. I also found differences

across product categories in the way consumers revise their expectations about future purchases. Clothing and electronics are the categories where intended purchases changed more as the uncertainty about future deals changes. Cosmetics/fragrances is the category where intended purchases changed less with uncertainty about future deals. The empirical findings suggest that there are hidden costs of advertisement, such as consumers who spend less when they become more aware of future deals.

The third chapter, Optimal Pricing Strategies: The Effects of Uncertainty about the Timing of Deals on Consumer Behavior, I discuss pricing implications using the empirical finding from the first chapter that uncertainty about the timing of deals affects consumers' purchase decisions. Consider a monopolist manufacturer that sells directly to the final consumer or dictate prices to the retailer. I describe the five step algorithm to find the optimal pricing strategy for the case of the monopolist manufacturer. Using numerical simulations, I find situations where a predictable deal pattern achieves the highest profit among the three possible strategies: constant price, predictable deal pattern and unpredictable deal pattern. Under the framework presented here, I could not find any situation where unpredictability achieves the highest profit, among the three possible strategies, beyond gains from discounting. I then suggest ways to extend the model in order to find unpredictability as the optimal outcome.

CHAPTER 2

The Effects of Uncertainty about the Timing of Deals on Consumer Behavior

2.1 Introduction

It is well documented in both the marketing and economics literatures, that *deals*, defined as temporary price-reductions or discount sales, are a key component of firms' pricing strategies for both non-durable and durable goods. As a result, the nature of the consumer response to deals is of substantial importance to both academics and managers. Recent studies demonstrate that demand anticipation (at low prices consumers store for future consumption) is present in many frequently purchased non-durable goods[1]. Therefore, we should expect consumers to strategically time their purchases to coincide with deals. Then uncertainty about the timing of a deal for a brand might affect consumers' purchases decisions.

The objective of this paper is to test and understand whether and how uncertainty about deals' timing affects consumers' decisions, about both the allocation of their purchases over time and the quantity purchased at the time of a particular deal. I also investigate how these effects vary across different types of consumers and product categories. I develop a dynamic model of consumer choice where consumers' just form beliefs about future prices when they are uncertain about deals' timing. Otherwise they know the entire price distribution. I use the model to derive implications for purchase behavior and test them empirically using two years of scanner data for

[1] Among these recent studies are Erdem, Imai and Keane (2003); Sun, Neslin and Srinivasan (2003); Van Heerde, Gupta and Wittink (2003) and Hendel and Nevo (2006b).

soft drinks, laundry detergents, and yogurts. The bottom line from the empirical results is that loyal shopper consumers' decisions, both on the allocation of their purchases over time, and on the quantity purchased at a particular deal, are affected by the timing of the brand's deals. And, unlike previous studies, I am able to support this claim with scanner data. This result holds for products that are frequently purchased, like soft-drinks and yogurts, but not for products that are less frequently purchased, like laundry detergents. This result also has distinct managerial implications. It suggests that it is crucial for both manufacturers and retailers to incorporate the effects of deals' timing on consumers' purchasing decisions when deriving optimal pricing strategies.

Similarly to other analysts of this phenomenon[2], I investigate how uncertainty about deals' timing affects consumers' choices using a dynamic context and let consumers endogenously choose the amount to consume. The unique aspect of the model presented here is the crucial assumption about the way consumers form their beliefs about future prices. Consumers form these beliefs only when they are uncertain about deals' timing. In the case of predictable deal patterns, consumers know the entire price distribution. This assumption differs from these previous works and also from other related works in the economics literature that studies demand anticipation using a dynamic inventory model of consumer choice. They all assume either that consumers form expectations about future prices according to a Markov process or that the way expectations are formed is the same independent of the level of uncertainty about deals' timing. I then describe the optimal consumer behavior in both cases. I take the case of predictable deal patterns as the benchmark and derive implications for purchase behavior. I then consider the case

[2] Examples of papers in this literature are Assunção and Meyer (1993) and Krishna (1994).

of an unpredictable deal pattern and compare the implied purchasing behavior to the behavior under the benchmark case.

In the model, consumers purchase for two reasons: for current consumption (endogenously determined) and to build inventory. How much consumers buy in each period depends on their current inventory level, the current shock to utility from consumption and current prices. In the unpredictable case, how much consumers buy also depends on their beliefs about future prices while in the predictable case it depends on the number of weeks between two consecutive deals, which consumers know in advance. Prices can take on two values: on deal, p_L, and off deal, p_H such that $p_L<p_H$. Consumers know both prices, they do not know before coming to the store which price will be offered.

I focus on four types of consumers: loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper. Both kinds of loyal consumers are in the market for their particular brand often; in some sense they need the brand. They choose the brand most of the time regardless of price. When their favorite brand is not offered at a deal they generally do not substitute for another brand. Instead they either buy their favorite brand at the regular price or consume it from inventory. In the theoretical model of consumer behavior, I define *loyal* as the consumer whose marginal utility from consumption of the brand is high enough such that he is willing to purchase this brand at the regular price if necessary, i.e. his stock is zero. Non-loyal consumers have no compelling need to buy a brand. They buy a brand only if its price is low enough. Empirically, I identify a *loyal* as the consumer whose share of purchases on a particular brand is at least 70% of his total purchases in the category.

A *shopper* consumer buys not only for immediate consumption, but also to stockpile. In the model, *shopper* is defined as the consumer who has a storage cost low enough such that he is

able to stockpile for the average number of weeks between two consecutive deals. Empirically, I identify a *shopper* by the characteristics of his purchase pattern that arise from his stockpiling behavior. For instance, a consumer for whom the difference of the time to the next purchase is larger for purchases on sale than for purchases not on sale is defined as a shopper. The intuition is that these consumers buy a larger quantity when purchasing on sale to be able to last longer without purchasing.

There are two implications derived from the model. The first is that, at the time of a particular deal, loyal shopper consumers increase their quantity purchased the more time has passed since the previous deal and the higher the uncertainty about deals' timing. The second implication is that, as compared to other consumers, loyal shoppers buy a higher fraction of their overall purchases during deals, and, as a result, save more, as uncertainty about deals' timing decreases. Non-shopper consumers don't stock up so they buy only to the extent of their consumption. Non-loyal consumers may be affected in the same way by the uncertainty about the deal timing of other competitive brands.

In terms of empirical analysis, this paper also contributes to the literature on the effects of deal patterns on purchase decisions. Previous works rely on experiments to test their model implications[3]. To the best of my knowledge, I am the first to use scanner data to study how uncertainty about the timing of deals affects consumers' purchase decisions. Unlike previous work I also investigate how these effects vary across different types of consumers and product categories.

The theoretical implications are tested using two years of scanner data for soft drinks, laundry detergents, and yogurts. These data were collected using scanning devices in nine

[3] Examples of previous works are Krishna (1994) and Meyer and Assunção (1990).

supermarkets, belonging to five different chains, in two sub-markets of Chicago. The store level data includes weekly prices, quantities and promotional activities. The household level data follows the purchases of 1,042 households over a period of 104 weeks. I know when each household visited a store, how much was spent in each visit, which products were bought, and where they were bought.

I define the unpredictability of the deal pattern of a product as the coefficient of variation of the number of weeks between two consecutive deals[4]. The higher the standard deviation of the number of weeks between two consecutive deals, for a given average number of weeks between two consecutive deals, the less predictable the deal pattern is. I define consumers' gains from buying a higher fraction of their overall purchases during deals as savings. The savings are defined as the difference between how much consumers actually spent and how much they would have spent if they had bought the same amount randomly and therefore, paid the average of the prices they observed at their trips to the store.

I first estimate the effects of uncertainty about deals' timing on savings separately for loyal and non-loyal consumers after controlling for other relevant characteristics of the deal pattern, such as frequency of deals (percentage of the total time the product was offered during a deal), and average discount (average of all the percentage discounts for which the product was offered). Then I include all consumers together in a single regression and add two new independent variables: the actual shares each consumer buys of each brand in the category and an interaction term between uncertainty about deals' timing and shares. I also interact loyalty with the shopper classification. The main finding is that uncertainty about deals' timing significantly affects loyal

[4] The Coefficient of variation is the standard deviation of the number of weeks between two consecutive deals divided by the average number of weeks between two consecutive deals. This measure is defined per UPC, per store, per consumer.

consumers' savings. Loyal consumers buy a higher fraction of their overall purchases during deals (save more), as uncertainty about deals' timing decreases. This effect increases with an increase in the product's share of a given consumer's purchase in the category or if the consumer stockpiles (is a shopper). For non-loyal consumers these effects are not significant.

I also regress the quantity purchased per visit to the store on price, promotional activities, number of weeks since the previous deal, uncertainty about deals' timing and an interaction term between the last two. I find that loyal and shopper consumers increase the quantity they purchase on a particular deal both as more time passes since the previous deal and as there is greater uncertainty about deals' timing. These results for consumers' decisions, both for the allocation of their purchases over time, and for the quantity purchased during a particular deal, hold for products that are frequently purchased, like soft-drinks and yogurts, but do not hold for products that are less frequently purchased, like laundry detergents.

I assume that prices and deals' timing are exogenously given at the present work. An interesting extension is to determine manufacturers' and retailers' optimal pricing strategies incorporating the effects of deals' timing on consumer behavior. This is going to be the focus of the discussion at chapter four.

The remainder of the paper is organized as follows. In section two I review the relevant literature. In section three I present the dynamic inventory model of consumer choice and derive testable implications. In section four I describe the data and identification strategies. In section five I present the empirical results for the effects of uncertainty about deals' timing on consumers' allocation of their purchases over time. In section six I show the empirical results for the effects of uncertainty about deals' timing on the quantity purchased during a particular deal. In section seven I present a cross-category analysis. In section eight I conclude.

2.2 Related Research

This paper contributes to two main streams of research. In the following sections, I review the relevant research in these two areas and discuss how they relate to my work.

2.2.1 Literature on Demand Anticipation

One branch of the literature on demand anticipation focuses on exploring the more fundamental question of whether data supports the argument that demand anticipation is an important effect of promotion. In the marketing literature, Gupta (1988) distinguishes three components of household response: category purchase timing, brand choice, and purchase quantity. In the coffee category, Gupta finds that the percentage of own-brand sales elasticity with respect to a particular promotion that is due to brand-switching elasticity is 84%, that is due to purchase acceleration elasticity is 14%, and that is due to quantity elasticity is 2%. Other follow-up papers extend Gupta's (1988) approach, and generalize for many categories and brands (e.g. Chintagunta (1993) and Bell, Chiang and Padmanabhan (1999)). Across these decomposition studies the authors find that, on average, brand switching accounts for the vast majority of total elasticity. In contrast, Van Heerde, Gupta & Wittink (2003) offer a complementary decomposition measure based, instead of elasticity, on unit sales. The authors apply their new method to previously reported elasticity decomposition results and find that the cross-brand

component, instead of accounting for 75% of the total elasticity effect, is actually 33%. This gives new evidence to the importance of demand anticipation effect of sales promotion.

In the economics literature, the question of whether data supports demand anticipation to be an important effect of promotion, is studied testing implications derived from a dynamic inventory model of consumer choice. Boizot, Robin and Visser (2001) present a dynamic inventory model that they test using consumer dairy data. They show that duration from previous purchase increases in current price and declines in past price, and quantity purchased increases in past prices. Hendel and Nevo (2006b) also present a dynamic inventory model and use it to derive implications about observable variables that stem from storing, but would not be expected under static framework. Using scanner data on three different product categories (laundry detergents, yogurt and soft-drinks) they find the results to be consistent with an inventory model. They find that aggregate demand increases as a function of duration from previous sale, and this effect differs between sale and non-sale periods. They also find that when buying on sale households tend to buy more quantity, buy earlier and postpone their next purchase.

This paper presents a dynamic inventory model of consumer choice based on Hendel and Nevo (2006b). A drawback from Hendel and Nevo (2006b) and some other papers in this literature is the assumption that either consumers form expectations about future prices according to a Markov process or that the way the expectations are formed is the same independent of the level of uncertainty about deals' timing. While this is a fine assumption for many applications, it is too restrictive if one's final goal is to study the effects of deals' timing on consumers' purchase decisions. Instead I assume that consumers' beliefs about future prices just follow a Markov process in the case that consumer is uncertain about deals' timing (unpredictable deal

pattern). In the case in which deals are predictable (there is no uncertainty), consumer's know the entire price distribution.

Another branch of the literature on demand anticipation focuses on structurally estimating dynamic inventory models of consumer choice. Erdem, Imai and Keane (2003) construct a structural model of demand in which consumers can store different varieties of the product. They focus on the role of price expectations and differences between short run and long run price responses. They show that temporary price cuts primarily generate purchase acceleration and category expansion, rather than brand switching. Sun, Neslin and Srinivasan (2003) also show that brand-switching elasticities are overestimated by stand-alone logit models. Hendel and Nevo (2006a) structurally estimate a dynamic inventory model of consumer choice using scanner data on laundry detergents and show that static demand models create biased price elasticity estimates.

This paper makes a first step in identifying the importance of letting consumers' form beliefs about future prices only when they are uncertain about deals' timing. An interesting future extension is to apply the estimation methods developed in previous papers (Erdem, Imai and Keane (2003) and Hendel and Nevo (2006a)) to structurally estimate the model presented here and generate normative pricing implications.

2.2.2 Literature on the Effects of Deal Patterns on Consumer Behavior

There is a stream of literature which builds rational models of purchasing under price uncertainty and investigates how deal patterns influence consumers' purchase behavior. The

starting point for much of this research is Golabi's (1985) zero-order model (prices in each period are independent of prices in prior periods) for the case of a single good and constant consumption rate. Golabi's model is extended by Krishna (1992) to the multiple brand case and by Assunção and Meyer (1993) to accommodate variable consumption rate and first-order dealing patterns. The model presented here is close to Assunção and Meyer (1993) in the sense that consumers endogenously chose the amount to consume. However, most of implications derived in Assunção and Meyer (1993) are based on the special case of markets characterized by bimodal prices where consumers' expectations about future prices are represented by a first order Markov process. Again, the way expectations are formed is the same independent of the level of uncertainty on deals' timing.

Of these studies, the paper closest to mine is Krishna (1994). She explores the effect of deal patterns on consumer behavior by developing a normative purchase quantity model that incorporates all deal patterns. One of the implications of her model is that the average quantity purchased during deals should be larger when there is greater certainty about deals' timing. I also investigate how certainty about deals' timing affects consumers' choices using a dynamic context. However, in contrast to her work, I let consumers endogenously choose the amount to consume (instead of assuming a constant consumption rate). I also explicitly account for consumer heterogeneity and differences across categories.

There is a significant lack of empirical research on the effects of deal patterns on purchase decisions. Krishna (1994) tests some of her model implications in a laboratory experiment. Meyer and Assunção (1990) also use an experiment to report how consumers make rational sequential purchase decisions with imperfect knowledge about future prices using different shapes of the distribution of prices and its trend over time. To the best of my knowledge, I am

the first to use scanner data to study how uncertainty about deals' timing affects consumers' purchase decisions, and how the effects vary across different types of consumers and product categories.

2.3 Model of Consumer Behavior

In this section, I present the dynamic inventory model of consumer choice. First, I describe the basic setup of the model. Next, I describe how consumers form their expectations about future prices. Then, I describe the optimal consumer behavior under both the predictable and unpredictable cases. I take the case of predictable deal pattern as the benchmark and derive implications for purchase behavior. I then consider the case of unpredictable deal pattern and compare the implied purchasing behavior to the behavior under the benchmark case. From this comparison I derive two theoretical implications that are tested with scanner data.

2.3.1 The Basic Setup

Household h purchases for two reasons: current consumption and to build inventories. At each period t, household h decides the amount it wants to consume, c_{ht}, and the quantity it wants to purchase, q_{ht}, of each single product. The household derives a utility from consumption that is described by the following equation:

$$u(c_{ht}) = \beta_h log(c_{ht} + v_{ht}) \tag{1}$$

where β_h is the marginal utility from consumption and v_{ht} is a shock to utility. The shock to utility, v_{ht}, introduces randomness in the household's needs, unobserved by the researcher. Low realizations of v_{ht} increase the household's need, making it more inelastic. Households know the current realization of the shock when they reach the store. But they don't know the future realizations of the shock. I assume that v_{ht} can take on three values, $v_{ht} \in \{0,1,2\}$, with equal probabilities. I also assume that the shocks are i.i.d. across each type h of households.

Household h also buys to take advantage of deals and to store for future consumption. The cost of storing inventory is given by:

$$C_{ht}(i_{ht}) = \theta_h i_{ht} \tag{2}$$

where i_{ht} is the inventory level of household h at period t, and θ_h is the marginal disutility of storing inventory.

Prices can take on two values: on deal, p_L, and off deal, p_H such that $p_L < p_H$. Consumers are aware of both prices, they do not know before coming to the store which price will be offered.

Define d_{ht} as follows, with each consumer at each date having a potentially different d_{ht}:

$$d_{ht} = \begin{cases} 0 & \text{stay home} \\ 1 & \text{visit store} \end{cases} \tag{3}$$

Each consumer is given an exogenously determined vector of d_{ht}'s. Consumers do not decide on when to go to the store, they just know when are the next times they are going to be in the store. At each period consumers visit a store, they must decide on the quantity to purchase. They observe the price of each good even if they decide not to purchase the good. At all periods consumers decide on the quantity to consume. When consumers do not visit the store, they do not observe the price of the good. This assumption introduces heterogeneity in consumers' beliefs about future prices. Since different consumers might visit stores at different periods, they possibly experience different price distributions for the same good, at the same store.

The consumer's problem can be represented as:

$$\max_{c_{ht},q_{ht}} \sum_{t=0}^{\infty} \delta^t E\left[\beta_h \log(c_{ht} + v_{ht}) - C_{ht}(i_{ht}) - d_{ht}\gamma_h p_t q_{ht} \middle| \Psi_{ht}\right] s.t.$$

$$C_h(i_{ht}) = \theta_h i_{ht}$$

$$i_{ht} = i_{h,t-1} + d_{ht} q_{ht} - c_{ht} \tag{4}$$

$$i_{ht} \geq 0 \quad c_{ht} \geq 0 \quad q_{ht} \geq 0$$

where Ψ_{ht} is the information set at time t, and δ the discount factor. At each time t, household h derives non-negative utility from current consumption of the good. At time t, household h also incurs the cost of storing, whenever it ends period t with a positive inventory, and the cost of purchase, whenever it visits a store and decides to purchase a positive amount. Quantity not consumed is stored as inventory.

2.3.2 Information Set

The contents of the information set, Ψ_{ht}, depend on the type of deal pattern being offered. Deal patterns can either be *predictable* (no uncertainty about deals' timing) or *unpredictable* (some level of uncertainty about deals' timing). More precisely define by D the number of periods the good is offered on deal. Also define by N_z the number of weeks between two consecutive deals for $z=1,...,D-1$ and $N=[N_1,\ldots,N_{D-1}]$. $\mu(N)$ stands for the average number of weeks between two consecutive deals and $\sigma(N)$ the respective standard deviation. A product has a predictable deal pattern when $\sigma(N)=0$. Any deal pattern such that $\sigma(N)>0$ is classified as unpredictable. For instance, a product that is promoted on alternate weeks or every 3 weeks has a predictable deal pattern.

In the case in which deals are unpredictable, the information set at time t consists of the beginning of the period inventory, i_{ht-1}, current prices, p_t, the shock to utility from consumption, v_{ht}, and the vector of d_{ht}'s: $\Psi_{ht}=\{i_{ht-1}, p_t, v_{ht}, d_{ht}, d_{ht-1}, d_{ht-2},\ldots\}$. Consumers' expectations about future prices are represented by a first-order Markov process with two prices, a deal price (p_L) which is thought to occur with probability $\pi_{H,L}$ if p_H was the price in the previous period, and $\pi_{L,L}$ if p_L was the price in the previous period, and a regular price (p_H) which is thought to occur with probability $\pi_{L,H}$ and $\pi_{H,H}$ after the occurrence of price p_L and p_H. Formally the probability function can be described by the Markov chain:

$$\begin{array}{cccc} & & \textit{price at } t+1 & \\ & & p_L & p_H \\ \textit{price at } t & p_L & \pi_{L,L} & \pi_{L,H} \\ & p_H & \pi_{H,L} & \pi_{H,H} \end{array} \tag{5}$$

The transition probabilities describe how predictable, consumers believe, the deal pattern is. Consumers form their expectations (give value to the transition probabilities) during an initial learning period. Those beliefs are defined per product, per consumer, per store. Consumers that visited the same store at the same periods have identical beliefs. Consumers use these transition probabilities defined at this initial learning period to make decisions on the quantities to buy and consume. The utility maximization problem described in (4) happens after this initial learning period is over. There is no further learning in my model.

The closer the transition probabilities, $\pi_{L,H}$ and $\pi_{H,L}$, are to 0 and 1, the more predictable the deal pattern is. The closer $\pi_{L,H}$ and $\pi_{H,L}$ are to 0.5, the more unpredictable the deal pattern is. Due to the Markov assumption, the only predictable deal pattern that can be represented by the Markov chain is deals happening every odd period, i.e., $\pi_{L,H}=\pi_{H,L}=1$ or the cases of constant price, i.e., either $\pi_{L,H}$ or $\pi_{H,L}$ equal to 0. For any other deals' timing consumers face some source of uncertainty.

We expect consumers to have more information about deals' timing when deals are predictable than when there is some uncertainty about timing. Due to the Markov assumption, I am not able to distinguish between a predictable deals pattern, like deals happening every 3 weeks, from an unpredictable one. To solve this issue I consider that consumers know the entire price distribution when deals are predictable. They know exactly when it was the last deal. Therefore, for the case of a predictable deal pattern, consumers information set at time t consists not only of the beginning of the period inventory, $i_{h,t-1}$, current prices, p_t, shock to utility from consumption, v_{ht}, and the vector of d_{ht}'s, but also of the number of weeks between two consecutive deals, N: $\Psi_{ht}=\{i_{ht-1}, p_t, v_{ht}, d_{ht}, N, d_{ht-1}, d_{ht-2},\ldots\}$.

2.3.3 Consumer Behavior

Independently of the type of deal pattern being offered, in each period consumers compare the costs of holding inventory and the benefits from buying at a current price instead of future expected prices. Their decisions also depend on the exogenously determined vector of d_{ht}'s. Consumers might want to purchase more at a given visit to store for consumption at the later periods they are going to stay home. To simplify, in the following analysis I consider the case in which all consumers visit the store every period, i.e, $d_{ht}=1$ for $\forall t$ and h.

At the regular price consumers might purchase for immediate consumption, depending on their inventory, price sensitivity, γ, marginal utility from consumption, β, and the realization of the random shock to utility. Consumers do not buy for storage at the regular price unless I relax the assumption that $d_{ht}=1$ for $\forall t$. Ceteris paribus[5], at the regular price consumers' decisions on how much to purchase are the same, independent of the type of deal pattern being offered.

At the deal price consumers might purchase for immediate consumption depending on their inventory, price sensitivity, γ, marginal utility from consumption, β, and the realization of the random shock to utility. However, consumers might also purchase for storage. This last decision depends on their storage cost, θ, discount factor, δ, the regular price, p_H, deal price, p_L, and, in the case consumers are uncertain about deals' timing, also on their expectations about future prices. In the case of predictable deal pattern, the decision to purchase for storage also depends on the number of weeks between two consecutive deals, N.

[5] Given the same inventory level, price sensitivity, γ, marginal utility from consumption, β, and the realization of the random shock to utility.

In the case of an unpredictable deal pattern, ceteris paribus, the smaller the probability that after a promotion has been offered another promotion occurs, $\pi_{L,L}$, and the higher the probability that after a regular price has been offered another regular price occurs, $\pi_{H,H}$, the bigger the quantity purchased at a particular deal. Of course this conclusion depends, among other things, on the storage cost and discount factor. If the storage cost is too high or discount factor too small this conclusion might not hold. And for a given range of average number of weeks between two consecutive deals, $\mu(N)$, an increase in the variance of the price distribution leads to a decrease in $\pi_{L,L}$ and to an increase in $\pi_{H,H}$.

