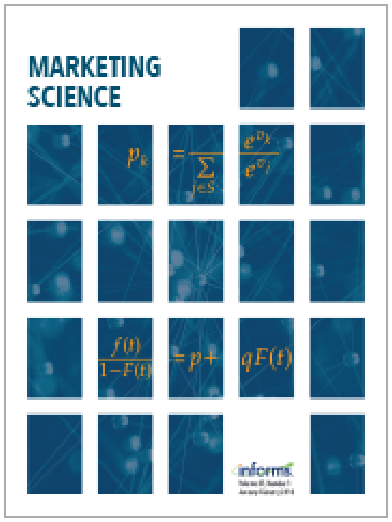

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An Empirical Investigation of the Dynamic Effect of Marlboro's Permanent Pricing Shift

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The strategy Philip Morris adopted in 1993 featured a one-time, permanent, publicly announced price cut, an event referred to as Marlboro Friday. Little is known about the impact of permanent and publicly announced price cuts on consumer brand switching behaviors for an addictive product. In the context of Marlboro Friday, we investigate (1) how consumers' brand choices are affected by a permanent price cut, (2) whether differential and dynamic effects of permanent price cuts occur for different types of consumers, and (3) the implications of publicly announced permanent price cuts on consumer brand switching behavior in the long run. We develop a dynamic structural brand choice model that allows for consumer forward-looking behavior, learning, and addiction, and investigate how consumers adjusted their brand choice behaviors before and after this permanent price cut. Using unique consumer panel data pertaining to cigarette purchases before and after the event, we provide behavioral explanations of whether and how the drastic and permanent price cut represented an effective step to encourage brand switching for an addictive product and a necessary step for Philip Morris to combat the growing market share of generic brands.

Key words: Marlboro Friday; permanent price cut; brand switching; choice model; uncertainty; learning; price expectation; risk aversion; addiction; dynamic structural model
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1. Introduction

In the past two decades, discount brands, such as private labels and generics, have experienced tremendous growth. Consumers traditionally viewed these products as poor substitutes for branded goods and were willing to pay a premium price to avoid an unknown brand. As the quality of discount brands improved and they started to gain market share, many national brand manufacturers raised their prices to recoup their losses. The increasing price gap reinforced opportunities for generic brands to exploit price-sensitive consumer segments, and by the early 1990s, generic brands had risen from a marginal force to leading the dynamics of the marketplace in many industries. National brand manufacturers tried to counter the growth of discount brands through traditional marketing approaches, such as promotion and advertising increases, new product introductions, product-line management, and aggressive temporary price promotions (see Hoch 1996). For most national brands, these methods failed to counter the gains discount brands had achieved. With the continuing growth of generic brands, analysts argued that premium brands would face increasing difficulties wooing back consumers. On April 2, 1993, one of the most famous and valuable brands in the world, Marlboro, announced it would reduce its prices permanently by 20% across the United States to cope with the growing threat from generic brands.

Marlboro Friday (as that date came to be known) was heralded as a milestone in marketing history. The competitive pricing strategy initiated by Philip Morris (hereafter, PM), the parent company of Marlboro, has been a topic of contention and intense debate for several reasons. First, the announcement of the price cut was widely interpreted as a watershed event in marketing, and Marlboro Friday saw the stock prices of PM fall 23%, knocking off billions of dollars in market value. Second, the fallout from the event spread far beyond the tobacco industry as several other major household brands, including Heinz, Coca-Cola, Quaker Oats, and Procter & Gamble (P&G),

collectively lost $50 billion in value on the same day. The rationale for the reaction was that competing with generics on prices by reducing the price gap was a signal of overvaluation of the brand-intensive stocks. Third, other manufacturers, such as P&G, have since taken similar initiatives to substitute everyday low prices (EDLP) for the previous myriad of promotions and coupon offers. A similar pattern has emerged at the downstream retail level, with systematic growth in EDLP operators that offer low prices all the time instead of frequent deep promotions (Bell and Lattin 1998). Fourth and finally, Marlboro Friday was significant because it touched off an extended debate about the wisdom and long-term implications of PM's drastic action, in which several commentators criticized the objectives, execution, and timing of the strategy. For its part, PM described it as a decisive action to increase market share and grow long-term profitability in a price-sensitive market environment.

Despite its historical significance, the event has received little attention in academic literature other than some articles that cite it as an example of strategic brand management.[1] Several questions persist about the effectiveness of Marlboro's event. For example, did PM's actions represent a necessary and effective strategy for preserving Marlboro's diminishing market share? How did the strategic shift in pricing policy change consumer brand switching behavior? Existing marketing literature focuses on short-term price promotions for frequently purchased packaged goods, such as ketchup and detergent (Blattberg and Neslin 1989), and establishes that short-term promotions represent an effective strategy for combating the threat of generics because national brands can draw more market share from discount brands through promotions than can discount brands (Blattberg and Wisniewski 1989, Allenby and Rossi 1991, Bronnenberg and Wathieu 1996). However, the strategy adopted by PM in 1993 denoted a permanent strategic shift of pricing policy because it featured a one-time, permanent, publicly announced price cut. Little is known about the impact of permanent and publicly announced price cuts (or, in general, about permanent changes in marketing strategies) on consumer brand switching decisions.[2, 3]