In the case of a predictable deal pattern, ceteris paribus, the bigger the number of periods the product is offered at the regular price, N, the bigger the quantity purchased at a particular deal. Again this conclusion depends, among other things, on the storage cost and discount factor. If the storage cost is too high or discount factor too small this conclusion might not hold. The optimal consumer's purchase decisions are described in proposition 1.The generalization of proposition 1 including shocks to utility, proposition 2, is described in the appendix. Proofs are provided in the appendix. In all the following analysis I drop the subscript h, to simplify notation.

Proposition 1: *(Benchmark case) Consider the case of a predictable deal pattern. Prices are cyclic with a cycle defined by one period of deal price followed by N consecutive periods of regular price. Assume no shocks to utility (v_t =1). The optimal quantities to purchase and consume for the N+1 periods of the cycle can be described as:*

$$c^*_j = \frac{\beta}{\gamma \vartheta_j} - 1 \qquad for \qquad j = 1,...,n \tag{6}$$

$$q^*_1 = \sum_{j=1}^{n} c^*_j, q^*_2 = ... = q^*_n = 0 \tag{7}$$

$$q^*_H = q^*_{n+1} = ... = q^*_{N+1} = c^*_{n+1} = ... = c^*_{N+1} = \frac{\beta}{\gamma p_H} - 1 \tag{8}$$

$$n = max\, k \big| \vartheta_k < p_H, k \in IN \tag{9}$$

$$\begin{cases} \vartheta_1 = p_L \\ \vartheta_k = \dfrac{p_L + \theta \sum_{j=0}^{k-2} \delta^j}{\delta^{k-1}} \qquad for \qquad k = 2,...,n \end{cases} \tag{10}$$

The intuition for proposition 1 is the following. First define υ_k as the virtual price. It is the unit cost of purchasing at the first period low price for a later consumption at period $j=k$, where $k=2,\ldots,n$. It is composed by the cost of purchasing at the deal price, p_L, plus the cost of carrying the inventory up to period k of consumption. Consumers compare the virtual price with the cost of purchasing the same unit at period k regular price, when deciding on the amount to be purchased for storage at the first period deal price. For all periods such that the virtual price is smaller than the regular price it is optimal to purchase in advance at the first period promotional price. n is the last period from the N periods of regular price where the virtual price is smaller than the regular price. During these $n>1$ periods of the cycle there is no need for purchase. Consumption comes from inventory. For the remaining periods of the cycle, from $t=n+1$ to $t=N+1$, purchases are only for immediate consumption.

A main difference of consumers' purchase behavior under predictable deal pattern and unpredictable deal pattern is the probability of overstocking and understocking. Consumers *overstock* when they have a positive inventory on hand when a deal occurs. Consumers *understock* when they have zero or insufficient inventory during a regular price when it would be ex-post optimal to have a positive inventory. If we consider no shocks to utility, the probability of overstocking and understocking is zero for the benchmark case, and positive for the unpredictable deal pattern.

In order to derive implications for consumers' decisions on the allocation of their purchases over time, I first describe (Proposition 3) how consumers' gains from buying a higher fraction of their overall purchases during deals vary with the parameters of the model in the benchmark case.

Proposition 3: *In the case of predictable deal pattern, consumers' gains from buying a higher fraction of their overall purchases during deals increases as p_H, v_t and δ increases or as θ, p_L and N decreases.*

Given that the fraction of overall purchases during deals is given by the ratio *n/N,* and *n* is the number of periods where the virtual price is smaller than the regular price, the smaller the virtual price and the higher the regular price the larger is *n* and consequently, the higher the ratio. The virtual price increases as p_L, θ and N increases or as δ decreases. Also low realizations of the shocks to utility increase consumers' needs, increasing the probability of purchase at the regular price.

2.3.4 Testable Implications

I now focus on those predictions of the model that help us understand how consumers' purchase decisions vary with uncertainty about deals' timing, for a given average number of weeks between two consecutive deals. I am also interested in how this behavior varies across different types of consumers. In particular, I am interested on four main types of consumers: loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper.

Loyal is the consumer whose marginal utility from consumption of the good is high enough such that he is willing to purchase at the regular price if necessary, i.e. stock is zero. More formally, loyal is the consumer for whom $\beta_h > \gamma_h p_H$. *Non-loyal* is the consumer whose marginal utility from consumption of the good is smaller than the same threshold, i.e., $\beta_h \leq \gamma_h p_H$. These consumers are not willing to perform an inter-temporal substitution of this product.

Shopper is the consumer who has a storage cost low enough such that he is able to stockpile for the average number of weeks between two consecutive deals. More formally, shopper is the consumer for whom $\theta_h < \frac{\left(\delta^{\mu(N)_h - 1}\right) p_H - p_L}{\sum_{j=0}^{\mu(N)_h - 2} \delta^j}$. Note that for the benchmark case a shopper has $n=N$, i.e., he is able to have 100% of his purchases during deals. *Non-shopper* is the consumer who has a storage cost higher than the same threshold.

The following two implications are derived using the case of unpredictable deal pattern and comparing to the benchmark case. Proofs are provided in the Appendix.

Implication 1: *Loyal shopper consumers increase their quantity purchased on a particular deal both as more time passes since the previous deal and the higher the uncertainty about deals' timing*[6].

The first part of this implication, namely that the quantity purchased on a particular deal increases as more time passes since the previous deal, comes from the fact that purchases in non-deal periods are only for consumption. As the number of weeks from the last deal increases, inventory declines (both because consumers do not buy for storage at non-deal periods and because consumption might be positive in most of these periods). And since the quantity purchased increases as inventory decreases we get the result. For non-loyal consumers their quantity purchased on a particular deal does not necessarily increases as inventory on this product decreases.

The rest of this implication is a consequence of the fact that as $\pi_{L,L}$ decreases and $\pi_{H,H}$ increases, the quantity purchased at a particular deal increases. And for a given range of average number of weeks between two consecutive deals, an increase in the variance of the price distribution leads to a decrease in $\pi_{L,L}$ and an increase in $\pi_{H,H}$. More precisely, this result holds in the case where the average number of weeks between two consecutive deals is not too large, so that the long-term stationary probability of the low price state is big enough, $\Pi_L \in [1/2,1]$.

Implication 2: *Loyal shopper consumers buy a higher fraction of their overall purchases during deals as uncertainty about deals' timing decreases.*

[6] For a given average number of weeks between two consecutive deals, all else constant, and also for the long term stationary probability of the low price state big enough, $\Pi_L \in [1/2,1]$.

For the case of unpredictable deal pattern, the probability that the next deal happens earlier/later than expected is positive. This probability increases as uncertainty about deals' timing increases. I showed in Implication 1 that the quantity purchased at a particular deal increases as uncertainty about deals' timing increases. If a deal happens earlier than expected, consumers have overstocked and if it happens later, consumers have understocked. In the case consumers have understocked, and if they are loyal, they purchase at the regular price. If consumers are non-loyal, they might find it optimal not to purchase the product at the regular price. Therefore, the higher the uncertainty about deals' timing the bigger is the number of loyal consumer's purchases at the regular price. Consequently the smaller is the fraction of overall purchases during deals.

Comparing to the benchmark case with no shock to utility, loyal shopper consumers have 100% of their overall purchases during deals since $n=N$. So loyal shopper consumers can only do worst when they are uncertain about deals' timing[7].

2.4 Data and Identification Strategies

[7] These implications are similar to those showed in implication 1 of Krishna (1994) coming from a different model. Concerning deals' timing the implications of her model are that the probability of overstocking (having a positive inventory when the next deal occurs) is smaller the greater the certainty of when the next deal will occur. She also finds that the proportion of quantity purchased on deal is larger and the buyer's average cost is smaller when deals' timing is more certain. These implications are similar to my implication 2. Krishna (1994) also finds that the average quantity purchased on deal is larger when deals' timing is more certain. Compare that to implication 1 where I find that higher uncertainty leads to higher quantity purchased at a particular deal. One result seems to contradict the other. Not necessarily. The quantity purchased on a particular deal increases as uncertainty about deals' timing increases for a given level of inventory. If this level of inventory is higher because uncertainty about deals' timing lead consumers to overstock, then consumers might purchase less in a particular deal than they would have purchased in the benchmark case. Whether the average quantity purchased on deal is smaller when deals' timing is more uncertain depends on how much consumers overstocked and understocked over time.

In this section, I first present a description of the dataset. Then I discuss how the main variables of the model are identified from consumers' purchase decisions.

2.4.1 Data Description

I use the Stanford Market Basket Dataset consisting of scanner data for 1,042 households in the Chicago Metropolitan area, collected between June 1991 and June 1993 in two submarkets (494 urban panelists and 548 suburban) for seven different stores. This dataset has two components, store and household-level data. From the household level data I know when a household visited a store, how much was spent in each visit, which products were bought, and where it was bought. The store level data includes weekly prices, aggregate quantity sold and promotional activities. The data is available for twenty-four product categories.

I focus on the soft-drinks category. This is a category of particular interest for the questions analyzed here. First, because it is a category frequently purchased, non-perishable, and easy to store. We expect most consumers to purchase not only for immediate consumption, but also to stockpile. Second, because it is also a frequently promoted category. Moreover, there is a significant difference in the way the same products are promoted across stores. I also replicate the results for two other categories: yogurts and laundry detergents. Both are less frequently promoted than soft-drinks but they are still non-perishable[8] and easy to store.

I define a product as a brand. For each brand I include the 4 highest market shares UPCs as long as they can be argued to be perceived as the same product. When aggregating UPCs, I am

[8] Unlike detergents and soft-drinks, yogurt can be stored for a limited time only. Nevertheless, relative to the frequency of visits to the store, yogurt is still a storable product, especially because I just consider here the smallest size of 6oz.

implicitly assuming that consumers have stronger preferences for the brand, but are indifferent among the different UPCs included in a brand. I also require the prices of these UPCs that constitute a brand to be at least 90% correlated for most of the stores at the dataset. The reason for this requirement is not to introduce measurement errors in my definition of deal.

The soft drinks category embraces several sub-categories such as cola, flavored soda and club soda/mixer all of which can be divided into regular, low calorie and caffeine free. The two main brands are Coke and Pepsi that dominate most of the cola and low-calorie cola sub categories. The flavored soda sub-category is less concentrated. The products in the soft drinks category are sold in either cans (that can be sold as singles or bundled into 6, 12 or 24-unit packs) or bottles (that can be sold in different sizes such as 16 oz. 1, 2 and 3 liter). I focus on 2 liter bottle colas. I also focus on the two main brands, Pepsi and Coke. Table 2.1 shows the percent market share for each selected product (UPC) at this selected 2 liter bottle cola sub-category. I included only four out of the seven stores I have data for soft-drinks, as for only these four stores the prices of the UPCs that constitutes a brand are at least 90% correlated.

The yogurt category is very concentrated at the brand level with two main brands: Dannon and Yoplait. These brands are offered in many different flavors (like vanilla, strawberry, cherry, peach, raspberry, among others) that also differs by fat contents. Yogurts are also sold in different sizes such as 6 oz., 8 oz., 16 oz., and 32 oz. I focus on regular 6 oz. yogurts. I also focus on the two main brands: Dannon and Yoplait. Table 2.1 shows the percent market share for each selected product (UPC) at this selected 6 oz. regular yogurt sub-category. Unlike detergents and soft-drinks, yogurts can be stored for a limited time only, especially after the unit is opened. This is why I focus on the smallest size. This size is more storable than the bigger sizes. The smallest size is also more frequently promoted than the other sizes.

Laundry detergents come in two main forms: liquid and powder. Liquid detergents account for 70% of the quantity sold. The leading firms are Procter and Gamble, which produces Tide and Cheer, and Unilever, which produces All, Wisk and Surf. I focus on liquid detergents. Liquid detergents are sold in different sizes such as 32 oz., 64 oz., 96 oz., 128 oz., and 256 oz. I focus on 128 oz. liquid laundry detergents. I also focus on two brands: Wisk and All, both produced by Unilever. Purex is the leading brand for the 128 oz. liquid detergent market but there is missing data for prices. Tide is also among the top brands for this selected market but again there is missing data for prices. Table 2.1 shows the percent market share for each selected product (UPC) at this selected 128 oz. liquid detergent sub-category. I focus on the 128 oz. because this size is more frequently promoted than the other sizes and also preferable for storage[9]. I included only five out of the seven stores I have data for detergents, as for only these five stores the prices of the UPCs that constitutes a brand are at least 90% correlated.

I do not account for some possible substitution effects at the three selected categories. For instance, at the soft-drinks category I assume cans and bottles are different products and I do not account for possible substitution effects between them. The reason is that I expect cans to be more useful for individual consumption while large bottles are more used for parties and big families. I also do not account for substitution effects between liquid and powder detergents or between different sizes of yogurts again because I expect consumers to perceive them as different products.

In the model of consumer behavior, I assumed that consumers form their expectations (give value to the transition probabilities) about future prices during an initial learning period. For

[9] Given that there are gains in buying a larger size given by quantity discounts (non-linear pricing) and differently from the other categories, the product does not suffer any alteration after opened.

consumers to learn about the prices in a specific store they need to visit this store frequently enough. This is why in my empirical application I only include those households that visited a particular store at least 20 times. I also only include households that purchased at least 6 (4, 2) units of a particular brand, either Coke or Pepsi (Dannon or Yoplait, Wisk or All)[10], at a particular store during the 104 weeks. These restrictions considerably reduce the size of my sample.

2.4.2 Identification Strategies and Preliminary Analysis

In the model section I showed that consumers' purchase decisions of a product over time and at a particular deal are affected by the product's deals' timing if consumers are loyal to the product. One main result is that loyal shopper consumers buy a higher fraction of their overall purchases during deals as uncertainty about deals' timing decreases. In order to test this implication empirically I first need to define a deal. Next, I need to identify what are the relevant characteristics about deals that affect consumers' purchase decisions and how to measure their allocation of purchases over time. Finally, I need to identify the four types of consumers: loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper.

2.4.2.1 Definition of Deal

[10] I used different cutoffs for different categories because the average total quantity purchased per consumer, per store, is significantly different for each of the three categories.

Consistent with the previous literature, I define regular price as the modal price for each product (UPC), at each store along the 104 weeks of data. Deal is any deviation at least 5% below the modal price.

2.4.2.2 Relevant Characteristics about Deals

There are four main characteristics about deals that may affect consumers' purchase decisions:

Average Discount. Products are offered on deals with different percent discounts off the regular price. Average discount is the average of all the observed percent discounts the product was offered on, over the 104 weeks.

Table 2.2 shows summary statistics on the *average discount*. The first four columns show statistics on the percent discounts off the regular price. The statistics are calculated per UPC, per store. The last column shows the standard deviation, across all stores, of the average percent discount off the regular price. The figures suggest that each store offers different percent discounts for the same product over time. Stores also differ from each other on the average discount the same product is offered on. Soft-drinks have the highest average discounts, followed by yogurts and detergents. The yogurt category has the higher variation on the average discount the same product is offered on, across stores.

Frequency of Deals. This is the percentage of weeks each product was offered on deal, independently of the particular percent discount offered on a particular deal.

Table 2.3 shows summary statistics on *frequency of deals*. The first column shows the average, across all stores, of the percent of weeks a deal was offered for each product at each

store. The second column shows the standard deviation, across all stores, of the percent of weeks a deal was offered for each product at each store. On average, soft-drinks are offered on deal half of the time followed by yogurts, 21% of the time, and by detergents, 15% of the time. There is also a significant variation on the frequency each product is offered on deal across stores.

Average Duration: Average number of weeks between two consecutive deals. This measure is related to frequency of deals. The higher the average duration is the smaller the frequency.

Variation of the Duration: Standard deviation of the number of weeks between two consecutive deals. It is related to the predictability of the deal pattern. The higher the variation of the duration the less predictable (more uncertain) the deal pattern is.

Table 2.4 shows summary statistics on *average duration*[11]. On average products are offered on deal with one week interval for soft-drinks, five weeks interval for yogurts and six weeks interval for detergents. Again there is variation of the average duration across stores (part B of the table). The maximum number of weeks between two consecutive deals observed is seventeen for soft-drinks but it can reach 50 weeks for detergents. Table 2.5 shows summary statistics on *variation of the duration*. The first column shows that the *average duration* varies over time. The second column shows that how much the *average duration* varies over time also varies across stores. Some stores have more certain deals' timing, with a smaller *variation of the duration*, while others have more uncertain deals' timing, with a bigger *variation of the duration*.

[11] Note that the minimum number of weeks between two consecutive deals is one which means that the product was offered on deal in consecutive weeks.

The main characteristic I am interested on is the unpredictability (uncertainty) of deals' timing. In the model of consumer behavior predictability of the deal pattern was described by the transition probabilities of the Markov chain for prices. In the empirical application I define *unpredictability* of the deal pattern of a product as the coefficient of variation of the number of weeks between two consecutive deals, i.e:

Unpredictability = Coefficient of Variation of Duration

= (Variation of the Duration) / (Average Duration)

2.4.2.3 Measures of Allocation of Total Purchase Over Time

A direct way of measuring how much consumers concentrate their purchases on deals over time is to calculate the fraction that was bought on sale, from the total amount purchased. Another way of measuring it, is by using the difference between how much consumers actually spent and how much they would have spent if they had bought the same amount randomly and therefore, paid the average of the prices they observed at their trips to the store. These are my two measures of allocation of purchases over time:

Fraction: Fraction that was bought on sale, from the total amount purchased.

Savings: Difference between how much consumers actually spent and how much they would have spent if they had bought the same amount randomly and paid the average observed price. Note that the average observed price is different for each consumer as consumers visit the stores at different periods and consequently, observe different prices.

To find this last measure I first calculate how much each consumer spent in each UPC, at each store, over the 104 weeks. Consistent with the model, I assume that the decision of visiting a store is exogenous. This decision does not depend on the deals' characteristics of a particular UPC or brand. I record the exact weeks each consumer visited each store, to buy any type of product, and not just the products considered here. Average observed price is the average of all the prices offered per UPC, per store, at the weeks the consumer visited the store. I also record the amount each consumer purchased of each UPC in each store. Savings is the difference between the actually amount spent and the total amount they would have spent if they bought the same quantity for the average observed price.

2.4.2.4 Types of Consumers

There are four types of consumers: loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper. In the model, I defined loyal as the consumer whose marginal utility from consumption of the good is high enough such that he is willing to purchase the product at the regular price if necessary. However I do not have information on the marginal utility of consumption. Instead, I identify as a loyal the consumer whose share of purchases on a particular brand is at least 70% of his total purchase in the category[12]. A Non-loyal is the consumer whose share of purchases on a particular brand is less than 70% of his total purchase in the category. Consumers who are loyal to one brand are automatically non-loyal to the other brand. Some consumers are non-loyal to both brands considered at each category.

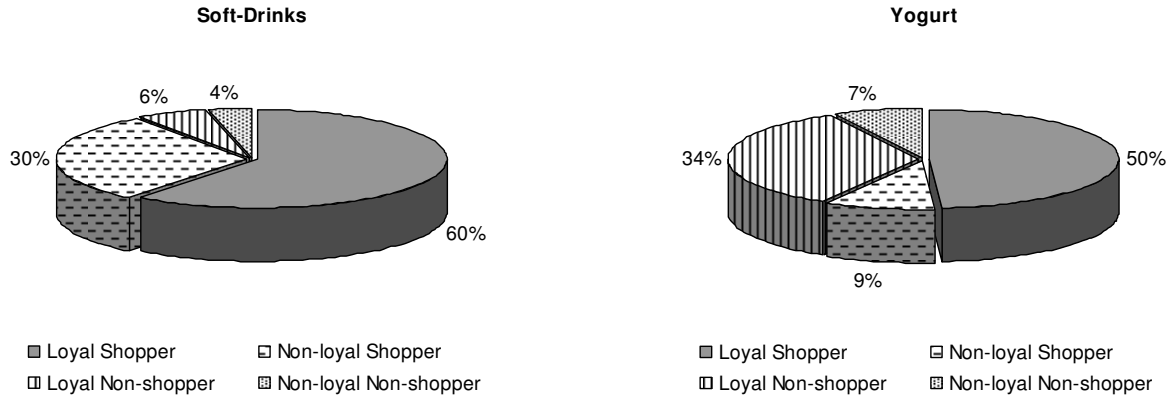
[12] Later I include a robust check on this definition of loyalty.

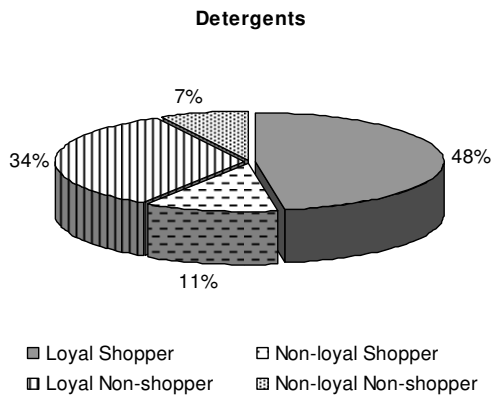
A shopper consumer buys not only for immediate consumption, but also to stockpile. They can be loyal to a brand or not. In the model, shopper is defined as the consumer who has a storage cost low enough such that he is able to stockpile for the average number of weeks between two consecutive deals. However I don't have information on the storage cost of each household. Instead, I identify a shopper by characteristics of his purchase pattern that arises from his stockpiling behavior. Some characteristics, like households buy more on deals, are consistent not only with small storage cost and stockpiling, but also with an alternative theory: when prices go down households consume more. This is why I look at other characteristics and use different robust checks on the definition of shoppers. For now I define a shopper as any consumer who presents the first characteristic and at least one or more of the other three characteristics:

- *The difference of the time to the next purchase is larger for purchases on sale than for purchases not on sale.* That's because consumers buy a larger quantity when purchasing on sale to stay longer without purchasing.
- *The difference between the average quantity purchased on sale and out of sale is positive.* The intuition is that, if stockpiling, consumers buy a larger quantity when purchasing on sale.
- *The average time from the previous purchase is shorter for purchases on sale than for purchases not on sale.* In other words, even if the consumer does not have a current consumption need for the product, he still buys on sale to stockpile.
- *The probability the previous purchase was not on sale given that the current purchase was not on sale is higher.* The intuition is that since non-sale purchases have a lower inventory threshold, a non-sale purchase informs us that inventories are low which in turn means, other things equal, that the last purchase was not on sale.

To check the robustness of this definition I also use, alternatively, the first characteristic together with each of the other three characteristics as the definition of a shopper. The results I present in the empirical sections are robust for these different definitions of a shopper. Note that the first and the last two characteristics could only arise from a stockpiling theory and not from an increased consumption theory. Finally non-shopper is a consumer who does not present any of the four characteristics stated above. Table 2.6 presents summary statistics of household's savings, proportion bought on sales and characteristics of deal patterns calculated per household, per brand, per store for both the loyal and non-loyal groups for soft-drinks, yogurt, and detergents. The distribution of households in my sample across the four types is summarized at figure 2.1 for each category.

Figure 2.1: Distribution of Households across Types of Consumers Per Product Category





2.5 Results on Allocation of Purchases Over Time

I now turn to the implications of the model presented in section three. Those implications generate several testable hypotheses. I focus here on the soft-drinks category. The results for the two other categories, detergents and yogurts, are discussed separately in section seven.

Hypothesis 1. *(from Implication 2) Loyal consumers buy a higher fraction of their overall purchases during deals (save more in monetary terms) as uncertainty about deals' timing decreases. This effect is not significant for non-loyal consumers.*

Hypothesis 1 is derived from implication 2 of the model. The intuition is the following. When facing a deal period, consumers buy more in order to stockpile for future consumption. When facing a non-deal period, they may consume from inventory. The ability of stocking the right amount at the deal period to prevent purchase at the regular price depends, among other

things, on how precise is the information on when the next deal is. For a given average duration, as the variation of the duration decreases, the information consumers have on when the next deal is becomes more precise. So the smaller the coefficient of variation of duration (the smaller the unpredictability), the more consumers are able to buy on deal periods. We should also expect this effect to be significant just for loyal consumers. Those are the consumers willing to perform inter-temporal substitution. Non-loyal consumers do not follow the deals of the brand they are not loyal to and as so, should not be affected by its timing.

I first estimate the effect of uncertainty about deals' timing on savings separately for loyal consumers and non-loyal consumers after controlling for other relevant characteristics of the deal pattern, such as frequency of deals (percentage of the total time the product was offered on deal), and average discount (average of all the percentage discounts the product was offered on). Under this specification I am implicitly assuming that all loyal (non-loyal) consumers respond to unpredictability in the same way. Then I include all consumers together in a single regression and add two new independent variables: the actual shares each consumer buys of each brand in the category and an interaction term between unpredictability and shares. This second specification checks whether different degrees of loyalties imply different responses to unpredictability. In both specifications the identification comes from the variation of deals' timing for the same brand across stores and the variation of the observed deal pattern for the same brand at the same store across consumers.

Table 2.7 presents the results, for the soft-drinks category, of regressing savings on unpredictability, average discount, frequency of deals, total number of trips for each store and for each consumer and total number of units purchased for each brand, per consumer, per store. A unit of observation is the value of the respective variable per household, per brand, per store

averaged across time. I also include brand and store dummies. The first column shows the results for the regressions just for loyal consumers. The main finding is that uncertainty about deals' timing significantly affects loyal consumers' savings. The coefficient of unpredictability is significant and negative. For a given average duration, as the variation of the duration increases the savings decrease. Loyal consumers buy a higher fraction of their overall purchases during deals (save more in monetary terms), as uncertainty about deals' timing decreases. This result is also robust to another measure of gains from concentrating purchases on deals, fraction. The second column shows the results for the regressions just for non-loyal consumers. The effect of unpredictability on savings/fraction is not significant. The third column shows the results for the regressions that include all the consumers together and add two new independent variables: shares and the interaction term between unpredictability and shares[13]. They support the claim that the results are robust to the definition of loyalty. Not only unpredictability affects the allocation of purchases over time, but this effect increases with an increase in the product's share of a given consumer's purchase in the category.

Implication 2 also states that the effect of uncertainty about deals' timing on loyal consumers' allocation of purchases over time increases if the consumer stockpiles (is a shopper).

Hypothesis 2. *The effects of deals' timing on allocation of purchases over time increases if the loyal consumer stockpiles.*

[13] The interaction term is defined as deviations from the averages namely:
[(coef. of variation of duration) – (average coef. of variation of duration)]*[share – (average share for loyal consumers)].

Table 2.8 presents the results, for the soft-drinks category, of regressing savings on unpredictability, average discount, frequency of deals, total number of trips and total number of units purchased per brand, per consumer, per store. I estimate the effect of unpredictability on savings separately for shopper consumers (first column), loyal shopper consumers (second column), and non-loyal shopper consumers (third column). The coefficient of unpredictability is significant and negative for the regressions including just loyal shopper consumers. The results are not significant for the regressions including just shoppers.

The data also includes two types of promotional activities: feature and display. The feature measures if the product was advertised by the retailer, in other words, if a flyer was sent to consumers that week. The display measures if the product was displayed differently than usual within the store that week. So, instead of looking directly at the price distribution, consumers could have used feature and/or display as an alternative source of information to learn about deals. This creates my third testable hypothesis:

Hypothesis 3. *Consumers use display and/or feature as alternative sources of information about deals. If so, uncertainty about feature's timing and/or display's timing affects the fraction of the overall purchases loyal consumers do during deals.*

Table 2.9 presents summary statistics, for the soft drinks category, on the characteristics of deal patterns using display and feature as the main source of information about deals, instead of prices.

I first estimate the effect of unpredictability on savings separately for loyal consumers and non-loyal consumers using display as the main source of information about deals, after

controlling for other relevant characteristics of the deal pattern. The results were not significant[14]. Uncertainty about display's timing does not affect loyal consumers' fraction of their overall purchases during deals.

Next I estimate the effect of unpredictability on savings separately for loyal consumers and non-loyal consumers using feature as the main source of information about deals, after controlling for other relevant characteristics of the deal pattern. Table 2.10 presents the results for these regressions. The results are very similar to the ones found using prices (table 2.7). Again, the coefficient of unpredictability is significant and negative. Uncertainty about features' timing affects loyal consumers' fraction of their overall purchases during deals. A possible explanation for these results is that consumers associate more feature with deal than display. So they use feature as a source of information about deals but not displays.

Finally I include both unpredictability of deals' timing and features' timing in the same specification. The results turn out to be individually insignificant due to multicollinearity, since feature and deals are very correlated. However, both coefficients are jointly significant.

2.6 Results on the Quantity Purchased at a Particular Deal

I now look at consumers decisions at each particular deal. Hypothesis 4 is derived from implication 1 of the model.

[14] Since the results were not significant I omitted the outcome of the regressions in the present work.

Hypothesis 4. *(Implication 1) Loyal shopper consumers increase their quantity purchased at a particular deal both as more time passes since the previous deal, and the higher the uncertainty about deals' timing.*

To test this hypothesis I use the first 26 weeks of purchases for each consumer as the learning period[15]. For this period I calculate the variation of the duration (standard deviation of the number of weeks between two consecutive deals) for each household. With the remaining weeks I regress log of quantity purchased per consumer, per visit, per brand, per store on log of price, the variation of the duration, number of weeks since the previous deal, promotional activities and an interaction term between number of weeks since the previous deal and variation of the duration. The identification comes from both the variation of the observed deal pattern for the same brand at the same store across consumers and from the variation of the quantity purchased at a deal period for the same consumer over time.

Table 2.11 presents the results for the soft-drinks category. The first column of table 2.11 presents the results for the loyal shopper group for purchases only at deal periods. I find that, as expected, the coefficient on number of weeks from previous deal is positive and significant and the coefficient on the interaction term is positive and significant. These results support my claim, not only the quantity purchased at a particular deal increases as more time passes since the previous deal, but also this effect is bigger as uncertainty about deals' timing increases. This result does not hold for non-loyal consumers. The effect of uncertainty about deals' timing on quantity purchased is also not significant for purchases at the off deal periods.

[15] I checked the robustness of the results to the definition of initial learning period by looking at different initial learning period's intervals. Qualitatively the results are robust to the different definitions examined.

2.7 Cross-Category Comparison

I replicate the same regressions described in sections 5 and 6 for the two other categories: detergents and yogurts. Table 2.12 presents the results, for the yogurt category, on the effects of uncertainty about deals' timing on the allocation of purchases over time. The main finding is that uncertainty about deals' timing significantly affects loyal consumers' savings. This effect increases with an increase in the product's share of a given consumer's purchase in the category or if the consumer stockpiles (is a shopper). The results were not significant for detergents. I also replicated the regression using uncertainty about features' timing and displays' timing as alternative sources of information about deals. The results were not significant for both yogurts and detergents.

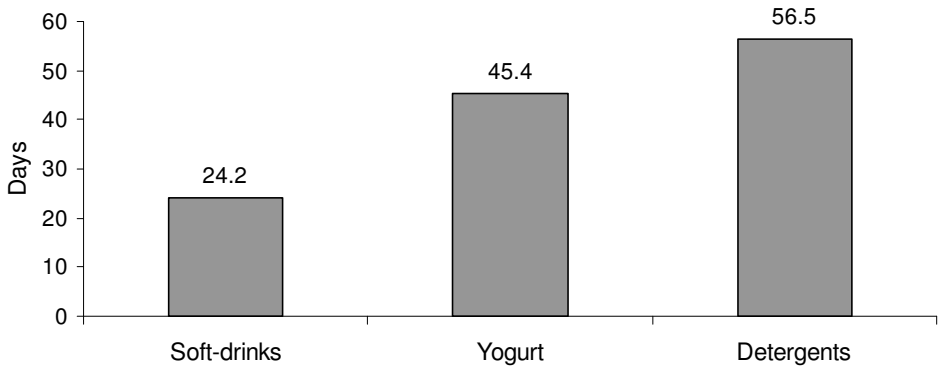
Finally I replicated the regressions for the effects of uncertainty about deals' timing on the quantity purchased at a particular deal. For detergents, I find that the quantity purchased at a particular deal increases as more time passes since the previous deal, but the effect of uncertainty about deals' timing on the quantity purchased was not significant. Table 2.13 presents the results for yogurts. The main finding is that loyal shopper consumers increase their quantity purchased on a particular deal both as more time passes since the previous deal and the higher the uncertainty about deals' timing.

An important difference between the three categories is the frequency of purchase. Figure 2.2 shows the average annual interpurchase time (in days) for households that make at least two purchases in the category during the year, between 1983 and 1997, using aggregate data from

IRI's 1986 Marketing Factbook. The data are collected for more than 20,000 participating scanner panel households living in 12 different domestic U.S. markets.

Figure 2.2: Average Interpurchase Time

Per Product Category



Detergents are the least frequently purchased of the three, followed by yogurts and soft-drinks. Note that the figure above shows the average annual interpurchase time for the entire category. Given that I use data just for 6oz. yogurts and 128 oz. detergents, I expect the difference between the specific UPCs I use for detergents and yogurts to be even bigger than the one described in the figure. Therefore, uncertainty about deals' timing just affects consumers purchase' decisions if the product is frequently purchased. One possible explanation is that when consumers don't buy the product frequently enough, they are not able to learn about the deals' timing.

2.8 Conclusions

I showed that loyal shopper consumers' decisions, both about the allocation of their purchases over time, and about the quantity purchased during a particular deal, are affected by the product's deal pattern. And, unlike previous studies, I support this claim with scanner data.

I develop a dynamic model of consumer choice where consumers are forward looking and buy in advance, at lower prices, to stock for future consumption. In the model, consumers form beliefs about future prices only when they are uncertain about deals' timing. In the case of a predictable deal pattern, consumers know the entire price distribution. This model generates implications for purchase behavior that I test empirically.

I use scanner data on soft drinks, laundry detergents and yogurts. For soft-drinks and yogurts I find several pieces of evidence consistent with the model. (1) The more predictable the deal pattern, the higher the fraction of the overall purchase that loyal consumers buy during deals. (2) This effect increases with an increase in the product's share of the consumer's purchase in the category. (3) This effect also increases if the loyal consumer stockpiles. (4) The effect is not significant for non-loyal consumers. (5) The more time that has passed since the previous deal and the less predictable the deal pattern, the more loyal shopper consumers increase the quantity they purchase during a particular deal.

The results are not significant for laundry detergents. An important difference between the three categories is the frequency of purchase. Detergents are the least frequently purchased of the three, followed by yogurt and soft-drinks. Therefore, uncertainty about deals' timing just affects consumers purchase decisions if the product is frequently purchased. One possible explanation is that when consumers don't buy the product frequently enough, they are not able to learn about the deals' timing. An interesting extension would be to replicate the results for more

product categories and understand the product characteristics for which uncertainty about deals' timing affects consumer behavior.

The findings suggest that it is crucial for both manufacturers and retailers to incorporate the effects of deal patterns on consumer purchases' decisions when deriving optimal pricing strategies. In the present work, I assume that prices and deals' timing are exogenously given. An interesting extension would be to determine manufacturers and retailers optimal pricing strategies incorporating the effects of deals' timing on consumer behavior.

I also assumed that, for the case of unpredictable deal patterns, consumers form their expectations during an initial learning period and that there is no further learning after that. An interesting extension would be to allow consumers to Bayesian update their beliefs about future prices.

CHAPTER 3

Purchasing Intentions: The Effect of Uncertainty about Christmas Deals

3.1 Introduction

It is well documented in both the marketing and economics literatures that deals, defined as temporary price-reductions or discount sales, are a key component of firms' pricing strategies for both non-durable and durable goods. As a result, how much stores spend on marketing their deals is a crucial decision. Assuming that acquiring information about deals is costly for consumers, generally speaking, the more stores spend on advertising their future deals, the lower the cost to the consumer of finding those deals. Also, if stores spend more on deal advertising, consumers have less uncertainty about the timing of deals, their duration, and, the percentage off the regular price that will be offered. However we don't know if making all consumers more informed about future deals is actually profitable for stores. Not all consumers expect to increase the amount they are going to spend if deals become more certain. On the contrary, some consumers may not change the total amount they expect to spend, or they may actually spend less because they purchase the same number of units whether or not there is a deal. Especially in periods of peak sales, when consumers are more prone to search for deals, such as the Christmas period, it is crucial for stores to understand how increasing consumers' awareness of future Christmas deals affects their intentions to make purchases.

The objective of this paper is to understand how uncertainty about future deals affects consumers´ intentions to make purchases. I focus on intentions to make purchases instead of actual purchases. The amount stores decide to spend on marketing their future deals affects consumers' intentions to make purchases[16]. I focus on Christmas deals and look at four product categories: CDs/DVDs, clothing, cosmetics/fragrances and electronics. Using a method to elicit and measure revisions to subjective expectations, I conduct an e-mail survey using what I call *beliefs in a predetermined uncertainty scenario*. First, I elicit respondents' prior beliefs about the likelihood that a sale of 20 to 35% off or of over 35% will occur during the next Christmas period in each of four product categories. I also elicit the amount the respondents expect to spend in each of these four product categories. Next, I present five different uncertainty scenarios to the respondents where the probability that no deals at all will occur during the next Christmas season or a deal from 20 to 35% will occur during the same period is stated in the question. Then, I ask the respondents again how much they expect to spend in each of the four product categories, given the five predetermined probabilities of a sale of 20 to 35% off. This way I elicit the respondents' posterior beliefs for the five different uncertainty scenarios.

In the survey responses, I find considerable heterogeneity in the revision of expectations. Given the same uncertainty scenario, respondents have very different revisions of their expectations. This finding has important implications for the need to consider flexible updating processes when modeling expectations of future purchases. The survey results also show that the revision of expectations varies across product categories. Clothing and electronics are the categories where intended purchases change more as the uncertainty about future deals changes.

[16]Advertisements about future deals directly affect consumers' intentions to purchase and also indirectly affect the actual purchase. Whether consumers' actual purchases exactly correspond to their intentions to purchase is a question beyond the scope of this paper. Note that this is a different situation from an instantaneous price reduction that directly affects the actual purchase, since, in the latter case, consumers are already at the store shopping when they learn about the deal.

Cosmetics/fragrances is the category where intentions to make purchases change less with uncertainty about future deals. The empirical findings suggest that there are hidden costs of advertisement, such as consumers who spend less when they become more aware of future deals.

Christmas seems to be a perfect period to study how uncertainty about future deals affects consumers' intentions to make purchases. First, it is a period of peak sales. Many retail organizations rely on Christmas for an annual boost in revenues. Thus, the choice of price, quality, marketing and special discounts should be carefully designed since it will have a great impact on the total yearly revenue of the industry. There is also a significant amount of advertising before Christmas. And the information released in those advertising campaigns affects consumers' expectations about future purchases. "Finally, as shown by Warner and Barsky (1995), consumers are more prone to search for deals during this period. On days characterized by an exogenously high intensity of shopping activity, (such as Friday nights, Saturdays and the Christmas period) the search for the lowest price takes place more efficiently. Customers for whom it does not pay to search or travel very much when only one item is to be purchased will invest more in information and transportation to obtain the lowest possible price when purchasing a number of units of the same good or a number of different items for which search and travel costs can be at least partly shared."

There are also some interesting idiosyncrasies in consumers' purchase decisions that are particular to the Christmas season. Waldfogel (2002) described the Christmas deadweight loss. This is the idea that gift giving is an inefficient mean of allocating resources since, as he finds in his paper, consumers own purchases generate between 10 and 18 percent more value, per dollar spent, than items received as gifts. I collect the demographic characteristics of the respondents and relate them to the way respondents revise their expectations. I find that, for some product

categories, females are more sensitive to sales during the Christmas season than males. Age and religion do not explain differences in the way respondents updated their beliefs.

But the main contribution of the present study is that, unlike most previous work, I focus on expectations about future purchases instead of actual purchases. To the best of my knowledge, this is the first paper to use the elicitation and measurement of revisions to subjective expectations to study how uncertainty about future deals affects consumers' intentions to make purchases.

In general, a prevailing practice in economics is to assume that decision-makers maximize expected utility. Under this assumption, decision-making under uncertainty can be thought of as a sequential process: first, the decision maker uses the information available to her to form expectations about the uncertain events, and then she relies on these subjective expectations to make decisions. In order to use econometric decision models to credibly predict behavior after events that may modify subjective expectations, such as advertising future deals, it is crucial to understand both how individuals formulate their expectations and how expectations and preferences are combined to make a decision. Researchers commonly make exogenous assumptions about expectations. In contrast, this study measures expectation by the method called subjective probabilities by modern economic theory. I use data to relax or validate assumptions about expectations.

An example of this approach is to be found in the marketing literature in Jacobson and Obermiller (1990). They obtain information on price expectations from students in an introductory marketing class to test whether future price expectation formation is consistent with rational expectations or with other theories of expectations formation. Each week, for eight weeks, students were given a nearby supermarket's current and list prices for five brands of

canned tuna. Each week they were asked to predict the price for each of the five brands in the upcoming week. As an incentive, the authors announced that awards of $15, $10, and $5 were to be given to the students with the three most accurate sets of forecasts over the seven-week period. Their findings challenge the validity of rational expectations as a mechanism for describing the formation of price expectations. Instead, their results suggest the applicability of a serial correlation model. Consumers' future price expectations are influenced by current price information and autocorrelated, unobserved factors.

Unlike Jacobson and Obermiller, I do not attempt to find the best theory to describe how consumers form their expectations. Instead, I focus on how uncertainty about the occurrence of future deals affects consumers' intentions to purchase (in other words, the sign of the derivative of the expectation of future purchase with respect to the uncertainty), independent of the way they form their expectations. With a similar but larger dataset than the one used here, one could use nonparametric estimation to further explore the best theory to describe the formation of the expectations.

In the economics literature since the early 1990's, researchers have increasingly undertaken to elicit probabilistic expectations of some concrete, personally significant events from survey respondents. However, little is known about how decision-makers process concrete information, such as government and media announcements and advertisement campaigns, to form and revise their expectations. This paper develops a new method of eliciting and measuring revisions to subjective expectations, and provides empirical evidence about the way consumers update their expectations about future purchases, given how uncertain they are about the occurrence of future deals. Manski (2004) provides a survey of the literature on measuring expectations. Some of the recent works he outlines provide descriptions of expectations data regarding important personal

events, like the chance of survival or loosing one's job, and show that respondents are willing and able to meaningfully answer questions eliciting their expectations in probabilistic form. Expectations have also been elicited for macroeconomic events (stock market returns), risks that a person faces (crime victimization, mortality), future income (earnings and Social Security benefits), and choices that people make (voting choices). Manski also suggests that, to enable people to express ambiguity, the probability of events of interest should be elicited by means of ranges rather than precise probabilities. As Manski suggests, in this study I allow respondents to answer with ranges rather than precise numbers.

The work closest to mine is Delavande (2004). In her work, she conducts a face-to-face survey to provide empirical evidence of the way women update their expectations about the effectiveness of contraceptives. She employs an innovative elicitation strategy using both concrete scenarios and new wording to capture the uncertainty attached to the probability of pregnancy. I also use an elicitation process based on concrete uncertainty scenarios and new wording to capture uncertainty that I call the *beliefs in a predetermined uncertainty scenario*. As in Delavande (2004), the scenarios replicate real life situations, prior beliefs are elicited directly instead of being artificially provided to respondents, and the focus of the revision is a very concrete event for consumers. These contrast with experimental settings where subjects are required to update a given probability after observing realizations of a stylized sampling process. But unlike in Delavande (2004), the sources of information are not relevant to my analysis. She emphasizes that the nature and source of information may affect the way information is perceived and processed. While this is also true for the case of deals advertisements, I explicitly describe to the respondents the uncertainty they should expect, without the need to give further

details about the source of information. This proves to be a more direct and easier way of eliciting their posterior beliefs in the present application.

Using e-mail interviews, I construct a new dataset to analyze how uncertainty about future Christmas deals affects intended purchases for four different product categories. The product categories chosen are, according to Deloitte's Christmas Retail Survey from winter 2003, among the top five categories consumers purchase for Christmas in the United States.

The elicitation methodology proved successful since the 63 respondents, all Northwestern University undergraduates, could understand the wording of the questions and provided consistent answers. I found substantial heterogeneity in the way respondents revised their expectations. Also, some respondents did not change the amount they expected to purchase as they were introduced to different uncertainty scenarios. As the respondents themselves replied to me, they do not care about deals. The empirical findings suggest that there are hidden costs of advertisement, such as consumers who spend less or don't change the amount they expect to purchase when they become more aware of future deals. (17.5% of the respondents did not change their expectations of future purchases as uncertainty about deals decreased.) There was also a significant fraction of the sample that decreased the total amount they expected to purchase in each product category as they became 100% sure that deals would occur in the next Christmas period. These consumers take the opportunity to save. I also found differences across product categories in the way consumers revise their expectations about future purchases.

The remainder of the paper is organized as follows. In section two I describe the data collection methodology, the survey, and present some preliminary analyses. In section three, I present the empirical results. In section four I conclude.

3.2 Data (The Survey) and Preliminary Analysis

In this section I first describe the methodology employed to collect the data and the survey. Then I present some preliminary analysis.

The survey was conducted via e-mail with undergraduate students from Northwestern University with different majors in November and December of 2004. After randomly selecting students' names from the student directory, I sent 500 e-mails. The e-mail message can be found in the appendix. Among these 500 students I initially received 48 replies. In the first 200 e-mails, more than 60% of the replies were from male students. So, in the last 300 e-mails I selected more female names, increasing my reply rate from females to 50%. Two weeks before Christmas of 2004 (the 25th of December), I re-sent the same message to the students who did not reply before. I received 17 more replies. I ended up with a sample of 65 respondents, 50% of whom were females.

The first part of the survey consists of general directions to the students explaining how to answer the probability questions. I emphasize that that they do not need to give single answers. Instead, they are encouraged to give ranges when unsure about the answer. This method enables respondents to express ambiguity, as previously outlined by Manski (2004). Two preliminary questions are asked in order to evaluate if the respondents understand probabilities. First they are asked, "What is the percentage chance that you will eat at the Norris Center (Northwestern's student union) tomorrow?" and then they are asked, "What is the percentage chance that you are going to eat at Norris Center tomorrow and that you are going to be satisfied with the food?"

Most of the students give a consistent answer with the probability of the second event being smaller or equal to the probability of the first event.

I also collect demographic information such as age, sex, ethnicity, family income, employment condition, religion, family size and average expenses per month. A summary of these demographic characteristics is displayed in table 3.1. Most of the respondents are about the same age, which is to be expected since they are all undergraduate students. Both sexes are well represented; -- the final sample consists of almost 50-50 male and female respondents. There is some variability in ethnicity but the majority (63.5%) of respondents is white. There is also some variability in religion but the majority (44.4%) is Christian. For the purposes of the survey, this is helpful, because we should expect Christians and Jews (since there is also a Jewish holiday in December) to have a greater incentive than those of other religions to shop in December. Most of the respondents are temporarily employed and work less than 10 hours per week. Therefore, the students have their own money and can use it to purchase Christmas gifts. Some of them may also count on family income. Most of the respondents have a family income of less than $100,000 dollars per year. The size of the family is another important characteristic determining the amount the respondents spend on Christmas gifts. Most of the respondents come from a family with less than four people including themselves. Finally, for almost 40% of the respondents, their expenses vary between $200 and $500 dollars per month.

The second part of the survey consists of the Christmas sales (temporary price cuts/deals) questions. I specify the Christmas period as the entire month of December. I also restrict attention to four product categories: CDs/DVDs, clothing, cosmetics/fragrances and electronics. The first nine questions of this second part of the survey are designed to elicit respondents' prior subjective beliefs. The first question asks directly, "How much are you planning to spend on

Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories?" I emphasize to the respondents that, when answering this question, they must have in mind that there are often sales during the Christmas season. Next, I ask the respondents the percentage chance that when they go shopping at the approaching 2004 Christmas season they will find sales from 20 to 35% or over 35% off for each product category. With these eight questions (two for each product category) I elicit respondents' prior beliefs about sales.

Figures 1 through 8 display the answers to the eight questions that elicit respondents' prior subjective beliefs about the occurrence of sales anywhere from 20 to 35% (or over 35%) for each of the four product categories. Each histogram plots the ranges of prior subjective probabilities about the occurrence of specific sales on the x-axis and the percentage of the total sample that presents such priors on the y-axis. Respondents' answers seem to be coherent. Prior subjective probabilities are higher for the occurrence of sales from 20 to 35% than for the occurrence of sales over 35%, reflecting the accepted wisdom that, in general, consumers do not expect high percentage discounts off the regular price to occur during/just before Christmas. Clothing is the product category where consumers predict the highest probability of sales from 20 to 35%. More than 50% of the sample has prior subjective probabilities (over 70%) that sales from 20 to 35% will occur, as can be verified in figure 1. In contrast, CDs/DVDs is the product category where consumers expect the lowest probabilities of sales from 20 to 35%. More than 50% of the sample has prior subjective probabilities lower than 30% that sales from 20 to 35% will occur, as can be verified in figure 3. Prior subjective probabilities of the occurrence of sales over 35% are in general very low. For CDs/DVDs and cosmetic/fragrances, almost 50% of the sample have prior subjective probabilities lower than 10% that sales over 35% will occur, as can be verified in

figures 4 and 6. Therefore, stores need to spend more in advertising their deals if they want consumers to be aware of sales over 35% in comparison with smaller discounts. Product categories such as CDs/DVDs and cosmetic/fragrances also require higher expenditures in advertising their deals, as consumers do not expect many discount sales to occur in those two categories. It is also important to note that there are not many 50% subjective probability answers to these eight questions. In general respondents answer 50% when they are unsure about their answers. So we can conclude that consumers do have prior coherent knowledge about the occurrence of deals for each of the product categories studied here during the Christmas season.

The last five questions of the survey are designed to elicit respondents' subjective posterior expectations. Eliciting posterior expectations is a more challenging task. I employ the same methodology used in Delavande (2004). She first elicited the subjective distribution about the prior for each respondent and then gave a scenario or "controlled information" to respondents and elicited the new belief distribution.

After eliciting respondents' prior subjective expectations, I provide them with a short introduction emphasizing that in the last five questions I am going to describe some different situations where "the main difference among these situations is that your uncertainty about sales during the Christmas season period (December) will vary. Please pay attention to the uncertainty when answering the questions." I introduce new wording for these last five questions that I call *belief in a predetermined uncertainty scenario*. The idea is to present five different uncertainty scenarios where the probability that no sales at all will occur and a sale from 20 to 35% will occur is predetermined by the question. In contrast to the work of Delavande (2004), the sources of information are not relevant to my analysis. She emphasizes that the nature and source of information may affect the way information is perceived and processed. While this is also true

for the case of advertisements of deals, I explicitly determine the uncertainty the respondents should expect, without giving further details about the source of information. This proves to be a more direct and easier way of eliciting their posterior beliefs. The five scenarios are described below. For each scenario, the respondents are asked to answer the same question separately for each of the four product categories.

- *Scenario 1* (question 10 of the survey): The following text was given to the respondent: *Now suppose that you are 100% sure that no sales at all will occur in each of the product categories. How much are you planning to spend on Christmas presents this year and on any special occasions around the time (December) of Christmas for each of the four product categories listed below?*

- *Scenario 2* (question 11 of the survey): The same text from scenario 1 was given to the respondents with different probabilities: *Suppose that you are 75% sure that no sales at all will occur and that with 25% probability a sale from 20% to 35% may occur*. This represents the case where respondents are very unsure that a sale from 20 to 35% will occur. They believe that most likely there will be no sales during the Christmas season.

- *Scenario 3* (question 12 of the survey): Again, the same text from scenario 1 was given with different probabilities: *Suppose that you are 50% sure that no sales at all will occur and with 50% probability a sale from 20% to 35% will occur*. This represents the case where respondents have little information about sales and are unsure if any sales will occur.

- *Scenario 4* (question 13 of the survey): The respondents were given the same text as the first three scenarios with different probabilities: *Suppose that you are 25% sure that no sales at all will occur and with 75% probability a sale from 20% to 35% will occur*. This represents the case where respondents are very unsure that no sales at all will occur. They believe that most likely a sale from 20 to 35% will occur.

- *Scenario 5* (question 14 of the survey): This scenario has the same text as the previous ones but with different probabilities: *Suppose that you are 100% sure that a sale from 20 to 35% will occur and no sale at all is an event with null probability*. This represents the case where respondents are completely sure that a sale from 20 to 35% will occur.

Comparing respondents' prior subjective expectations with their respective subjective posterior expectations, I can verify if they report consistent priors. Priors are consistent if the respondents who answer sales anywhere from 20 to 35% are highly probable (probability over 70%), also report an amount they expect to purchase when introduced to scenarios four and five similar to their prior expectation. Consider the sub-sample that reported as their prior subjective expectation, a probability of over 70% for the occurrence of sales from 20 to 35%. Call this sub-sample the *optimistic consumers*. To verify if the optimistic consumers have consistent priors, I first compute the percentage change between the amount each optimistic consumer expects to purchase prior to and after s/he is introduced to scenarios four and five. Next, I plot a histogram where the x-axis represents the different ranges of percentage changes between the answers, and the y-axis is the percentage of the optimistic consumers that changed their answers. Figures 9 through 12 present a histogram for each product category and compare the priors separately with

scenarios four and five. Observing these figures we can conclude that optimistic consumers' priors are consistent for all four product categories. 50% or more of the optimistic consumers do not change the prior amount they expected to purchase when introduced to scenarios four and five. In particular, for electronics, almost 90% of optimistic consumers do not change their answers. Thus, a large fraction of consumers who are almost sure that some kind of sales from 20 to 35% would occur, maintain their purchasing plans when they are informed that, with 75 to 100% probability, such sales will actually occur.

3.3 Empirical Results

I now turn to the empirical results. One of the main objectives of the present work is to verify the way beliefs are updated. Tables 2 through 5 present the results for the revision of expectations for each product category, uncertainty scenario and prior subjective probability range. First, for each product category, I classify respondents' subjective beliefs about the 20 to 35% probability of sales/deals. Next, I compute the percentage change between the prior and the new amounts they expect to purchase after they are introduced to the five different uncertainty scenarios. Finally, for respondents in the same range of prior subjective probabilities, I compare the percentage changes in their answers between the priors and posteriors elicited for each scenario. There is a significant amount of heterogeneity in the way respondents update their expectations. For each product category, uncertainty scenario and prior subjective probability range, there is significant variance across respondents in the way they change their answers between priors and posteriors. This emphasizes the need to consider flexible updating processes

when modeling purchasing expectations. Note that for small prior subjective probability ranges, such as from 0% to 20%, the percentage change between priors and posteriors is relatively homogenous across respondents. For instance, in clothing, 75% of the sub-sample that presents prior subjective probabilities between 0% to 20% for the occurrence of sales from 20 to 35%, did not change their answers when introduced to scenario 1. In CDs/DVDs, this number increases to 80% of the sub-sample and in cosmetics/fragrances to 85% of the sub-sample. This can also be interpreted as further evidence of the consistence of the priors as those respondents did not assign a high prior probability to the occurrence of sales and did not change the prior amount they expected to purchase when they were introduced to a scenario where they are 100% sure that no sales at all will occur.

For all product categories, uncertainty scenarios and prior subjective probability ranges, there is a significant fraction of the respective sub-samples in the "no change between answers" category. 17.5% of the respondents did not change their expectations of future purchases when they were introduced to different uncertainty scenarios. Among the remaining 82.5% who changed at least one answer, there is still a significant fraction that did not change their answers for all uncertainty scenarios for at least one of the product categories. One explanation for this result is, as reported by some respondents, they do not care about sales and they prefer to maintain the total amount they plan to purchase regardless of the sale they are going to face at the moment they go shopping. For instance, one of the respondents added the following comment: "I think I'd spend the same amount even if there were sales. I usually set the amount that I want to spend on certain people and then pick stuff around that range. If the stuff was cheaper, I'd just buy more of it." Another insightful comment given by another respondent is:

"Even if sales are amazing, I still would not spend my life savings on it! Spending limits are kind of good." For these types of consumers there are hidden costs of advertisement, since they are insensible to the presence of deals. These results raise two important questions to be answered by future research. First, what fraction of this type of consumer is from the total potential market? Second, do these results only hold for the Christmas season, as it is more of a gift giving period than own purchase, or do they hold for other periods as well?

As can be concluded from the results in tables 2 through 5, the revision of expectations varies across product categories. Clothing and electronics are the categories in which intended purchases change more, compared to prior expectations, as the uncertainty about future deals changes. Cosmetics/fragrances is the category where intended purchases change the least, as a result of uncertainty about future deals.

I divide the data into sub-samples according to age, religion, family size and average expenses per month, sex, ethnicity, family income, employment condition, and compare the way respondents update their beliefs within each of these sub-samples. Age is not relevant to explain differences in the way respondents update their beliefs, as most of the respondents have similar ages and there is not enough variation in the sample. Religion also is not relevant because even though there is some variability in religion choice, the majority of the sample is of the same religion (Christian). Differences in family size and expenses per month do not present any clear behavior pattern.

Unlike age, religion, and family size/expenses, sex does seem to have an effect on the survey responses. For some product categories, females are more sensitive to sales during the Christmas season than males. For instance, compared to their prior expectations, females on average change

the amount they expect to purchase on electronics by 80%, after they are introduced to scenario five, while males change their answers by only 30%. One possible explanation is that males have a higher utility for purchasing electronics than females. Females, on the other hand, need some incentive to buy more electronics. The situation is quite different for clothing. Males on average change by 51% the amount they expect to purchase after they are introduced to scenario five, compared to their prior expectations, while females change their answers by only 23%. Again this result may be explained by differences in preferences between males and females.

Ethnicity may also affect response characteristics. White respondents gave lower prior subjective probabilities to the occurrence of sales than other ethnic groups. They also change their answers less frequently when introduced to different uncertainty scenarios from their prior expectations. However, most of the respondents are white, so we should not make any final conclusion about the other ethnic groups, as they are misrepresented in the sample. Finally, respondents with family income between U$50,000 and U$100,000, tend to change their answers when introduced to uncertainty scenarios that differ from their prior expectations, as compared to other income range groups.

How much stores spend on marketing their deals is a crucial decision. Assuming that acquiring information about deals is costly for consumers, in general, the more stores spend on advertising their future deals, the smaller the cost to all types of consumers to detect those deals and therefore, the smaller the consumers' uncertainty about the occurrence of deals. For stores to reproduce in reality the situations described in uncertainty scenarios four and five, where consumers are 75% or 100% sure that a sale from 20 to 35% will occur, they would need to

spend a lot on advertising their deals. It is only profitable for stores to make consumers sure about the deals, and incur this extra cost of advertisement, if the percent of the amount consumers expect to purchase increases significantly as a result of a lessening of uncertainty about upcoming sales.

The empirical findings suggest that there are hidden costs of advertisement. 17.5% of the respondents do not change their expectations about future purchases as uncertainty about deals decreases. There is also a significant fraction of the sample that decreases the total amount they expect to purchase in each product category, as they become 100% sure that deals will occur in the next Christmas period. For clothing, 13% of the total sample decreases the amount they expect to purchase after they are introduced to scenario five. This number increases to 17% of the total sample for electronics. For CDs/DVDs, 10% of the total sample decreases the previous amount they expect to purchase after being introduced to scenario five, and this number is even smaller, 5%, for cosmetics/fragrances. These consumers take the opportunity to save. But there are also respondents who increase the amount they expect to purchase after they are introduced to scenario five. For clothing, 19% of the total sample increases by more than 60% the amount they expect to purchase after they are introduced to scenario five. This number decreases to 15% of the total sample for electronics.

For further investigation of whether the hidden costs of advertisement (such as the existence of consumers who spend less when they become more aware of future deals) are present, I would need information on the advertisements' costs, penetration and efficiency in informing consumers. But from the present descriptive analysis we can conclude first, that not all consumers increase the amount they expect to purchase as uncertainty about future deals decreases, and second, that for some product categories, such as CDs/DVS and

cosmetics/fragrances, stores need to spend more in advertising their deals because the majority of consumers believe that it is not highly probable to find deals on these product categories during Christmas. Hidden costs of advertisement may or may not exist, depending on the product category, distribution of types of consumers across the population and, of course, the costs and efficiency of the advertisement campaigns.

3.4 Conclusions

I show that uncertainty about future deals affects consumers' intended purchases during the Christmas period for four product categories: CDs/DVDs, clothing, cosmetic/fragrances and electronics. Unlike previous studies, I focus on intended purchases instead of actual purchases and I support the previous claim with a new dataset I collected via an email survey of undergraduate Northwestern University students in November and December 2004. The advantage of focusing on intended purchases is that the amount stores decide to spend on marketing their future deals affects consumers' intentions to make purchases in the future instead of actual purchases.

Using a method to elicit and measure revisions to subjective expectations, I conduct an e-mail survey using new wording I called *belief in a predetermined uncertainty scenario*. First, I elicit respondents' prior beliefs about the probability that a sale anywhere from 20 to 35% or a sale over 35% will occur during the next Christmas period in each of four product categories. I also elicit the amount the respondents expect to spend in each of the four product categories. Next, I present five different uncertainty scenarios to the respondents, where the probability that

no deals or a deal from 20% to 35% will occur during the Christmas season is predetermined in the question. Then I asked the respondents again how much they expect to spend in each of the four product categories, given the five predetermined probabilities of occurrence of a sale from 20 to 35%. In this way I elicit the posterior beliefs for the five different uncertainty scenarios.

The elicitation methodology proves successful since 63 out of 65 respondents understand the wording of the questions and provide consistent answers. I also find that consumers' priors are consistent with their posterior beliefs for all four product categories. There is also substantial heterogeneity in the way respondents revise their expectations. Some consumers do not change the amount they expect to purchase as they are introduced to different uncertainty scenarios. As the respondents themselves reply to me, they do not care about deals. I also find differences across product categories in the way consumers revise their expectations about future purchases. This finding emphasizes the need to consider flexible updating processes when modeling expectations of future purchases.

I collect the demographic characteristics of the respondents and relate them to the way they revise their expectations. I find that, for some product categories, females are more sensitive to sales during the Christmas season than males. Age and religion are not relevant to explain differences in the way respondents update their beliefs.

The empirical findings suggest that there are hidden costs of advertisement, such as consumers who spend less when they become more aware of future deals. 17.5% of the respondents do not change their expectations of future purchases as uncertainty about deals decreases. There is also a significant fraction of the sample that decreases the total amount they expect to purchase in each product category as they become 100% sure that deals will occur in

the next Christmas period. These consumers take the opportunity to save. Product categories such as CDs/DVDs and cosmetic/fragrances also require higher expenditures in advertising their deals, as consumers do not expect many discount sales to occur in those two categories. If the store does not specialize in one product category, but is a department store, like Macy's, the hidden costs of advertisement may disappear, even if for some product categories the total amount the store expect to receive from sales decreases after the advertisement campaign. The department store can use these categories as "loss leaders", i.e., categories that the store promotes just to attract consumers to the store.

For further investigation of whether there are hidden costs to advertising deals, I would need information on the advertisement's costs, penetration and efficiency in informing consumers. It would also be interesting to look at other product categories that are less popular than the ones studied here for Christmas purchases. I would expect advertisements to have a higher impact on consumers' intended purchases than the results found here. My sample is also limited, since it consists of only 65 Northwestern undergraduates. An interesting extension would be to expand the dataset presented here and include a more heterogeneous sample with a greater variety of ages and ethnic groups. I could also replicate the survey presented here for non-holiday periods. This way, I could compare how consumers' revisions of expectations about future purchases change when they are purchasing for their own consumption instead of purchasing gifts for others.

An important limitation of the survey used here is that I elicit information about total expenses. From this data, I cannot draw conclusions about own and cross price elasticities. An important extension would be to separate out price and quantity effects from the total purchase

amount. This would probably require more survey questions. Given the already low rate of response, one would probably need monetary incentives or many survey collectors to be able to get enough responses for a quality analysis.

One could also use the methodology presented here to elicit and measure revisions to subjective expectations to explore other sources of uncertainty that affect purchases. For instance, Fay and Xie (2007) analyze a novel selling strategy, *Probabilistic Selling*. *Probabilistic Selling* denotes the selling strategy under which the seller creates "probabilistic goods" using distinct products or services and offers such probabilistic goods to potential buyers as additional purchase choices. A probabilistic good is not a concrete product or service but an offer involving the probability of getting any one of a set of multiple distinct items. The probabilistic selling strategy allows the seller to benefit from introducing a new type of buyer uncertainty, i.e., uncertainty in product assignments. Examples of probabilistic goods and selling are *Priceline* and *Hotwire*. One could use a modified version of the present survey to understand how uncertainty about probabilistic goods affects consumers' intended purchases of the proposed goods.

Finally, instead of focusing on four product categories, I could instead just focus on four specific products. I could then compare differences in the motivations and intentions to make future purchases within a product category. Here, I focus on product categories because of the small size of the sample. To proceed with a product level analysis one would need a much larger sample to guarantee that enough consumers would purchase each of the products.

CHAPTER 4

Optimal Pricing Strategies: The Effects of Uncertainty about the Timing of Deals on Consumer Behavior

4.1 Introduction

In chapter two, I showed that for some product categories, such as soft-drinks and yogurt, loyal shoppers' decisions about the allocation of their purchases over time and the quantity purchased during a particular deal, are affected by the product's deal pattern. These findings suggest that it is crucial for both manufacturers and retailers to incorporate the effects of deal patterns on consumers' purchases when deriving optimal pricing strategies. For instance, if a large fraction of the retailer potential consumers behave strategically, trying to time their purchases to coincide with deals, the manufacturer/retailer might have a hard time selling his products at the regular price. In this case, unpredictability could be used as a means of avoiding the type of consumer who would be willing to purchase at the regular price, to concentrate all his purchases on deals.

In chapter two I assumed that prices and the timing of deals were exogenously given, this enabled me to focus on consumer behavior. The objective of this chapter is to relax this assumption and describe how manufacturers and retailers can incorporate the effects of the timing of deals on consumers' purchasing decisions when determining optimal pricing strategies. I consider the case of a monopolist manufacturer who is able to sell directly to the final

consumer or dictate the prices to the retailer, so that I can ignore the vertical relationship between the manufacturer and the retailer. I describe a five step algorithm to solve for the monopolist manufacturer's optimal pricing strategy incorporating these effects of timing of deals on consumers' decisions to purchase. I also assume that the monopolist manufacturer faces two different types of final consumers, has a constant marginal cost of production and can only offer two different prices at a time: the regular price and the deal price.

The monopolist manufacturer has a choice of three pricing strategies: to offer an optimal constant price, to follow an optimal predictable deal pattern or to exhibit an optimal unpredictable deal pattern. Using numerical simulations, I find situations where, out of the three possible strategies, a predictable deal pattern achieves the highest profit. I could not find any situation where unpredictability achieves the highest profit, beyond gains from discounting. This result seems counterintuitive and I suggest ways to extend the present framework in order to find unpredictability as the main outcome. Aside from the avoidance of the type of consumer who times his purchases to coincide with deals, there are other reasons that an unpredictable deal pattern may be the most attractive one for the firm. Examples are models with stochastic demand and models without stockpiling (such as the airline industry's weekend specials). So it is important to underline that the result discussed here is a very specific one and that one should be very cautious about using it as the basis for generalizations.

Like other analysts of this phenomenon[17], I investigate under which conditions offering deals is a better strategy than charging a constant price. There is a stream of literature that explains the existence of deals as a seller's mechanism to price discriminate among buyers. Most of the

[17] Examples of papers in this literature are Varian (1980), Jeuland and Narasimnhan (1985) and Colinski, Gerstner and Sobel (1984).

theoretical work in this literature focuses on deriving analytical implications of when and under what conditions offering deals is an optimal strategy for a monopolist seller. The authors compare two different strategies: charging a constant price or offering deals.

Here I add a new dimension to the problem -- the (un)predictability of the distribution of deals. As I found in chapter two, deal unpredictability affects consumers' purchase decisions. So, the monopolist seller should actually compare three different strategies: predictable deal pattern, unpredictable deal pattern and constant price. In this paper, I assume that, when there are predictable deal patterns, consumers know the entire price distribution. For the case of unpredictable deal patterns, consumers form beliefs about future prices according to a Markov process. The transition probabilities of the Markov chain are determined by the average and standard deviation of the number of weeks between two consecutive deals, which is determined by the monopolist manufacturer. However these two measures are not mapped one to one into transition probabilities. To simplify the problem, I assume that the monopolist seller, in the unpredictable deal pattern case, directly chooses the transition probabilities of the Markov chain that enter the consumer expected utility maximization problem. Even though this is a simplification of the seller real decision problem, it allows the state space of the monopolist's profit maximization problem to reduce dramatically.

Here, the model of consumer behavior is similar to the one presented in chapter two. Consumers purchase for two reasons: for future consumption (endogenously determined) and to build inventories. How much consumers buy in each period depends on their current inventory level, the current shock to utility from consumption and current prices. In the unpredictable case, how much consumers buy also depends on their beliefs about future prices, while in the predictable case it depends on the number of weeks between two consecutive deals, which

consumers know in advance. Prices can take on two values: on deal, p_L, and off deal, p_H, such that $p_L<p_H$. Consumers know the prices but they do not know before coming to the store which price will be offered. I focus on four types of consumers: loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper. The loyal shopper is the consumer whose marginal utility from consumption of the brand is high enough such that he is willing to purchase this brand at the regular price if necessary, i.e., his stock is zero. Non-loyal shoppers have no compelling need to buy a brand. They buy a brand only if its price is low enough. Shopper is the consumer who has a storage cost low enough such that he is able to stockpile for the average number of weeks between two consecutive deals.

In this model , I suppose that there is a monopolist manufacturer who faces two different types of final consumers and that he knows the distribution of these two types of consumers across the population. The monopolist manufacturer is able to sell directly to the final consumer or to dictate prices to the retailer. The marginal cost of production is constant over time. The seller can only choose two prices, the regular price p_H and the deal price p_L, known to the consumers. The seller also chooses the constant number of weeks between two consecutive deals, in the case of a predictable deal pattern, or the probabilities of transition between regular price and deal price, in the case of an unpredictable deal pattern. The seller can only commit to a single strategy: to offer a constant price, predictable deal pattern or unpredictable deal pattern. Consumers know which strategy the seller chooses. Sellers are not able to deviate from their initial strategy once they commit to it.

To find the optimal pricing strategy for the monopolist manufacturer I propose a five step algorithm. The first step consists of choosing/estimating parameter specifications for the consumer and firm behavior. In the second step, given these parameter specifications, I find the

optimal constant price and the corresponding profit. In the third step, I assume the monopolist manufacturer finds it optimal to offer an upredictable deal pattern. I then find the fixed point of the consumer maximization problem and search for the combination of transition probabilities and prices that achieves the highest profit. In the fourth step, I assume the monopolist manufacturer finds it optimal to offer a predictable deal pattern and I derive the optimal prices and number of weeks between two consecutive deals for the respective parameter specification. Finally, I compare profits achieved with 1) optimal constant prices, 2) the optimal combination of transition probabilities and prices (in the case of the unpredictable deal pattern) and 3) the optimal combination of prices and number of weeks between two consecutive deals (in the case of a predictable deal pattern) and conclude with the optimal strategy.

Using different simulations, my main findings are the following. In the case where no consumers stockpile or where they have a very high storage costs, the monopolist's optimal pricing strategy is to charge a constant price. In the other case, in which consumers do stockpile, and there is demand from two types of consumers: – the loyal non-shopper with small price sensitivity and the non-loyal shopper with very high price sensitivity – and the second group is the largest one, the monopolist finds it optimal to offer predictable deals.

In the present framework, I could not find any parameter specification for consumer and firm behavior where unpredictability achieves the highest profit, beyond gains from discounting. This result seems counterintuitive and I discuss ways to extend the present framework in order to find unpredictability as the main outcome. Again, I should emphasize that there are other reasons, besides avoiding the type of consumer who times his purchases to coincide with deals and would purchase otherwise at the regular price, which can generate unpredictable deal pattern as the most attractive strategy for the firm. So it is important to underline that the result discussed here

is a very specific one. But even in the present framework, unpredictability can be used as a source of increasing the overall consumption of the brand; as it is documented that, for some products, the presence of additional inventory on hand induces additional consumption per period. If we introduce competition in the model, unpredictability can also be used as a way to keep consumers away from competitors longer. Unpredictability might trigger some consumers to purchase a larger amount of a brand during a particular deal, postponing their need to purchase this product category again and to switch to a competitive brand. Unpredictability may also be the best outcome if we allow for more than two types of consumers and/or prices can take on more than two values. Finally, as already suggested by previous works, unpredictability might turn out to be an optimal strategy for sellers, not because they are trying to avoid strategic behavior from some types of consumers, but mainly because it can be used as a strategy to beat their competitors, as explored in Braido (2005).

The remainder of the paper is organized as follows. In section two I review the relevant literature. In section three I present the dynamic inventory model of consumer choice, the monopolist manufacturer profit maximization problem and the five steps solution procedure to determine optimal pricing strategies. In section four I present some simulations. In section five I discuss the simulation results for the optimal pricing strategies and propose extensions of the present model that might explain unpredictability as an optimal outcome. In section six I conclude.

4.2 Related Research

There is a stream of literature that explains the existence of deals as a seller's mechanism to price discriminate among buyers. The questions,Why do discount sales exist? Why is this a better strategy than charging a unique constant price?, have been extensively studied in the literature. There are different approaches to answering this question: price discrimination (Jeuland and Narasimhan, 1985; Conlisk, Gerstner and Sobel, 1984), asymmetric information (Varian, 1980), signaling (Anderson and Simester, 1998), and many others. Let us focus on the price discrimination argument.

Jeuland and Narasimnhan (1985) explain the existence of deals as a mechanism for discriminating between more and less intense demanders. They also hypothesize a positive relationship between demand elasticity and holding costs. Buyers with more intense demand, with high holding costs, are those who will be buying the product at its regular price. The low-holding-cost buyers take advantage of deals by forward buying. One important difference between the model present here and Jeuland and Narasimnhan's (1985) paper, is their assumption that demand in one period is independent of demand in previous periods, in which case the (un)predictability of deals is not an issue. As they state in the section of possible extensions of their model: "Our model assumes that demand in one period is independent of demand in previous periods. In this case, the predictability of deals is not an issue. However, in the likely case of demand interdependencies over time, predictability of deals might lead consumers who would buy at the regular price to time their consumption with the deal pattern – if the latter is predictable. Offering deals at random might minimize this opportunistic behavior."

Conlisk, Gerstner and Sobel (1984) show that a monopolist seller of a durable good holds periodic sales as a means of price discrimination. In their model, a new cohort of consumers enters the market in each period, interested in purchasing the good either immediately or after a

delay. Within each cohort, consumers vary in their tastes for the good. The seller finds it optimal to charge a price just low enough in most periods, to sell immediately to consumers with a high willingness to pay. But periodically he will drop the price far enough to sell to an accumulated group of consumers with a low willingness to pay.

Like the papers mentioned above, I also investigate under which conditions offering deals is a better strategy than charging a constant price. However most of the previous works compare two different strategies: charging a constant price or offering deals. I add a new dimension to the problem, the (un)predictability of the distribution of deals. This dimension has already been explored in the literature but from a different perspective, not, as here, from the perspective of a seller using unpredictability to minimize the opportunistic behavior of some types of consumers, but from the perspective of a seller using unpredictability to beat his competitors. Braido (2005) shows that, in the case of identical retailers serving homogeneous consumers, the optimal result for the retailers is to act unpredictably when setting prices, otherwise they would be easily beaten by their competitors. In this way, random sales can result in the equilibrium of a multiproduct retailer competition model. In a different venue, Swait and Erdem (2002) investigate the effects of the temporal consistency of sales promotions and availability on consumer choice behavior under a static framework. In their work, temporal (in)consistency captures the degree of variability of prices, displays, and features, as well as availability over time for each type of product. The authors show that lack of sales promotion consistency is generally deleterious to consumer brand evaluation. So, unpredictability can also hurt the seller because consumers may view it as a lack of consistency in the seller strategy and decrease their evaluation of the brand.

There are still many other works in both the economics and marketing literatures that focus on deriving the analytical implications of when and under what conditions offering deals is

an optimal strategy for a seller. The main difference between those works and mine is that I incorporate, in a single framework, the effects of deal patterns on consumer purchase decisions when deriving optimal pricing strategies. And I also propose a way to simplify the state space of the profit maximization problem and solve for the optimal pricing strategy. This is a first step in a future research direction that emphasizes the importance of endogenizing the effects of uncertainty about the timing of of deals on consumer behavior when solving for optimal pricing strategies.

4.3 Model and Solution Algorithm

In this section I summarize the dynamic model of consumer behavior presented in chapter 2, present the monopolist manufacturer profit maximization problem and describe the five steps solution procedure to determine the optimal pricing strategies.

4.3.1 Model of Consumer Behavior

The model of consumer behavior is similar to the one described in chapter two. Household h purchases for two reasons: current consumption and to build inventories. At each period t, household h decides the amount it wants to consume, c_{ht}, and the quantity it wants to purchase, q_{ht}, of each single product. The household derives utility from consumption. There is a shock to utility, v_{ht}, which introduces randomness in the household's needs, unobserved by the researcher. Low realizations of v_{ht} increase the household's need, making it more inelastic. Households

know the current realization of the shock when they reach the store. But they don't know the future realizations of the shock. I assume that v_{ht} can take on three values, $v_{ht} \in \{0,1,2\}$, with equal probabilities. I also assume that the shocks are i.i.d. across each type h of households.

Household h also buys to take advantage of deals and to store for future consumption. I assume the cost of storing inventory to be linear, where i_{ht} is the inventory level of household h at period t.

Prices can take on two values: on deal, p_L, and off deal, p_H, such that $p_L < p_H$. Consumers are aware of both prices; they do not know before coming to the store which price will be offered.

Again, define d_{ht} as in equation 3 of chapter 2, with each consumer at each date having a potentially different d_{ht}. Each consumer is given an exogenously determined vector of d_{ht}s, in other words, consumers do not endogenously decide on when to visit the stores. At each period consumers visit a store, they must decide on the quantity to purchase. They observe the price of each good even if they decide not to purchase the good. For all periods, consumers decide on the quantity to consume. When consumers do not visit the store, they do not observe the price of the good.

The consumer's problem can be represented by equation 4 of chapter 2 shown as equation 11 below:

$$\max_{c_{ht}, q_{ht}} \sum_{t=0}^{\infty} \delta^t E\left[\beta_h \log(c_{ht} + v_{ht}) - C_{ht}(i_{ht}) - d_{ht}\gamma_h p_t q_{ht} \middle| \Psi_{ht}\right] s.t.$$

$$C_h(i_{ht}) = \theta_h i_{ht}$$

$$i_{ht} = i_{h,t-1} + d_{ht} q_{ht} - c_{ht} \tag{11}$$

$$i_{ht} \geq 0 \quad c_{ht} \geq 0 \quad q_{ht} \geq 0 \quad ,$$

where Ψ_{ht} is the information set at time t, and δ the discount factor. At each time t, household h derives non-negative utility from current consumption of the good. At time t, household h also incurs the cost of storing, whenever it ends period t with a positive inventory, and the cost of purchase, whenever it visits a store and decides to purchase a positive amount. Quantity not consumed is stored as inventory.

The contents of the information set, Ψ_{ht}, depend on the type of deal pattern being offered. Deal patterns can either be *predictable* (no uncertainty about deal timing) or *unpredictable* (some level of uncertainty about deal timing). More precisely, the number of periods the good is offered on sale is defined by D. Also define by N_z the number of weeks between two consecutive deals for $z=1,...,D-1$ and $N=[N_1,\ldots,N_{D-1}]$. $\mu(N)$ stands for the average number of weeks between two consecutive deals and $\sigma(N)$ the respective standard deviation. A product has a predictable deal pattern when $\sigma(N)=0$. Any deal pattern such that $\sigma(N)>0$ is classified as unpredictable. For instance, a product that is promoted on alternate weeks or every 3 weeks has a predictable deal pattern.

In the case in which deals are unpredictable, the information set at time t consists of the beginning of the period inventory, i_{ht-1}, current prices, p_t, the shock to utility from consumption, v_{ht}, and the vector of d_{ht}'s: $\Psi_{ht}=\{i_{ht-1}, p_t, v_{ht}, d_{ht}, d_{ht-1}, d_{ht-2},\ldots\}$. Consumers' expectations about future prices are represented by a first-order Markov process with two prices, a deal price (p_L) which is thought to occur with probability $\pi_{H,L}$ if p_H was the price in the previous period, and $\pi_{L,L}$ if p_L was the price in the previous period, and a regular price (p_H) which is thought to occur with probability $\pi_{L,H}$ and $\pi_{H,H}$ after the occurrence of price p_L and p_H. Formally, the probability function can be described by the Markov chain found in equation 5 of chapter 2.

The transition probabilities describe how predictable, consumers believe, the deal pattern is. Consumers form their expectations (give value to the transition probabilities) during an initial learning period. Those beliefs are defined per product, per consumer, per store. Consumers who visited the same store during the same periods have identical beliefs. Consumers use these transition probabilities defined at this initial learning period to make decisions about the quantities to buy and consume. The utility maximization problem described in (11) happens after this initial learning period is over. There is no further learning in my model.

I assume that consumers know the entire price distribution when deals are predictable. Therefore, for the case of a predictable deal pattern, consumer information set at time t consists not only of the beginning of the period inventory, $i_{h,t-1}$, current prices, p_t, shock to utility from consumption, v_{ht}, and the vector of d_{ht}s, but also of the number of weeks between two consecutive deals, N: $\Psi_{ht}=\{i_{ht-1}, p_t, v_{ht}, d_{ht}, N, d_{ht-1}, d_{ht-2},\ldots\}$.

I focus on four types of consumers: the loyal shopper, loyal non-shopper, non-loyal shopper, and non-loyal non-shopper. *Loyal* is the consumer whose marginal utility from consumption of the good is high enough such that he is willing to purchase at the regular price if necessary, i.e. stock is zero. More formally, loyal is the consumer for whom $\beta_h>\gamma_h p_H$. *Non-loyal* is the consumer whose marginal utility from consumption of the good is smaller than the same threshold, i.e., $\beta_h\leq\gamma_h p_H$. These consumers are not willing to perform an inter-temporal substitution of this product.

Shopper is the consumer who has a storage cost low enough such that he is able to stockpile for the average number of weeks between two consecutive deals. More formally,

shopper is the consumer for whom $\theta_h < \frac{\left(\delta^{\mu(N)_h - 1}\right) p_H - p_L}{\sum_{j=0}^{\mu(N)_h - 2} \delta^j}$. Note that for the predictable deal pattern case (benchmark case) a shopper has *n=N,* i.e., he is able to obtain 100% of his purchases during deals. *Non-shopper* is the consumer who has a storage cost higher than the previous stated threshold.

4.3.2 Model of Manufacturer Behavior

To keep things as simple as possible, suppose a monopolist manufacturer is able either to sell directly to the final consumer or to dictate prices to the retailer (so that the vertical relationship between the manufacturer and the retailer can be ignored.) In reality we know that retailers adopt more complex mark-up strategies and that there is not a monopolist brand but an oligopoly of brands in a single product category. Ideally a complete pricing model should include the vertical relationship between manufacturer and retailers and a game-theoretic framework to account for the competitive strategies among the different brands. However this is beyond the scope of the present work.

The monopolist manufacturer faces two different types of final consumers, *h={1,2}*. A fraction Θ of the manufacturer's potential consumers is type 1, where Θ is known to the manufacturer. Define by K the marginal cost of production, which I assume to be constant over time, and δ the discount rate. The manufacturer can only choose two prices, the regular price, p_H, and the deal price, p_L, known to consumers. To find the optimal price distribution, the monopolist first decides if it is optimal to have a predictable or unpredictable deal pattern. If a

predictable deal pattern is optimal, the monopolist should also choose *N*, the optimal number of weeks between two consecutive deals. If an unpredictable deal pattern is optimal, the monopolist decides on the probabilities of transition between the regular price and the deal price. I assume that those are actually the transition probabilities of the Markov chain that enter the consumer expected utility maximization problem. Implicitly I am assuming that consumers have full information about the monopolist strategy. This is a simplification of the manufacturer's real decision problem. The manufacturer actually decides on the average and standard deviation of the number of weeks between two consecutive deals. These two measures can be mapped, not one to one, into a transition probability. However this simplification allows me to reduce dramatically the dimensionality of the state space of the monopolist profit maximization problem. Consumers might also not be fully aware of the real strategy adopted by the manufacturer. An interesting extension would be to introduce asymmetric information in the model.

In this model, the monopolist manufacturer can only commit to a single strategy: to offer a constant price, predictable deal pattern or unpredictable deal pattern. The manufacturer is not able to deviate from his initial strategy once he commits to it. Again, in a more realistic setting, one could imagine equilibrium where the manufacturer starts with one strategy, which might not be his most profitable one, to set the desired consumers' expectations, and later change to another strategy, which becomes the most profitable one, after consumers' expectations are set accordingly. This type of analysis is beyond the scope of the present work, as it significantly complicates the manufacturer's profit maximization problem and drastically increases the state space.

The monopolist manufacturer's profit maximization problem can be represented as:

$$\max_{[(\pi_{L,H},\pi_{H,L};N],p_L,p_H} \sum_{t=0}^{\infty} \delta^t \{[\Theta q_{1t}^*(p_t) + (1-\Theta) q_{2t}^*(p_t)](p_t - K)\} \tag{12}$$

s.t. q^*_{1t} and q^*_{2t} are the arguments that maximize the consumer's problem.

4.3.3 Solution Algorithm

In order to show under what conditions offering deals is a better strategy than charging a unique constant price, first I need to derive the optimal constant price. In a situation where there is a constant price, $p_t=p_c$, the dynamic consumer maximization problem described in (11) simplifies to a static one with $i^*_{ht}=i^*_{h,t-1}=0$ and $c_{ht}=q_{ht}$. Assuming the shocks to utility are i.i.d. across each type of consumer, the optimal constant price can be described as[18]:

$$p_c = p^* = \sqrt{AK} \tag{13}$$

where

$$A = \Theta \frac{\beta_1}{\gamma_1} + (1-\Theta)\frac{\beta_2}{\gamma_2} \tag{14}$$

I therefore propose the following five-step procedure to examine if offering deals is a better strategy than charging a unique price. The first step consists of choosing/estimating parameter specifications for the consumer and firm behavior as described in equations (11) and

[18] The derivation is provided in the Appendix.

(12). In the second step, given these parameter specifications, I find the optimal constant price, as described by equations (13) and (14), and the corresponding profit. In the third step, I assume the monopolist finds it optimal to offer an unpredictable deal pattern and I use the algorithm described in the appendix to solve for the optimal pricing strategies, given the parameter specification. This algorithm involves finding the fixed point of the consumer maximization problem and searching for the combination of transition probabilities, $(\pi_{L,L}, \pi_{H,H})$ and prices, (p_L,p_H) that achieves the highest profit. In the fourth step, I suppose the monopolist finds it optimal to offer a predictable deal pattern. From the assumption that, in the case of predictable deal patterns, consumers know the entire price distribution, I can derive a closed form solution to their optimal behavior. This solution is described in chapter 2, Proposition 1. Given the description in chapter 2, Proposition 1, of optimal consumer behavior, I derive the optimal prices and length of the cycle, (p_L,p_H,N), as described in the appendix, for the respective parameter specification. Finally I compare the profits achieved with 1) the optimal constant price, 2) the optimal combination of $(\pi_{L,L},\pi_{H,H})$ and (p_L,p_H) in the case of an unpredictable deal pattern and 3) the optimal combination (p_L,p_H,N) in the case of a predictable deal pattern, and conclude with the optimal strategy. The monopolist manufacturer's optimal pricing strategy is the one that achieves the highest profit out of those three strategies.

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4.4 Simulations

In what follows I am going to use different specifications for the parameters that characterize consumers' behavior and manufacturer's behavior, as described in equations (11)

and (12), and the five step algorithm to solve for the manufacturer's optimal pricing strategy, as described in the previous section, to simulate the resulting optimal pricing strategy.

First, suppose consumers do not stockpile or have a very high storage cost. In this case the dynamic problem simplifies to a static one. Consumers purchase just for immediate consumption. It is easy to see that the static problem has a unique maximum and the monopolist's optimal strategy is to a charge a unique price. This strategy is better than offering any sort of sales.

Next, consider the case where a monopolist manufacturer/retailer faces two types of consumers: the loyal non-shopper with small price sensitivity and the non-loyal shopper with very high price sensitivity. This situation is similar to the one presented in Jeuland and Narasimnhan (1985). I am also assuming a positive relationship between demand elasticity and holding costs. Of course the first group of consumers is the most attractive to the seller. So the seller may find it optimal to target just this group and sell the product by a unique constant price. For the seller to have an incentive to also sell to the second group and offer some sort of deal, this second group must be big enough or its demand cannot be too weak. This situation can be described by the following parameter specification: group one (loyal non-shopper with small price sensitivity) has α_1=0, β_1=4, γ_1=0.2, θ_1=1,000, and group two (non-loyal shopper with high price sensitivity) has α_2=0, β_2=2, γ_2=1, θ_2=0. Also suppose K =0.5, δ=0.999, no shocks to utility and the population equally divided between both types, i.e., Θ=0.5. For this parameter specification the optimal constant price for a monopolist is $4.46 per unit. At this price, group one finds it optimal to consume four units per period, and group two prefers not to consume. Compare the profit achieved using the optimal constant price with the profits achieved using predictable and unpredictable deal patterns. Constant pricing is the optimal strategy. The

monopolist gives up selling for the least attractive group (group two) and focuses on the most attractive group (group one). However, if I keep the same parameter specification but change Θ=0.2, constant price is no more the optimal pricing strategy. The combination that achieves the highest profit is given by a predictable deal pattern with p_L=\$1.38, p_H=\$4.46, N=2. This strategy achieves a profit 7.4% higher than the profit achieved with a constant price. The intuition for this result is simple. First, offering deals is a better strategy than charging a constant price because the less attractive group is large enough so that it is appealing for the seller to target them too instead of just selling to the loyal group. This result is similar to Jeuland and Narasimnhan (1985) and also related to Conlisk, Gerstner and Sobel (1984). As they mention in their paper, "Periodically the monopolist drops the price far enough to sell to the accumulated group of consumers with a low-willingness to pay." Second, a predictable deal pattern achieves a higher profit than an unpredictable deal pattern because the non-loyal group is too price sensitive and, consequently, unpredictability does not increase the amount they purchase at a particular deal/sale as compared to the predictable case. Those consumers do not purchase more than 5 units at any period. So unpredictability loses its main advantage: to induce a significant increase in the amount purchased at a particular deal/sale. Under the present framework, I could not find any parameter specification for consumers and manufacturer behavior that results in an unpredictable deal pattern as the manufacturer's optimal pricing strategy, other than gains from discounting.

4.5 Discussion of Optimal Pricing Strategies

From the simulations described in the previous section, I found that, when demand is composed of two types of consumers – the loyal non-shopper with small price sensitivity and the non-loyal shopper with very high price sensitivity – and the second group is the largest one, the monopolist find it optimal to offer predictable deals. Under the present framework, I could not find any parameter specification for consumers and manufacturer behavior that results in an unpredictable deal pattern as the manufacturer's optimal pricing strategy, aside from gains from discounting. The problem is that we would expect manufacturers to use unpredictability as a way to avoid the most attractive type of consumer, the one who would otherwise purchase at the regular price, just purchasing during deal periods because the deal pattern is completely predictable. However, because consumers are rational, they anticipate that, in the case of an unpredictable deal pattern, they have a higher chance of encountering *understock*, i.e., having zero or insufficient inventory during the regular price period when it would be ex-post optimal to have a positive inventory. So, as I found in chapter two, during a particular deal, the less predictable the deal pattern, the more loyal shopper consumers purchase. This means that the manufacturer will increase his profits, during this particular deal, due to unpredictability. But he will loose profits in future periods because these loyal consumers will take longer to make their next purchase. Manufacturers can still force loyal shopper consumers to purchase at the regular price using a predictable deal pattern if they make the number of weeks between two consecutive deals bigger than the average number of weeks loyal shopper consumers can survive from consuming from their stock. This result might seem counterintuitive. In what follows I discuss extensions of the present model that can result in unpredictable deal pattern as the optimal pricing strategy. But before doing that, I want to emphasize that I could not find an unpredictable deal pattern as the optimal pricing strategy in the very specific framework presented here. One

should be very careful when generalizing from this result. There are other reasons, besides the avoidance of the most attractive type of consumer timing his purchase(s) to coincide with deals, which can generate the unpredictable deal pattern as the most attractive strategy for the firm. Examples are models with stochastic demand, and models without stockpiling, such as the real world example of the airline industry's weekend specials.

However, in a context similar to that presented here, unpredictable deals can be used as a source of increasing overall consumption of the brand. For some product categories, like bacon, salted snacks and soft drinks, there is an additional consumption per period induced by the presence of additional inventory on hand, as reported by recent studies (Ailawadi and Neslin (1998), Bell et al. (1999) and Sun (2005)). And since I found that the less predictable the deal pattern, the higher the quantity purchased during a particular deal period, this extra inventory might trigger higher consumption rates. To capture this possibility, one needs to modify the consumer utility maximization problem described in equation (11) to account for the fact that consumers might not anticipate, when deciding on how much to purchase, that if they buy to stockpile to avoid purchase at the regular price, the extra inventory might trigger higher consumption rates.

One important extension is to include competition in the model. With competition, there is the possibility that the manufacturer might lose a big number of sales during the deal periods, due to the fact that the competitor also knows when the deal is coming (if predictable) and offers it before that, so that consumers stock up with the competitive brand. In this sense, unpredictability can be used as a way to keep consumers away from competitors. Unpredictability triggers loyal shopper consumers to purchase a larger amount of a brand at a

particular deal, postponing their need to purchase again in this product category and to possibly switch to the competitive brand.

Unpredictability may also be the best outcome if I allow for more than two types of consumers and/or prices can take on more than two values. I could also allow for asymmetric information between consumers and sellers. Finally, as already suggested by previous works, unpredictability might turn out to be an optimal strategy for sellers, not because they are trying to avoid strategic behavior from some types of consumers, but mainly because it can be used as a strategy to beat their competitors, as explored in Braido (2005).

4.6 Conclusion

I show how a monopolist manufacturer can incorporate the effects of the timing of deals on consumers' purchase decisions in order to determine the optimal pricing strategy. Unlike previous studies, I do not compare only two different strategies – charging a constant price or offering deals – but I add a new dimension to the problem: the (un)predictability of the distribution of deals. So, the monopolist manufacturer actually compares three different strategies: a predictable deal pattern, an unpredictable deal pattern and a constant price. I find situations where the monopolist manufacturer achieves a higher profit from offering predictable deals instead of a constant price but I cannot find, under the present framework, any situation where unpredictability achieves a higher profit, other than gains from discounting, in comparison to the predictable case. Caution should be used when generalizing from this result. There are also other reasons besides the one explored here, i.e., avoiding that the most attractive type of

consumer times his purchase to coincide with deals, that can generate unpredictable deal pattern as the most attractive strategy for the firm.

I also propose extensions of the model in order to find unpredictability as the main outcome. Examples of such extensions are the inclusion of competition in the model, the adoption of a different utility function that captures, for instance, the fact that, for some product categories, additional inventory on hand triggers a higher consumption rate, and the allowance of more than two types of consumers.

The framework presented here is a very specific one. I consider the case of a monopolist manufacturer who is able to sell directly to the final consumer or to dictate prices to the retailer, and can only offer one of two prices at a time: the regular price or the deal price. The monopolist manufacturer also faces just two different types of consumers. For this framework, I described a five step algorithm to solve for the monopolist manufacturer's optimal pricing strategy incorporating the effects of a deal's timing on consumers' purchases. An interesting extension is to relax the assumption that the monopolist manufacturer dictates the prices to the retailer and include the vertical relationship between manufacturer and retailer.

An important next step to be pursued is to structurally estimate the parameters of the dynamic inventory model of consumer choice with scanner data and generate normative pricing implications. This way one can perform counterfactual exercises to investigate how different pricing strategies affect profitability. Aguirregabiria (2002) presents a model of dynamic price competition among retailers who sell several varieties of a differentiated storable good and use sales promotion as a mechanism to discriminate inter-temporally among heterogeneous consumers. The author's objective is to compute counterfactual equilibria under different restrictions on the use of sales promotions. His focus is on how offering sales promotions affects

firms' profits and market structure. My objective for further research in this area would be to expand on this approach by also examining how offering different deal patterns affects firms' profits.

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APPENDIX

1 Appendix for Chapter 2: Proofs from the Text

Proof of Proposition 1: Assume no shock to utility, $v_t=1$. If consumers purchase just for immediate consumption (no stockpiling) the dynamic problem described in (4) simplifies to a static one. From the F.O.C. of the static maximization problem, the optimal quantity to purchase and consume is[19]:

$$c^* = q^* = \frac{\beta}{\gamma p_j} - 1 \tag{A1}$$

Assume the first deal price takes place at $t=1$. At this period consumer purchases for immediate consumption and to stockpile. The amount he purchases for immediate consumption is given by equation (A1) with $p_j=p_L$. Since consumer knows the number of weeks between two consecutive deals, N, the amount he purchases to stockpile is given by the following general decision rule: *"At the deal period, purchase in advance for consumption at the subsequent n periods, where n is an integer, and* $n \in [1,N+1]$*. If n=1, it is not worth purchasing in advance for future consumption. So* $q^*_1=c^*_1$*. If n>1, purchase at the first period the sum of the*

[19] In the following derivations I omitted the index for consumer's type, h, to simplify the notation.

consumptions of the subsequent n periods, i.e., $q_1^* = \sum_{j=1}^{n} c_j^*$. *In this case, there is no need for purchase at the later n periods, i.e,* $q^*_2=\ldots=q^*_n=0$."

To determine the optimal consumption at those n periods, and the optimal n, I define by υ_k the virtual price (equation 10). It is the unit cost of purchasing at the first period low price, p_L, plus the cost of carrying (storage cost + discount factor) the inventory up to period k of consumption, where $k=2,\ldots,n$. Consumers compare the virtual price, υ_k, with the cost of purchasing the same unit at period k regular price, p_H, when deciding on the amount to be purchased for storage at the first period deal price. For all periods such that $\upsilon_k<p_H$ it is optimal to purchase in advance at the first period promotional price. Therefore n is the last period from the N periods of regular price for which $\upsilon_k<p_H$ (equation 9). If $\upsilon_k>p_H$ for all k then $n=1$. For these n periods the optimal consumption is given by equation (A1) with $p_j=\upsilon_j$.

For the periods $j=n+1,\ldots,N+1$, inventory is zero, since n is the last period of zero purchase and consumption from inventory. Purchases are only for immediate consumption and the optimal amount to consume and purchase is given by equation (A1) with $p_j=p_H$.□

Proposition 2: Generalization of Proposition 1 including shocks to utility. The optimal quantities to purchase and consume for the $N+1$ periods of the cycle can be described as:

i) For t=1 where $p_t=p_L$*:*

$$q^*_1 = \sum_{j=1}^{n} c^e_j \tag{A2}$$

$$c^*_1 = c_1^e = \frac{\beta}{\gamma p_L} - \nu_1 \tag{A3}$$

$$c_j^e = \frac{\beta}{\gamma \vartheta_j} - 1 \qquad for \qquad j = 2,...,n \tag{A4}$$

$$n = max\, k \big| \vartheta_k < p_H, k \in IN \tag{A5}$$

$$\vartheta_k = \frac{p_L + \theta \sum_{j=0}^{k-2} \delta^j}{\delta^{k-1}} \qquad for \qquad k = 2,...,n \tag{A6}$$

ii) For t=2,…,N+1 where p_t=p_H:

$$c_j^v = \frac{\beta}{\gamma \vartheta_j} - \nu_j \tag{A7}$$

$$c_j^H = \frac{\beta}{\gamma p_H} - \nu_j \tag{A8}$$

For j=2,…,n:

$$\begin{cases} if \quad i_{j-1} \geq c_j^v \Rightarrow q_j^* = 0, c_j^* = c_j^v \\ if \quad i_{j-1} < c_j^v \Rightarrow q_j^* = c_j^H - i_{j-1}, c_j^* = c_j^H \end{cases} \tag{A9}$$

For *j=n+1,…,N+1*:

$$\begin{cases} if \quad i_{j-1} \geq c_j^H \Rightarrow q_j^* = 0, c_j^* = c_j^H \\ if \quad i_{j-1} < c_j^H \Rightarrow q_j^* = c_j^H - i_{j-1}, c_j^* = c_j^H \end{cases} \tag{A10}$$

Proof of Proposition 2: Consider the case of purchase for immediate consumption. From the F.O.C. of the static maximization problem, the optimal quantity to purchase and consume is:

$$c^* = q^* = \frac{\beta}{\gamma p_j} - \nu_j \qquad \text{(A11)}$$

where $\nu_j \in \{0,1,2\}$.

Assume the first deal price takes place at *t=1*. At this period consumer purchases for immediate consumption and to stockpile. The amount he purchases for immediate consumption is given by equation (A11) with $p_j=p_L$. Since consumer knows the number of weeks between two consecutive deals, *N*, but does not know a priori the realization of the future shocks to utility, the amount he purchases to stockpile for future consumption is given by the new decision rule: "*At the deal period, purchase in advance for consumption at the subsequent n periods, where n is an integer and* $n \in [1,N+1]$. *If n=1, it is not worth purchasing in advance for future consumption. So* $q^*_1=c^*_1$. *If n>1, purchase at the first period the sum of the expected consumptions of the subsequent n periods, i.e.,* $q_1^* = \sum_{j=1}^{n} c_j^e$. *Since this purchase is based on the expected consumption, consumers might need to purchase during these n periods. Whether consumers need to purchase or not depends on the realizations of the shocks to utility."*

To determine the optimal consumption at those *n* periods, the expected consumption, and the optimal *n,* I define by υ_k the virtual price. This is the same definition as before. For all periods such that $\upsilon_k<p_H$ it is optimal to purchase in advance at the first period promotional price. Therefore *n* is the last period from the *N* periods of regular price for which $\upsilon_k<p_H$. At *t=1*, the expected future consumption is described by equation (A4). It follows from the assumption that

$v_t \in \{0,1,2\}$ with equal probabilities and, consequently, $E_1(v_t)=1$ for $\forall t$. For these n periods the optimal consumption is given by equation (A11) with $p_j = \upsilon_k$, or $p_j = p_H$. Since for these n periods $\upsilon_k < p_H$, it follows that $c^v > c^H$. Consumers consider the virtual price as the price available whenever they are able to fulfill their higher consumption needs, c^v, with inventory. In this case there is no need for purchase at the period and consumption is according to c^v. Consumers consider the regular price as the price available whenever they are not able to fulfill their higher consumption needs, c^v, with inventory. In this case, consumption is according to c^H and the total amount to be purchased, if necessary, is given by the difference between c^H and the inventory left from the previous period, i_{j-1}.

For the periods $j=n+1,\ldots,N+1$, $\upsilon_k > p_H$. Consumers consider p_H as the available price and consumption is according to c^H. The total amount to be purchased, if necessary, is the difference between c^H and the inventory left from the previous period, i_{j-1}. □

Proof of Implication 1: Consider a deal period, t, and a consumer whose last purchase on deal was in period t-j. Consumers only purchase positive amounts in off deal periods for immediate consumption. As j grows, inventory declines, since at non-deal periods consumers may also consume from inventory. Therefore, the expected amount to be purchased on the deal period, t, conditional on having purchased at t-j, increases in j. In other words, the higher the number of weeks from the previous deal, the higher the amount purchased at the deal period t.[20]

The quantity purchased on a deal period, t, also increases in σ^2, the variance of the price distribution. This claim holds for the case where the average number of weeks between two consecutive deals is not too large, such that the long-term stationary probability of the low price

[20] That result is also showed in Hendel and Nevo (2006b).

state is big enough, $\Pi_L \in [1/2, 1]$. The stationary probability vector, Π, is defined as the vector whose elements can be computed by taking the limit:

$$\lim_{k \to \infty} \pi_{i,j}^{k} = \Pi_j \tag{A12}$$

This vector is the eigenvector of the probability matrix, associated with eingenvalue 1. Using the probability matrix described in (5) and this fact that $\pi\Pi = \pi$:

$$\begin{pmatrix} \Pi_L & \Pi_H \end{pmatrix} \begin{pmatrix} \pi_{L,L} - 1 & \pi_{L,H} \\ \pi_{H,L} & \pi_{H,H} - 1 \end{pmatrix} = 0 \tag{A13}$$

And using the fact that $\Pi_L + \Pi_H = 1$ I find that:

$$\Pi_L = \frac{\pi_{H,L}}{\pi_{H,L} + \pi_{L,H}} \tag{A14}$$

$$\Pi_H = \frac{\pi_{L,H}}{\pi_{H,L} + \pi_{L,H}} \tag{A15}$$

From (A14) and (A15) I calculate the average and variance of the price distribution:

$$\mu = p_L \Pi_L + p_H \Pi_H \tag{A16}$$

$$\sigma^2 = \Pi_L p_L^2 + \Pi_H p_H^2 - \Pi_L^2 p_L^2 - \Pi_H^2 p_H^2 - 2 p_L p_H \Pi_L \Pi_H \tag{A17}$$

As the variance increases, and for $\Pi_L \in [1/2, 1]$,both the probability that there is a deal tomorrow given that there was a deal today decreases, $\partial\pi_{L,L}/\partial\sigma^2<0$, and the probability that there is a regular price tomorrow given that there was a regular price today increases, $\partial\pi_{H,H}/\partial\sigma^2>0$ for. To see this I use the chain rule and I substitute at (A17) the fact that $\Pi_H=1-\Pi_L$:

$$\frac{\partial\sigma^2}{\partial\pi_{j,j}}=\frac{\partial\sigma^2}{\partial\Pi_j}\frac{\partial\Pi_j}{\partial\pi_{j,j}} \tag{A18}$$

for $j=L,H$.

$$\frac{\partial\Pi_j}{\partial\pi_{j,k}}=-\frac{\pi_{k,j}}{(\pi_{k,j}+\pi_{j,k})^2}<0\Rightarrow\frac{\partial\Pi_j}{\partial\pi_{j,j}}>0 \tag{A19}$$

for $k=H$ if $j=L$ and $k=L$ if $j=H$.

$$\frac{\partial\sigma^2}{\partial\Pi_j}=(1-2\pi_j)(p_H-p_L)^2 \tag{A20}$$

For $\Pi_L\in[0,1/2)$ and from equation (A20) I conclude that $\partial\sigma^2/\partial\Pi_L>0$ and $\partial\sigma^2/\partial\Pi_H<0$. For $\Pi_L\in[1/2,1]$ I conclude that $\partial\sigma^2/\partial\Pi_L\leq 0$ and $\partial\sigma^2/\partial\Pi_H\geq 0$. Therefore, $\partial\pi_{L,L}/\partial\sigma^2<0$ and $\partial\pi_{H,H}/\partial\sigma^2>0$ for $\Pi_L\in[1/2,1]$.

The rest of the implication is a consequence of that fact that as $\pi_{L,L}$ decreases and $\pi_{H,H}$ increases, the quantity purchased at a particular deal increases for loyal shopper consumers. The other types of consumers may not necessarily increase the quantity purchased at a particular deal period given that the total amount they are willing to purchase to store for future consumption is

restricted by either a high storage cost and/or by a low marginal utility of consumption the good (not willing to perform inter-temporal substitution).□

2. Appendix for Chapter 3

The survey e-mail:

Dear fellow student,

I am doctoral student at Kellogg. For one of my courses I was asked to conduct a survey. You are one of the few randomly selected students at Northwestern. Unfortunately, I do not have funds to give any monetary rewards (I am not MBA), so this is not like you have won a lottery.

Please, take a look at the survey below and send me your answers back, I have made it so it should not take more than 20 minutes of your time. I am thankful for your help; sorry for taking your time, and I really hope you reply (in part because my grade depends on the reply rate).

The Survey. (The survey is strictly for research purposes and no private information will be given out to anyone)

Directions: The survey has two parts - first one is asking you general questions, second one is asking you questions about Christmas shopping. If you do not know an answer, just write so. If you are unsure about it, please give me a range.

(For example:

Q: how many games do you expect the Bulls to win this season?

A: Somewhere between 25 and 40)

The survey will also ask you questions about percentage probabilities. You should evaluate the chance of an event on the scale from 0 to 100, with 0 being the events that are NOT

going to happen for sure (snow in the summer in Hawaii), and 100 being the events that are going to happen for sure (snow in Evanston this winter). 50 would be the probability that a fair coin lands tails after a flip. Just as for others, for the probability questions you can give ranges of probabilities if you are not sure.

(For example:

Q: what is the probability of the Cubs making the playoffs next year?

A: somewhere between 45 and 60 percent)

You should either hit the reply button now or type in your responses as you go, or if you prefer write them down on paper and drop it off to my mailbox in the MEDS department on the 5th floor of the Jacobs building.

Part 1 (General Questions):

1. What is the percent chance that you will eat at Norris center tomorrow?_____

2. What is the percent chance that you are going to eat at Norris center tomorrow AND that you are not going to be satisfied with the food there?_____

3. Age_____

4. Sex_____

5. Ethnic Origin (Asian, black, Hispanic, white or other) _____

6. Family income per year. (Just a reminder - you can give us a range if you are not sure or uncomfortable)_____

7. Employment (please pick one of the following: employed, unemployed, out of labor force, temporary leave (i.e. vacation)) _____

8. If you are employed or on temporary leave, how many hours do you work a week on average?_____

9. Religion (if any, and please do not give a range on this one) _____

10. Family size_____

11. How much do you, on average, spend per month? _____

Part 2 (Sales on Christmas questions):

1. How much are you planning to spend on Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase. ***It is important to have in mind when answering these questions that Christmas is a probably period to find sales***.)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

2.What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere from 20% to 35% on clothing?_____

3. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere over 35% on clothing?_____

4. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere from 20% to 35% on CDs/DVDs ?_____

5.What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere over 35% on CDs/DVDs?_____

6. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere from 20% to 35% on Cosmetic/Fragrances? _____

7. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere over 35% on Cosmetic/Fragrances? _____

8. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere from 20% to 35% on Electronics ?_____

9. What do you think is the percentage chance that when you go shopping this year the store you go will have a sale anywhere over 35% on Electronics ?_____

Now I am going to describe to you some situations. The main difference among these situations is that your uncertainty about sales happening in the Christmas seasonal period (December) will vary***. Please, pay attention to the uncertainties when answering the questions.***

10. Now suppose that you are ***100% sure that no sales at all will occur*** in each of the four product categories. How much are you planning to spend on Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

11. Now suppose that you are ***75% sure that no sales at all will occur*** in each of the four product categories but that with ***25% probability a sale from 20% to 35% will occur*** for each category. How much are you planning to spend on Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

12. Now suppose that you are ***50% sure that no sales at all will occur*** in each of the four product categories and that with ***50% probability a sale from 20% to 35% will occur*** for each category. How much are you planning to spend on Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

13. Now suppose that you are ***25% sure that no sales at all will occur*** in each of the four product categories and that with ***75% probability a sale from 20% to 35% will occur*** for each category. How much are you planning to spend on Christmas presents this year, and on any special

occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

14. Now suppose that you ***are 100% sure that a sale from 20% to 35% will occur*** in each of the four product categories and ***no sale at all is an event with null probability***. How much are you planning to spend on Christmas presents this year, and on any special occasions around the time (December) of Christmas for each of the four categories listed below? (Please give me some ranges if you are not sure and if you are thinking of buying something completely different than just put zeros in the categories you will not purchase)

A. CDs/DVDs_____

B. Clothing_____

C. Cosmetics/Fragrances_____

D. Electronics (include games here) _____

Thanks a lot for filling out my survey!!!!!!!!!!!!!!!!!!!

3 Appendix for Chapter 4: Proofs from the Text

Derivation of the Optimal Constant Price: In a situation of constant price, $p_t = p_c$ for $\forall t$, the dynamic consumer maximization problem described in (11) simplifies to a static one. The solution to this problem is described in equation (A11) in the appendix for chapter 2. Since the shocks to utility are i.i.d. across each type *h* of consumers, the monopolist maximization problem can be described as:

$$\max_{p_c}\left[\Theta\left(\frac{\beta_1}{\gamma_1 p_c}-1\right)+(1-\Theta)\left(\frac{\beta_2}{\gamma_2 p_c}-1\right)\right](p_c-K) \tag{A21}$$

From the F.O.C. of the above maximization problem I find the optimal constant price as described in equations (13) and (14) of chapter 4. □

Algorithm to Determine the Optimal Combination ($\pi_{L,L}$, $\pi_{H,H}$) and (p_H, p_L) in the Case of Unpredictable Deal Pattern: Suppose the monopolist finds it optimal to offer an unpredictable deal pattern. The algorithm used to solve for the optimal pricing strategies is the following. First, I find the policy functions for consumption and quantity to be purchased for any given prices and transition probabilities[21]. From the contraction mapping theorem it is easy to prove that the consumer problem described in (11) has a unique fixed point. To solve for the policy functions I

[21] I assume no shock to utility, $\nu_t=1$, in my derivations.

perform a grid search over a finite set of possible values of consumption and quantity to be purchased. I consider that consumers decide on integer quantities to purchase and consume. I also discretize the state space.

Define by q^*_f, the floor of the optimal unconstrained quantity, q^*, and by q^*_c, the ceiling of the optimal unconstrained quantity. By construction $q^*_c - q^*_f = 1$. Therefore, for a given constant price, the optimal integer quantity, $q^* int(v)$, consumers choose to purchase and consume at period t is:

$$q_t^* \, int(v) = max\left[U_t(q_{ct}^*), U_t(q_{ft}^*) \middle| v_t = \{-1;0;1\}\right] \quad \forall t \tag{A22}$$

where $U_t(.)$ stands for the static utility for period t.

The monopolist compares, for each type h of consumers, the prices that make consumers indifferent between the ceiling and the floor quantities. Using the fact that $q^*_c - q^*_f = 1$, after some trivial calculation I find that:

$$p \, int(v) = \frac{\beta}{\gamma} log\left(1 + \frac{1}{q_c^* + v}\right) \tag{A23}$$

Those are all the possible candidates for optimal constant price accounting for integer restrictions. The optimal constant price is an ε smaller than the price that among all these candidates maximizes profit. These prices are also the candidates for deal price and regular price

in the case of unpredictable deal pattern. Given that prices must be above the marginal cost[22] or above the price that set demand equal to zero[23], denoted by p_{max}, all the possible combinations of regular price and deal price are in the intervals $p_H \in [p_c, p_{max}]$ and $p_L \in [K, p_c]$ where p_c stands for optimal constant price. Given this finite set of prices' candidates and also considering a finite range of possible values for the transition probabilities, I find the optimal combination of (s_1,s_2) and (p_L,p_H) that maximizes profit.

Derivation of the Optimal Pricing Strategy in the Case of Predictable Deal Pattern: Suppose the monopolist find it optimal to offer a predictable deal pattern. Assume no shock to utility, $v_t=1$. Define by n_h, the last period consumer type h consumes from inventory and suppose $n_1>n_2$[24]. The monopolist problem can be described as:

$$\max_{p_L,p_H,N}\left[\Theta q_{1,1}+(1-\Theta)q_{2,1}+\sum_{t=n_2+1}^{n_1}\delta^t(1-\Theta)q_{2,t}+\sum_{t=n_1+1}^{N}\delta^t\left(\Theta q_{1,t}+(1-\Theta)q_{2,t}\right)\right](p_H-K)\ s.t. \tag{A24}$$

$q_{1,1}$, $q_{2,1}$, $q_{1,t}$, $q_{2,t}$, n_1, n_2 are the arguments that maximizes the consumer problem.

Consumers decide on integer quantities to purchase and consume. Define by c^*_f, the floor of the optimal unconstrained consumption, c^*, and by c^*_c, the ceiling of the optimal unconstrained consumption. The optimal integer consumption, c^*int, can be described as:

$$c_t^*\ int = max[U_t(c_{ct}^*),U_t(c_{ft}^*)] \tag{A25}$$

[22] Or the price that makes the more price sensitive consumer purchases the maximum amount he can purchase per visit, given that this price is higher than the marginal cost.
[23] That is the price that makes the less price sensitive type of consumer indifferent between purchasing or not the good.
[24] If the inverse is true, $n_2>n_1$, the same logic applies with the proper modifications in equation (A27).

The possible candidates for p_L are all the prices that at each period make consumers indifferent between consuming one extra unit or not. Since I don't know ex ante n_h, and given that the choice of p_L affects n_h, I start with the assumption that $n=N$.

After the period $t=min\{n_1, n_2\}$, some consumers might start to purchase at the regular price. The possible candidates for p_H are all the prices that at each period make consumers indifferent between consuming one extra unit or not. I then form a finite set of possible candidates for (p_L,p_H) and calculate the corresponding ns. With all the (p_L,p_H,n) possible combinations I finally calculate the optimal quantities to be purchased and consumed and obtain the corresponding profits. The optimal (p_L,p_H,n) is the one that achieves the highest profit.

TABLES

1. Tables for Chapter 2

Table 2.1

Percent Market Share for each UPC at the Selected Markets

Selected 2 Liter Bottle Cola Market

Pepsi	28.5
Coke Classic	15.8
Diet Coke	15.8
Diet Pepsi	14.7
Caffeine Free Diet Pepsi	9.2
Caffeine Free Diet Coke	6.8
Caffeine Free Pepsi	6.0
Caffeine Free Coke	3.2

Selected 6 oz. Yogurt Market

Yoplait Custard LMN	17.0
Dannon Blended STB	13.5
Yoplait STB	13.5
Yoplait VAN	12.3
Dannon Blended PCH	12.3
Dannon Blended RSB	11.7
Dannon Blended BUB	10.8
Yoplait Custard BNA	8.9

Selected 128 oz. Liquid Laundry Detergent Market

All Regular	37.4
Wisk Regular	29.1
All Free N Clear USC	17.9
Wisk Power Plus Regular	10.2
Wisk USC	3.1
Wisk Power PlusUSC	2.3

Table 2.2

A) Summary Statistics on Percent Discounts Off the Regular Price

Calculated per UPC, per Store

	Average for All Stores	Std per Store, Averaged Across Stores	Minimum for All Stores	Maximum for All Stores
Soft-drinks				
Coke Classic	26.0	11.6	5.0	61.5
Caffeine Free Coke	25.6	11.5	5.0	61.5
Diet Coke	26.4	11.4	5.0	61.5
Caffeine Free Diet Coke	26.3	11.4	5.0	61.5
Pepsi	23.7	11.3	5.0	61.5
Caffeine Free Pepsi	23.6	11.3	5.8	61.5
Diet Pepsi	23.7	11.2	5.0	61.5
Caffeine Free Diet Pepsi	23.8	11.1	5.0	61.5
Yogurt				
Yoplait Custard LMN	20.2	9.0	6.6	55.4
Yoplait STB	27.4	11.1	6.3	55.4
Yoplait VAN	27.4	11.1	6.3	55.4
Yoplait Custard BNA	27.0	10.0	6.3	55.4
Dannon Blended STB	28.0	13.0	5.9	57.6
Dannon Blended PCH	28.6	13.4	5.5	57.6
Dannon Blended RSB	26.7	10.7	5.5	57.6
Dannon Blended BUB	27.9	12.9	5.9	59.8
Detergents				
All Regular	18.8	10.4	5.0	51.7
All Free N Clear USC	19.8	10.9	5.0	51.7
Wisk Regular	21.1	9.1	5.1	45.0
Wisk USC	24.6	6.8	5.1	45.0

Table 2.2

B) Standard Deviation, Across Stores, of the Average Percent Discount Off the Regular Price

Averages Calculated per UPC, per Store, over 104 weeks

Soft-drinks		Yogurt		Detergents	
Coke Classic	5.0	Yoplait Custard LMN	5.0	All Regular	6.0
Caffeine Free Coke	5.1	Yoplait STB	11.2	All Free N Clear USC	6.1
Diet Coke	4.9	Yoplait VAN	11.2	Wisk Regular	4.0
Caffeine Free Diet Coke	4.9	Yoplait Custard BNA	12.6	Wisk USC	7.0
Pepsi	6.6	Dannon Blended STB	12.9		
Caffeine Free Pepsi	6.4	Dannon Blended PCH	11.0		
Diet Pepsi	6.7	Dannon Blended RSB	13.8		
Caffeine Free Diet Pepsi	6.6	Dannon Blended BUB	12.6		

Table 2.3

Summary Statistics on the Percent of Weeks each UPC was Offered on Deal

Calculated Per UPC, Per Store

Soft-drinks			Yogurt			Detergents		
	Average for All Stores	Std Across Stores		Average for All Stores	Std Across Stores		Average for All Stores	Std Across Stores
Coke Classic	52.4	14.6	Yoplait Custard LMN	20.5	4.0	All Regular	22.1	15.2
Caffeine Free Coke	52.1	14.0	Yoplait STB	15.6	8.8	All Free N Clear USC	16.2	12.7
Diet Coke	51.7	15.6	Yoplait VAN	15.6	8.8	Wisk Regular	20.1	16.2
Caffeine Free Diet Coke	52.2	15.3	Yoplait Custard BNA	14.1	8.8	Wisk USC	19.0	15.5
Pepsi	54.1	13.5	Dannon Blended STB	24.1	16.4			
Caffeine Free Pepsi	54.1	13.5	Dannon Blended PCH	29.1	22.6			
Diet Pepsi	54.8	14.2	Dannon Blended RSB	23.6	15.9			
Caffeine Free Diet Pepsi	54.1	15.0	Dannon Blended BUB	23.2	13.4			

Table 2.4

A) Summary Statistics on the Number of Weeks between Two Consecutive Deals

Calculated per UPC, per Store

Soft-drinks				Yogurt				Detergents			
	Average	Min	Max		Average	Min	Max		Average	Min	Max
Coke Classic	2.0	1	17	Yoplait Custard LMN	4.6	1	48	All Regular	9.3	1	52
Caffeine Free Coke	2.0	1	17	Yoplait STB	9.9	1	42	All Free N Clear USC	6.3	1	19
Diet Coke	2.1	1	17	Yoplait VAN	6.7	1	42	Wisk Regular	8.0	1	20
Caffeine Free Diet Coke	2.0	1	17	Yoplait Custard BNA	4.3	1	32	Wisk USC	8.1	1	20
Pepsi	1.9	1	13	Dannon Blended STB	5.3	1	27				
Caffeine Free Pepsi	1.9	1	13	Dannon Blended PCH	6.6	1	40				
Diet Pepsi	1.9	1	13	Dannon Blended RSB	6.1	1	28				
Caffeine Free Diet Pepsi	1.9	1	13	Dannon Blended BUB	5.6	1	27				

Table 2.4

B) Standard Deviation, Across Stores, of the Average Number of Weeks between Two Consecutive Deals

Averages Calculated per UPC, per Store, over 104 weeks

Soft-drinks		Yogurt		Detergents	
Coke Classic	0.5	Yoplait Custard LMN	1.3	All Regular	8.7
Caffeine Free Coke	0.5	Yoplait STB	7.6	All Free N Clear USC	3.4
Diet Coke	0.6	Yoplait VAN	3.6	Wisk Regular	6.4
Caffeine Free Diet Coke	0.6	Yoplait Custard BNA	0.8	Wisk USC	6.6
Pepsi	0.4	Dannon Blended STB	3.3		
Caffeine Free Pepsi	0.4	Dannon Blended PCH	4.1		
Diet Pepsi	0.4	Dannon Blended RSB	5.5		
Caffeine Free Diet Pepsi	0.5	Dannon Blended BUB	3.3		

Table 2.5

Summary Statistics on the Standard Deviation of the Number of Weeks between Two Consecutive Deals

Standard Deviation Calculated per UPC, per Store, over 104 weeks

Soft-drinks			Yogurt			Detergents		
	Average for All Stores	Std Across Stores		Average for All Stores	Std Across Stores		Average for All Stores	Std Across Stores
Coke Classic	1.3	1.2	Yoplait Custard LMN	8.2	3.8	All Regular	10.1	8.0
Caffeine Free Coke	1.3	1.1	Yoplait STB	8.8	4.3	All Free N Clear USC	3.0	2.9
Diet Coke	1.3	1.2	Yoplait VAN	9.8	4.6	Wisk Regular	3.7	1.6
Caffeine Free Diet Coke	1.3	1.2	Yoplait Custard BNA	6.9	1.1	Wisk USC	3.7	1.4
Pepsi	1.2	1.0	Dannon Blended STB	5.6	2.0			
Caffeine Free Pepsi	1.2	1.0	Dannon Blended PCH	7.2	4.5			
Diet Pepsi	1.2	1.0	Dannon Blended RSB	5.3	2.9			
Caffeine Free Diet Pepsi	1.2	1.0	Dannon Blended BUB	5.8	2.4			

Table 2.6

Summary Statistics on Characteristics of Deal Patterns and Allocation of Purchases Over Time

Calculated per Household, per Brand, per Store

Soft-drinks	mean	std	min	max
Loyal Group				
Savings (%)	21.3	16.3	-14.4	72.6
Fraction (%)	77.7	21.6	0.0	100.0
Average Duration (weeks)	3.3	1.5	1.4	9.6
Variation of the Duration (weeks)	2.9	1.6	0.4	9.6
Unpredictability (variation of the duration / average duration)	0.9	0.2	0.2	1.4
Discount (%)	25.1	4.5	12.9	32.8
Frequency of Deals (%)	48.3	10.9	31.0	76.7
Non-Loyal Group				
Savings (%)	22.4	14.6	-16.4	57.7
Fraction (%)	79.1	22.1	0.0	100.0
Average Duration (weeks)	3.0	1.2	1.4	9.8
Variation of the Duration (weeks)	2.7	1.6	0.9	10.3
Unpredictability (variation of the duration / average duration)	0.9	0.2	0.4	1.6
Discount (%)	26.8	3.9	15.0	33.7
Frequency of Deals (%)	51.0	11.9	30.0	75.9
All Consumers				
Savings (%)	21.7	15.7	-16.4	72.6
Fraction (%)	78.2	21.7	0.0	100.0
Average Duration (weeks)	3.2	1.4	1.4	9.8
Variation of the Duration (weeks)	2.9	1.6	0.4	10.3
Unpredictability (variation of the duration / average duration)	0.9	0.2	0.2	1.6
Discount (%)	25.6	4.4	12.9	33.7
Frequency of Deals (%)	49.2	11.3	30.0	76.7

Yogurt	mean	std	min	max
Loyal Group				
Savings (%)	18.6	25.8	-19.2	73.2
Fraction (%)	77.4	29.8	0.0	100.0
Average Duration (weeks)	6.5	4.4	1.0	28.0
Variation of the Duration (weeks)	8.1	4.3	0.3	22.8
Unpredictability (variation of the duration / average duration)	1.6	1.6	0.6	8.3
Discount (%)	35.3	9.6	7.3	45.8
Frequency of Deals (%)	19.8	7.2	1.7	42.9
Non-Loyal Group				
Savings (%)	9.9	22.6	-16.6	63.7
Fraction (%)	73.4	23.4	28.6	100.0
Average Duration (weeks)	5.7	4.0	1.2	20.3
Variation of the Duration (weeks)	7.5	3.5	3.6	17.3
Unpredictability (variation of the duration / average duration)	2.3	3.1	0.5	12.8
Discount (%)	31.7	12.5	8.5	41.9
Frequency of Deals (%)	20.7	8.7	5.3	48.6
All Consumers				
Savings (%)	17.1	25.4	-19.2	73.2
Fraction (%)	76.7	28.8	0.0	100.0
Average Duration (weeks)	6.3	4.3	1.0	28.0
Variation of the Duration (weeks)	8.0	4.2	0.3	22.8
Unpredictability (variation of the duration / average duration)	1.9	2.3	0.5	12.8
Discount (%)	34.7	10.2	7.3	45.8
Frequency of Deals (%)	20.0	7.5	1.7	48.6

Detergents	mean	std	min	max
Loyal Group				
Savings (%)	12.9	17.8	-12.9	71.2
Fraction (%)	63.4	41.3	0.0	100.0
Average Duration (weeks)	8.7	5.7	1.3	39.0
Variation of the Duration (weeks)	22.5	8.4	3.4	62.3
Unpredictability (variation of the duration / average duration)	6.2	3.1	0.2	23.9
Discount (%)	15.2	6.1	5.8	29.2
Frequency of Deals (%)	31.0	8.5	4.3	45.8
Non-Loyal Group				
Savings (%)	15.2	17.5	-4.9	60.2
Fraction (%)	75.0	37.7	0.0	100.0
Average Duration (weeks)	8.2	5.2	2.1	38.0
Variation of the Duration (weeks)	20.5	4.6	8.2	29.9
Unpredictability (variation of the duration / average duration)	6.2	1.3	2.8	8.0
Discount (%)	14.0	5.1	6.6	25.1
Frequency of Deals (%)	31.1	5.4	21.1	39.7
All Consumers				
Savings (%)	13.3	17.7	-12.9	71.2
Fraction (%)	65.6	40.7	0.0	100.0
Average Duration (weeks)	8.5	5.4	1.3	39.0
Variation of the Duration (weeks)	22.1	7.9	3.4	62.3
Unpredictability (variation of the duration / average duration)	6.2	2.8	0.2	23.9
Discount (%)	14.9	5.9	5.8	29.2
Frequency of Deals (%)	31.0	8.0	4.3	45.8

Table 2.7

Does Uncertainty About the Timing of Deals Affect Allocation of Total Purchase Over Time?

Results for Soft-Drinks Category

Dependent Variable: Percentage Savings / Fraction Bought on Sale

Explanatory Variable	Loyal Group (Standard Error)		Non-Loyal Group (Standard Error)		All Consumers (Standard Error)	
	Savings	Fraction	Savings	Fraction	Savings	Fraction
Unpredictability	-0.133	-0.275	0.081	-0.124	-0.119	-0.289
	(0.089)	(0.118)	(0.096)	(0.149)	(0.080)	(0.112)
Average Discount	2.589	3.307	0.332	-1.303	1.587	1.615
	(0.967)	(1.281)	(1.298)	(2.026)	(0.759)	(1.060)
Frequency of Deals	0.222	0.234	0.318	0.434	0.357	0.469
	(0.351)	(0.464)	(0.509)	(0.795)	(0.285)	(0.398)
Shares	No	No	No	No	0.018	-0.007
					(0.042)	(0.058)
Interaction term	No	No	No	No	-0.390	-0.417
(shares x unpredictability)					(0.167)	(0.233)
Number of Observations	150	150	75	75	225	225

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 6 units. Loyal is a consumer whose share of purchases on a particular brand (Coke or Pepsi) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables and some other controls not presented here such as total number of trips for each store and total number of units purchased for each brand, per consumer, per store.

Table 2.8

The Effect of Timing of Deals on Allocation of Total Purchase Over Time for Loyal Shopper Consumers

Results for Soft-Drinks Category

Dependent Variable: Percentage Savings / Fraction Bought on Sale

Explanatory Variable	Shopper Group (Standard Error)		Shopper Loyal Group (Standard Error)		Shopper Non-loyal Group (Standard Error)	
	Savings	Fraction	Savings	Fraction	Savings	Fraction
Unpredictability	-0.031	-0.205	-0.176	-0.330	0.075	-0.150
	(0.065)	(0.090)	(0.086)	(0.114)	(0.100)	(0.157)
Average Discount	1.443	1.764	2.921	3.870	-0.160	-1.224
	(0.797)	(1.111)	(0.980)	(1.307)	(1.397)	(2.190)
Frequency of Deals	0.414	0.535	0.376	0.248	0.265	0.710
	(0.295)	(0.410)	(0.342)	(0.456)	(0.576)	(0.903)
Number of observations	203	203	136	136	67	67

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 6 units. Loyal is a consumer whose share of purchases on a particular brand (Coke or Pepsi) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables and some other controls not presented here such as total number of trips for each store and total number of units purchased for each brand, per consumer, per store.

Table 2.9

Summary Statistics on the Characteristics of Deal Patterns Using Feature and Display Results for Soft-Drinks Category

Calculated per Household, per Brand, per Store

		mean	std	min	max
	Loyal Group				
Feature as the main source of information on deals	Unpredictability (variation of the duration / average duration)	0.9	0.2	0.2	1.4
	Average Duration (weeks)	3.7	1.4	2.1	10.1
	Variation of the Duration (weeks)	2.7	1.4	0.9	8.0
	Frequency of Deals (%)	42.6	4.8	27.8	55.4
Display as the main source of information on deals	Unpredictability (variation of the duration / average duration)	0.8	0.3	0.2	1.6
	Average Duration (weeks)	11.4	6.7	4.1	38.1
	Variation of the Duration (weeks)	8.8	4.9	2.8	32.1
	Frequency of Deals (%)	14.7	4.6	5.3	28.4
	Non-Loyal Group				
Feature as the main source of information on deals	Unpredictability (variation of the duration / average duration)	0.8	0.2	0.4	1.6
	Average Duration (weeks)	3.4	1.1	2.3	8.0
	Variation of the Duration (weeks)	2.8	1.4	1.0	7.7
	Frequency of Deals (%)	42.9	4.8	31.6	61.4
Display as the main source of information on deals	Unpredictability (variation of the duration / average duration)	0.8	0.2	0.0	1.3
	Average Duration (weeks)	10.9	5.7	4.1	30.2
	Variation of the Duration (weeks)	7.9	4.4	0.0	24.4
	Frequency of Deals (%)	15.9	5.0	4.0	26.7

Table 2.10

Does Uncertainty About the Timing of Features Affect Allocation of Total Purchases Over Time?

Results for Soft-Drinks Category

Dependent Variable: Percentage Savings / Fraction Bought on Sale

Explanatory Variable	Loyal Group (Standard Error)		Non-Loyal Group (Standard Error)	
	Savings	Fraction	Savings	Fraction
Unpredictability	-0.156	-0.267	0.113	-0.020
	(0.097)	(0.130)	(0.100)	(0.159)
Average Discount	2.4	2.996	0.633	-1.034
	(0.961)	(1.283)	(1.319)	(2.088)
Frequency of Deals	0.572	0.476	0.524	0.523
	(0.395)	(0.528)	(0.486)	(0.769)
Number of observations	150	150	75	75

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 6 units. Loyal is a consumer whose share of purchases on a particular brand (Coke or Pepsi) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables and some other controls not presented here such as total number of trips for each store and total number of units purchased for each brand, per consumer, per store.

Table 2.11

Does Uncertainty About the Timing of Deals Affect the Quantity Purchased at a Particular Deal?

Results for Soft-Drinks Category

Dependent Variable: Log of Quantity Purchased at a Deal Period

Explanatory Variable	Loyal Shopper Group (Standard Error)	Non-Loyal Group (Standard Error)
log (price)	-0.545	-0.324
	(0.103)	(0.145)
Variation of the Duration	0.009	0.027
	(0.010)	(0.014)
Average Discount	0.952	-0.865
	(0.456)	(0.557)
Number of Weeks from Previous Deal	5.096	2.852
	(3.109)	(5.552)
(Number of Weeks from Previous Deal)^2	-14.809	-78.463
	(30.036)	(65.411)
Interaction term between Number of Weeks and Variation of the Duration	1.664	0.844
	(0.862)	(1.212)
Number of observations	1118	441

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 6 units. Loyal is a consumer whose share of purchases on a particular brand (Coke or Pepsi) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables. Number of weeks from previous deal is divided by 100.

Table 2.12

Does Uncertainty About the Timing of Deals Affect Allocation of Total Purchase Over Time?

Results for Yogurt Category

Dependent Variable: Percentage Savings / Fraction Bought on Sale

Explanatory Variable	Loyal (Standard Error)		Shopper (Standard Error)		Loyal Shopper (Standard Error)		All Consumers (Standard Error)	
	Savings	Fraction	Savings	Fraction	Savings	Fraction	Savings	Fraction
Unpredictability	-0.078	-0.134	-0.132	-0.191	-0.152	-0.219	-0.050	-0.082
	(0.049)	(0.065)	(0.082)	(0.109)	(0.088)	(0.132)	(0.020)	(0.054)
Average Discount	0.388	0.137	2.516	2.669	5.119	5.624	0.417	0.110
	(1.083)	(1.451)	(1.236)	(1.639)	(1.709)	(2.569)	(1.001)	(0.935)
Frequency of Deals	0.743	1.528	0.836	1.870	1.281	2.549	0.689	1.535
	(0.721)	(0.966)	(0.725)	(0.961)	(0.822)	(0.045)	(0.647)	(0.865)
Shares	No	No	No	No	No	No	0.007	-0.116
							0.093	(0.355)
Interaction term	No	No	No	No	No	No	-0.026	-0.082
							(0.015)	(0.048)
Number of observations	124	124	87	87	73	73	149	149

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 4 units. Loyal is a consumer whose share of purchases on a particular brand (Wisk or All) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables and some other controls not presented here such as total number of trips for each store and total number of units purchased for each brand, per consumer, per store.

Table 2.13

Does Uncertainty About the Timing of Deals Affect the Quantity Purchased at a Particular Deal?

Results for Yogurt Category

Dependent Variable: Log of Quantity Purchased at a Deal Period

Explanatory Variable	Loyal Shopper Group (Standard Error)	Non-Loyal Group (Standard Error)
log (price)	-0.620	-0.560
	(0.220)	(0.294)
Variation of the Duration	0.021	0.014
	(0.012)	(0.045)
Average Discount	0.357	0.280
	(0.215)	(1.056)
Number of Weeks from Previous Deal	4.705	2.805
	(2.732)	(5.642)
(Number of Weeks from Previous Deal)^2	12.756	-84.805
	(20.057)	(78.440)
Interaction term between Number of Weeks and Variation of the Duration	2.284	1.125
	(1.102)	(1.942)
Number of observations	685	203

Notes: Numbers in parentheses are standard errors. Results considered households that visited at least 20 times each store and purchased at least 4 units. Loyal is a consumer whose share of purchases on a particular brand (Wisk or All) is at least 70% of his total purchase in the category. All regressions include brand and store dummy variables. Number of weeks from previous deal is divided by 100.

2. Tables for Chapter 3

Table 3.1

Summary of Demographics

		% of the Total
Age	17-19	52.4
	20-22	47.6
Sex	Female	50.8
	Male	49.2
Ethnic Origin	Asian	14.3
	Black	4.8
	Hispanic	11.1
	White	63.5
	Other	6.4
Family Income	Under $50,000	25.4
	$50,000-$100,000	36.5
	over $100,000	27.0
	Not Reported	11.1
Employment	Employed	46.0
	Unemployed	25.4
	Out of Labor Force	22.2
	Temporary Leave	6.4
Hours of Work per Week	Less 10 hours	28.6
	Over 10 hours	23.8
	Not Reported	47.6
Religion	Christian	44.4
	Jewish	17.5
	None	27.0
	Other	11.1
Family Size	Less than 4	58.7
	Over 4	41.3
Expenses per month	Under $100	14.3
	$100-$200	25.4
	$200-$500	39.7
	over $500	20.6
Number of observations		63

Table 3.2

Revision of Expectations for Clothing Category

Prior Subjective Prob. Ranges	Difference Between Answers	Percentage of the Subsample (%)				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
0-20%	no change	75	100	50	25	25
(N=5)	1-20%	0	0	25	25	0
	21-40%	25	0	0	25	50
	41-60%	0	0	0	0	0
	61-80%	0	0	0	0	0
	81-100%	0	0	0	0	0
	more than 100%	0	0	25	25	25
21-40%	no change	67	33	33	33	67
(N=6)	1-20%	0	33	17	50	0
	21-40%	33	17	50	17	33
	41-60%	0	17	0	0	0
	61-80%	0	0	0	0	0
	81-100%	0	0	0	0	0
	more than 100%	0	0	0	0	0
41-60%	no change	38	46	46	31	31
(N=13)	1-20%	8	23	15	23	15
	21-40%	31	8	15	23	15
	41-60%	15	8	8	8	15
	61-80%	0	8	0	0	0
	81-100%	8	8	8	8	8
	more than 100%	0	0	8	8	15
61-80%	no change	53	42	47	37	47
(N=19)	1-20%	11	21	16	21	11
	21-40%	16	16	16	5	5
	41-60%	5	5	5	5	16
	61-80%	11	11	5	11	0
	81-100%	0	0	5	16	5
	more than 100%	5	5	5	5	16
81-100%	no change	45	45	50	55	50
(N=20)	1-20%	5	20	15	20	25
	21-40%	25	20	15	10	5
	41-60%	10	0	10	10	10
	61-80%	5	10	5	5	5
	81-100%	10	5	5	0	0
	more than 100%	0	0	0	0	5

Table 3.3

Revision of Expectations for CDs/DVDs Category

Prior Subjective Prob. Ranges	Difference Between Answers	Percentage of the Subsample (%)				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
0-20%	no change	80	76	60	68	64
(N=5)	1-20%	0	4	4	8	12
	21-40%	16	8	8	4	0
	41-60%	0	12	20	12	8
	61-80%	0	0	0	4	0
	81-100%	4	0	4	0	12
	more than 100%	0	0	4	4	4
21-40%	no change	44	56	67	56	44
(N=6)	1-20%	0	0	0	0	11
	21-40%	44	22	22	22	11
	41-60%	0	0	0	22	22
	61-80%	0	11	0	0	11
	81-100%	11	11	11	0	0
	more than 100%	0	0	0	0	0
41-60%	no change	33	58	67	58	42
(N=13)	1-20%	8	8	8	8	17
	21-40%	25	17	17	17	17
	41-60%	25	8	0	8	8
	61-80%	0	0	0	8	0
	81-100%	8	8	8	0	8
	more than 100%	0	0	0	0	8
61-80%	no change	63	63	63	50	50
(N=19)	1-20%	0	13	25	25	13
	21-40%	0	13	0	0	0
	41-60%	25	0	0	13	25
	61-80%	0	0	0	0	0
	81-100%	0	0	0	0	0
	more than 100%	13	13	13	13	13
81-100%	no change	57	29	29	43	43
(N=20)	1-20%	0	14	14	0	0
	21-40%	0	14	14	14	14
	41-60%	0	14	14	29	14
	61-80%	0	0	0	0	0
	81-100%	43	29	29	14	14
	more than 100%	0	0	0	0	14

Table 3.4

Revision of Expectations for Cosmetics/Fragrances Category

Prior Subjective Prob. Ranges	Difference Between Answers	Percentage of the Subsample (%)				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
0-20%	no change	85	80	85	85	90
(N=5)	1-20%	0	0	0	0	0
	21-40%	0	0	0	5	0
	41-60%	0	5	0	0	0
	61-80%	0	5	5	0	0
	81-100%	10	5	5	5	0
	more than 100%	5	5	5	5	10
21-40%	no change	50	50	63	69	81
(N=6)	1-20%	13	19	13	19	6
	21-40%	13	6	6	13	0
	41-60%	0	6	19	0	0
	61-80%	13	13	0	0	6
	81-100%	13	6	0	0	6
	more than 100%	0	0	0	0	0
41-60%	no change	40	40	60	40	50
(N=13)	1-20%	10	10	0	0	0
	21-40%	10	20	10	20	10
	41-60%	20	10	10	20	20
	61-80%	0	0	0	0	10
	81-100%	20	20	20	20	10
	more than 100%	0	0	0	0	0
61-80%	no change	67	67	67	44	56
(N=19)	1-20%	0	0	11	22	0
	21-40%	0	0	0	0	11
	41-60%	11	11	0	0	0
	61-80%	0	0	0	0	0
	81-100%	22	22	22	22	22
	more than 100%	0	0	0	11	11
81-100%	no change	33	33	33	33	33
(N=20)	1-20%	0	0	0	0	0
	21-40%	33	0	0	0	0
	41-60%	0	33	33	33	33
	61-80%	0	0	0	0	0
	81-100%	33	33	33	33	0
	more than 100%	0	0	0	0	33

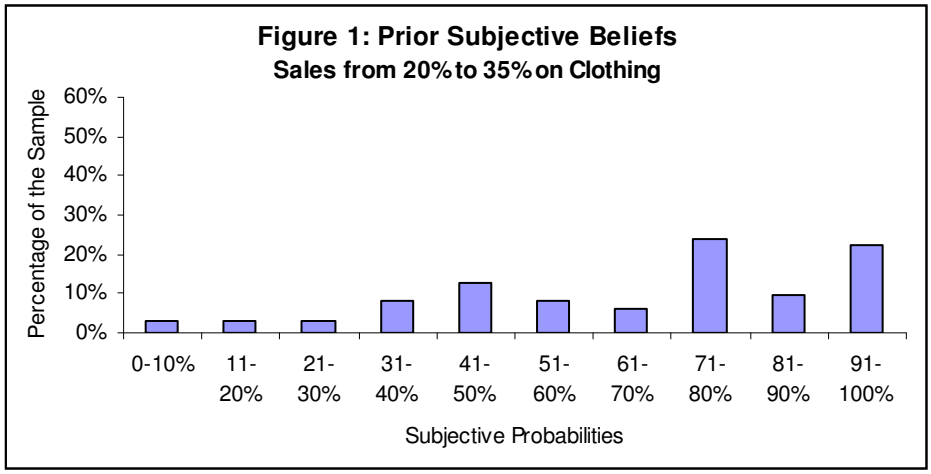
Table 3.5

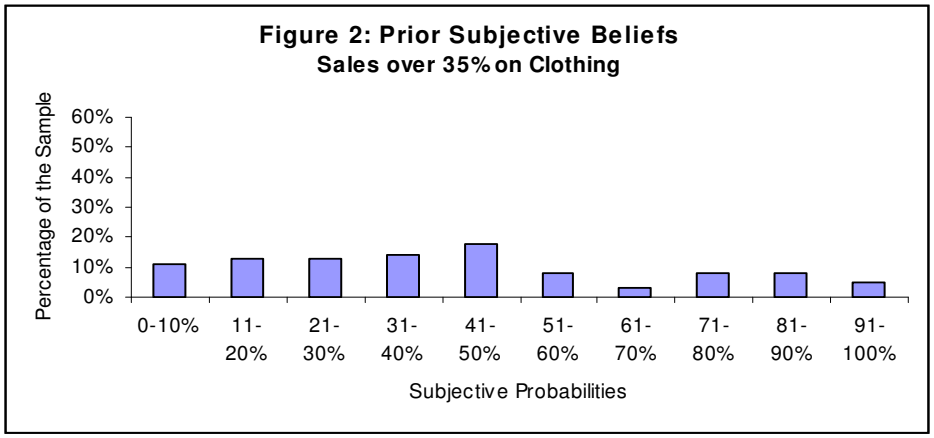
Revision of Expectations for Electronics Category

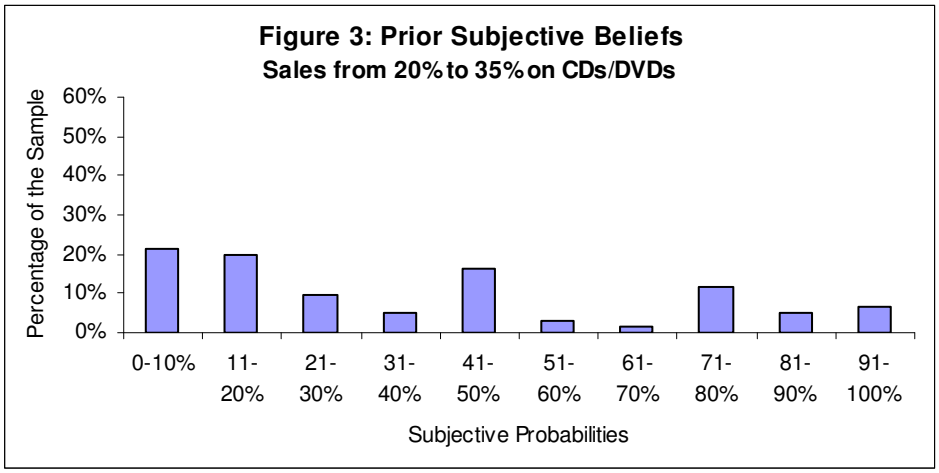
Prior Subjective Prob. Ranges	Difference Between Answers	Percentage of the Subsample (%)				
		Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
0-20%	no change	56	56	44	44	44
(N=5)	1-20%	13	6	13	19	19
	21-40%	0	13	13	25	13
	41-60%	13	6	19	0	6
	61-80%	6	6	0	0	0
	81-100%	13	13	6	6	6
	more than 100%	0	0	6	6	13
21-40%	no change	43	50	43	36	36
(N=6)	1-20%	21	14	21	29	14
	21-40%	29	14	14	14	14
	41-60%	0	14	0	0	14
	61-80%	0	7	14	14	7
	81-100%	7	0	7	0	0
	more than 100%	0	0	0	7	14
41-60%	no change	90	90	90	90	80
(N=13)	1-20%	0	0	0	10	10
	21-40%	10	10	10	0	0
	41-60%	0	0	0	0	0
	61-80%	0	0	0	0	0
	81-100%	0	0	0	0	0
	more than 100%	0	0	0	0	10
61-80%	no change	67	75	75	83	67
(N=19)	1-20%	8	0	0	0	8
	21-40%	0	8	8	17	17
	41-60%	8	0	0	0	0
	61-80%	0	0	0	0	0
	81-100%	17	17	17	0	8
	more than 100%	0	0	0	0	0
81-100%	no change	67	78	56	78	67
(N=20)	1-20%	11	11	22	0	0
	21-40%	11	11	11	11	11
	41-60%	11	0	11	11	11
	61-80%	0	0	0	0	0
	81-100%	0	0	0	0	0
	more than 100%	0	0	0	0	11

FIGURES

1. Figures for Chapter 3







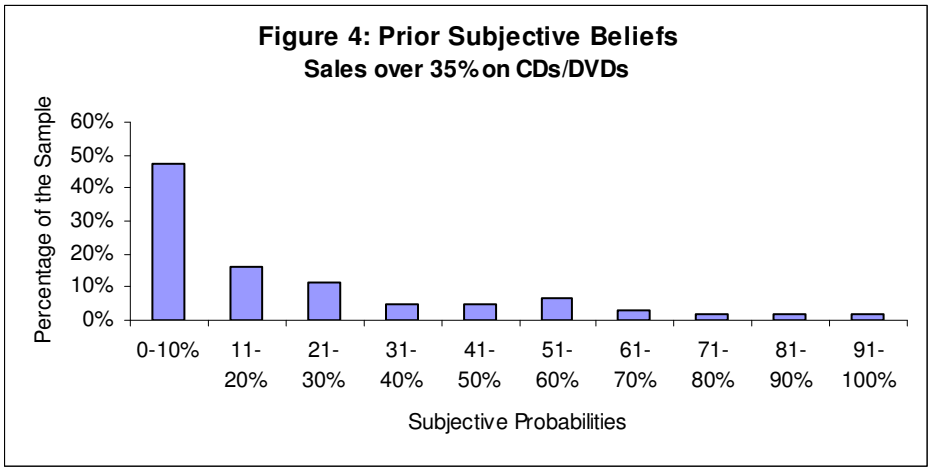


Figure 4: Prior Subjective Beliefs
Sales over 35% on CDs/DVDs
Percentage of the Sample
60%
50%
40%
30%
20%
10%
0%
0-10%
11-20%
21-30%
31-40%
41-50%
51-60%
61-70%
71-80%
81-90%
91-100%
Subjective Probabilities

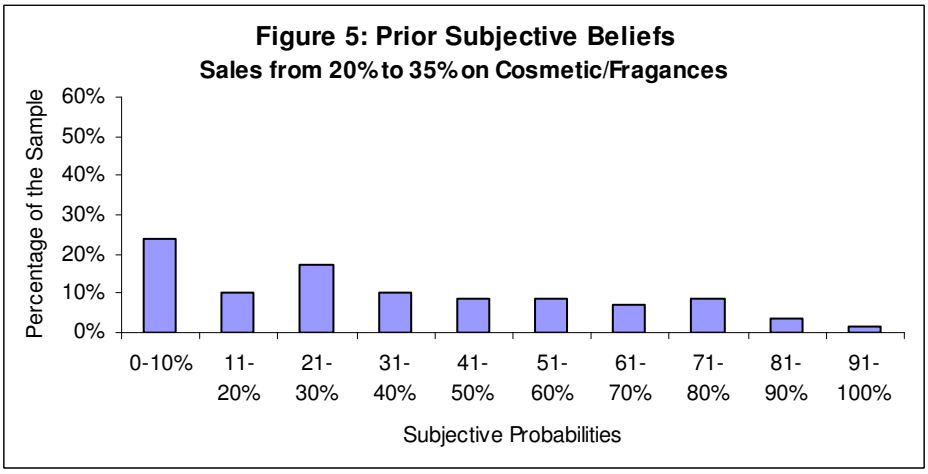


Figure 5: Prior Subjective Beliefs
Sales from 20% to 35% on Cosmetic/Fragances
Percentage of the Sample
60%
50%
40%
30%
20%
10%
0%
0-10%
11-20%
21-30%
31-40%
41-50%
51-60%
61-70%
71-80%
81-90%
91-100%
Subjective Probabilities

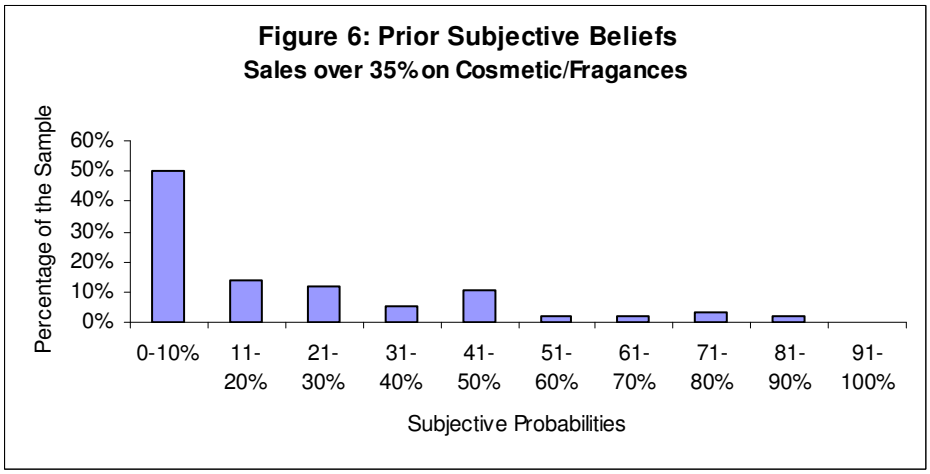


Figure 6: Prior Subjective Beliefs
Sales over 35% on Cosmetic/Fragances
Percentage of the Sample
60%
50%
40%
30%
20%
10%
0%
0-10%
11-20%
21-30%
31-40%
41-50%
51-60%
61-70%
71-80%
81-90%
91-100%
Subjective Probabilities

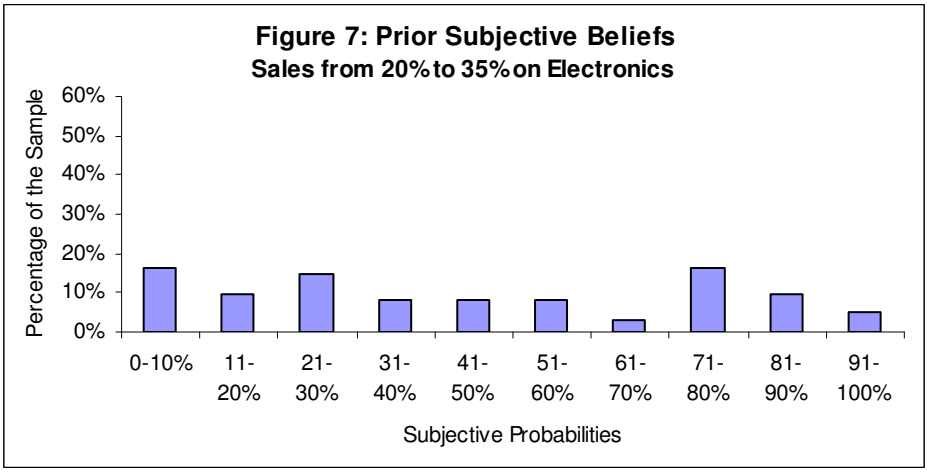


Figure 7: Prior Subjective Beliefs
Sales from 20% to 35% on Electronics
Percentage of the Sample
60%
50%
40%
30%
20%
10%
0%
0-10%
11-20%
21-30%
31-40%
41-50%
51-60%
61-70%
71-80%
81-90%
91-100%
Subjective Probabilities

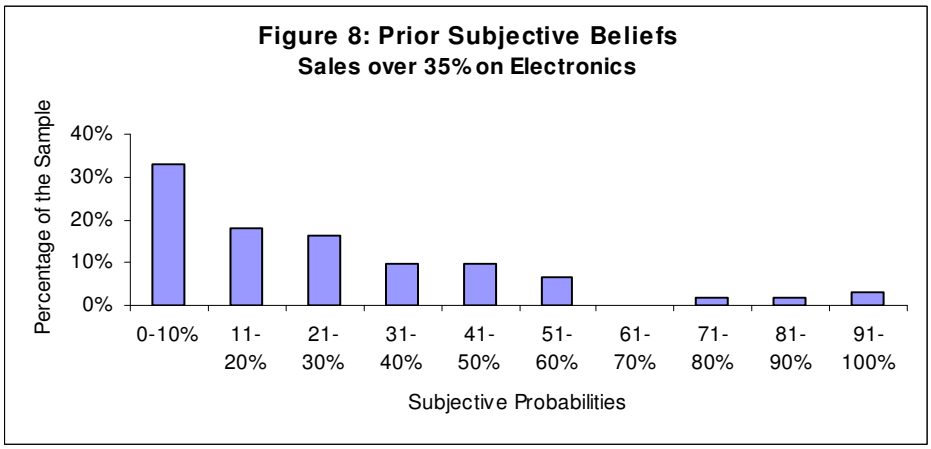


Figure 8: Prior Subjective Beliefs
Sales over 35% on Electronics
Percentage of the Sample
40%
30%
20%
10%
0%
0-10%
11-20%
21-30%
31-40%
41-50%
51-60%
61-70%
71-80%
81-90%
91-100%
Subjective Probabilities

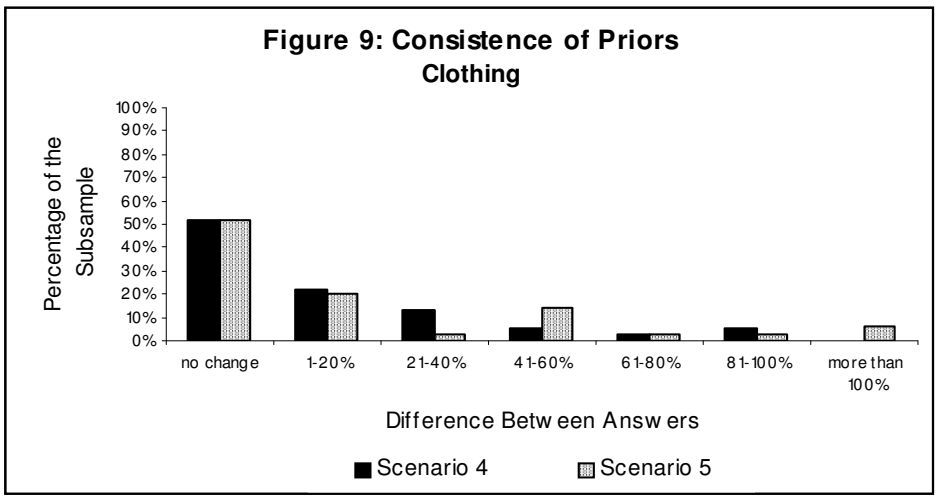


Figure 9: Consistence of Priors
Clothing
Percentage of the Subsample
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
no change
1-20%
21-40%
41-60%
61-80%
81-100%
more than 100%
Difference Between Answers
Scenario 4
Scenario 5

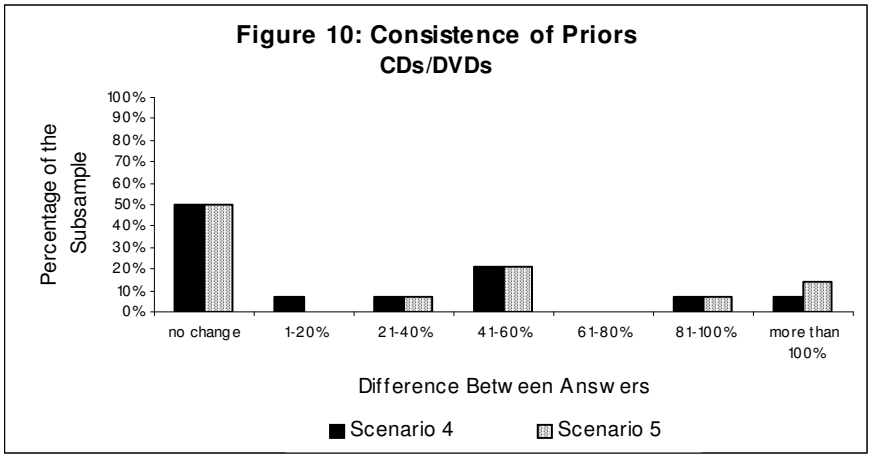


Figure 10: Consistence of Priors
CDs/DVDs
Percentage of the Subsample
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
no change
1-20%
21-40%
41-60%
61-80%
81-100%
more than 100%
Difference Between Answers
Scenario 4
Scenario 5

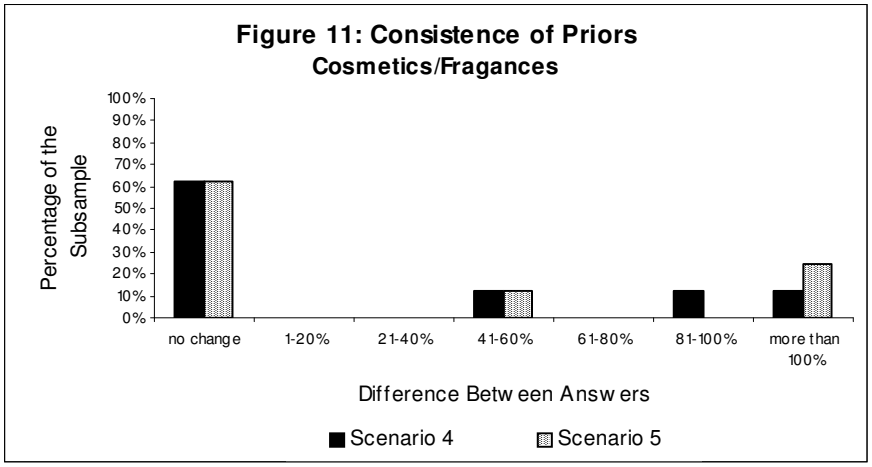


Figure 11: Consistence of Priors
Cosmetics/Fragances
Percentage of the Subsample
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
no change
1-20%
21-40%
41-60%
61-80%
81-100%
more than 100%
Difference Between Answers
Scenario 4
Scenario 5

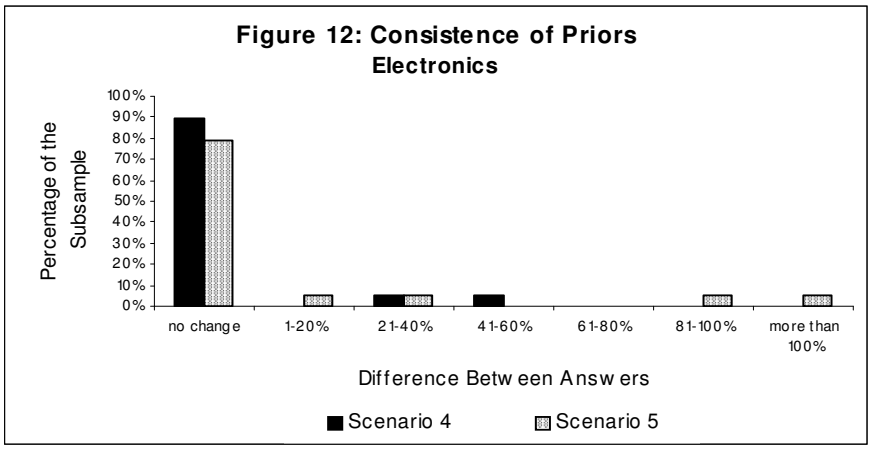


Figure 12: Consistence of Priors
Electronics
Percentage of the Subsample
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
no change
1-20%
21-40%
41-60%
61-80%
81-100%
more than 100%
Difference Between Answers
Scenario 4
Scenario 5

Vita

PRISCILLA YUNG MEDEIROS

E-mail: p-medeiros@kellogg.northwestern.edu

Web: www.kellogg.northwestern.edu/faculty/medeiros

EMPLOYMENT

Senior Associate, CRA International, 2008 –

Senior Analyst, Derivatives & Credit Risk Research Department, BBM Bank, Brazil, 2001 -2003

Junior Analyst, Macroeconomic Research Department, Icatu Bank, Brazil, 1997 - 1998

DOCTORAL STUDIES

Ph.D., Managerial Economics and Strategy, Kellogg School of Management, Northwestern University, Evanston, Illinois

Dissertation: Essays in Empirical Analysis of Consumer Behavior and its Impact on Retailer's Optimal Strategies

Committee Chairpersons: Professors Igal Hendel and Scott Stern

Date of Completion: August 2008 (expected)

PREDOCTORAL STUDIES

M.S., Economics, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Brazil, 2001

B.A., Economics, Pontifical Catholic University of Rio de Janeiro (PUC-Rio), Brazil, 2008

TEACHING EXPERIENCE

Teaching Assistant, Kellogg School of Management, Northwestern University, 2006 - 2008

Statistical Methods for Management Decisions (MBA)

Professors: Karl Schmedders, Christoph Kuzmics and Peter Eso

Sales Promotion and Retailer Behavior (MBA)

Professor Eric Anderson

Teaching Assistant, PUC-Rio, Brazil, 1996

Introduction to Macroeconomics (BA Economics)

FELLOWSHIPS AND AWARDS

Kellogg School of Management Graduate Fellowship, 2003 - 2008

Brazilian Government (CNPQ): Master's Fellowship, 1999 - 2000

Brazilian Government (CAPES): Special Program of Training Fellowship, 1996 - 1997

PUBLISHED PAPER

"Applications of Real Options in the Real Estate Market Focusing the City of Rio de Janeiro", 2003, *Revista Brasileira de Finanças*, 1(1).

WORKING PAPERS

"The Effects of Uncertainty about the Timing of Deals on Consumer Behavior", Job Market Paper, 11/2007

"Measuring Expectations on Intentions of Future Purchases for Different Uncertainty Levels on Christmas' Deals", 12/2004

"Discussion on Optimal Pricing Strategies Given the Effects of Uncertainty about the Timing of Deals on Consumer Behavior", 04/2008

CONFERENCE AND SEMINAR PRESENTATIONS

"The Effects of Uncertainty about the Timing of Deals on Consumer Behavior", Toulouse School of Economics (Toulouse, France, 02/08), University of California at Davis Graduate School of Management (02/08), College of Business LeBow (Drexel University, 01/08),

Cornerstone Research (01/08), NERA Economic Consulting (01/08), The Brattle Group (01/08), Compass Lexecon (01/08), CRA International (01/08), Management and Strategy Seminar, Kellogg (09/07), Department of Economics at PUC-Rio (Rio de Janeiro, Brazil, 11/07), Department of Economics at Getúlio Vargas Foundation (Rio de Janeiro, Brazil), Department of Economics at IBMEC-RJ (Rio de Janeiro, Brazil).

"Deriving the Optimal Pricing Strategies Given the Effects of Uncertainty about the Timing of Deals on Consumer Behavior: A Structural Approach", North American Summer Meetings of the Econometric Society (Durham, NC, 06/07), Transatlantic Doctoral Conference (London, UK, 05/07).

"Applications of Real Options in the Real Estate Market Focusing the City of Rio de Janeiro", invited presentation - Economics seminar at Getúlio Vargas Foundation (Rio de Janeiro, Brazil, 08/01), Brazilian Finance Society Meeting, (Sao Paulo, Brazil, 06/01).