Furthermore, cigarettes differ from the typical consumer packaged goods categories studied in the literature because nicotine is addictive, and smoking represents the most widespread addictive behavior in modern society. The addictive nature of cigarettes implies "negative internality" such that current consumption builds future addiction and increases future financial payment (Becker and Murphy 1988). Intuitively, temporary price promotions may not be the most effective way to induce consumers to switch brands in this market because consumers must evaluate the long-term financial implications of adopting a new brand. The high price premium charged by national brands, coupled with the addictive nature of tobacco consumption, implies a lower benefit for consumers who respond to temporary promotions and experiment with promoted premium brands. This led to a fragmented market before Marlboro Friday in which each brand had a group of *sticky* consumers who were unlikely to be swayed to switch to other brands by short-term promotions. As Siegel et al. (1996) note, of 4,651 consumers surveyed, only 9% reported having smoked a different brand in the previous year from the brand they were smoking at the time of the survey. Indeed, despite the historical increase in spending for temporary price promotions by cigarette manufacturers (from $1.5 million to $4.5 million between 1986 and 1992), premium cigarette brands steadily lost market share to generic alternatives, whose share rose from negligible to 30% by 1992 (Silk and Isaacson 1995).

In this paper, to study the impact of Marlboro's permanent price cut in 1993 on consumer brand choice decisions for cigarettes, we develop a dynamic structural brand choice model with forward-looking, learning, and habit-forming consumers. By allowing for forward-looking behavior, our model is consistent with previous literature that establishes that forward-looking consumer models explain the observed patterns of drinking and smoking better than myopic models (e.g., Arcidiacono et al. 2007, Coppejans

[1] A significant stream of literature (primarily in economics) centers on tobacco usage among youth and adults and empirically attempts to estimate the effects of advertising spending on cigarette demand (Hamilton 1972, Schmalensee 1972, Baltagi and Levin 1986, Roberts and Samuelson 1988), changes in consumption following advertising bans (Saffer and Chaloupka 2000), and price and tax rates on cigarette consumption (Lewit and Coate 1982, Evans and Farrelly 1998, Chaloupka and Grossman 1997, Gruber 2001, Nijs et al. 2007). However, most of these studies rely on aggregate data or repeated cross-sectional survey data.

[2] According to Mela et al. (1997), long-term effects differ from the effects of a policy change. If a company changes its price in one period and evaluates its cumulative effect in future periods, it is measuring long-term effects. However, if the company cuts its prices permanently and studies its short-, medium-, and long-term effects on consumer choice, it is evaluating the effect of a strategy change. We focus on the latter.

[3] There are a few papers that use aggregate store-level data to develop reduced form approaches to study price and promotion effects and/or whether price changes cause time-varying parameters (Papatla and Krishnamurthi 1996; Mela et al. 1997, 1998, 1998; Foekens et al. 1999; Haaijer and Wedel 2001; Pauwels et al. 2002; Kopalle et al. 1999; Dekimpe et al. 1999; Pauwels and Srinivasan 2004).

et al. 2006). Our model allows consumers to take into account the greater financial commitment implied by the significant premium price charged by national brands. By allowing for the possibility that consumers face uncertainty about different brands, our model is consistent with empirical findings that, on average, consumers are uncertain about product categories, resulting from their insufficient experience, forgetting, misinformation, addition of newcomers, and so forth (Mehta et al. 2004). Such uncertainty might be even greater for cigarettes, because consumers may keep purchasing the same addictive product repeatedly and thus remain unfamiliar with other brands. Using quality as a summary statistic for each individual consumer's preference for a brand, we assume that consumers can gradually learn about other brands through usage experience over time. In this model setup, consumers are allowed to be willing to sacrifice short-term utility and respond to the permanent price cut by experimenting with unfamiliar brands to reduce uncertainty in the long term, despite the higher brand switching cost implied by addiction. Finally, because the impact of permanent price cut may differ across consumer groups, we take into account consumer heterogeneity using a latent class approach. Applying the model to a unique panel data set that includes consumer purchase behavior before and after the event, we provide behavioral explanations for the observed consumer inertia rooted in the addictive nature of tobacco consumption and impact of a permanent price cut on altering consumer purchase patterns. In particular, we address the following issues: (1) how consumers make brand choice decisions in response to a permanent price cut, (2) whether the dynamic effects of a permanent price cut vary across different types of consumers, and (3) the long-term implications of publicly announced permanent price cuts on consumer brand switching behavior.

Our results show that before the price cut, the industry was characterized by low brand switching and high consumer inertia and that short-term price promotions were ineffective in inducing consumers to switch brands. A publicly announced permanent price cut makes consumers realize the lower financial commitment in the long-run, which motivates them to break their purchase habits and experiment with Marlboro. The price-induced experimentation effectively reduces uncertainty with the previously unfamiliar brand. In the long term, better-informed consumers are more likely to purchase Marlboro because of lower expected long-term payment, lower uncertainty, and higher focus on quality. In addition, while the competitors matched Marlboro's pricing policy within a few weeks, the benefit from a permanent price cut was more pronounced for Marlboro compared with other premium brands. We use the model parameters to conduct a variety of what-if analyses, which show that the strategic step undertaken by PM made Marlboro more competitive and less vulnerable to the promotions offered by discounted brands in the long term. To our knowledge, ours is the first study of changes in consumer brand choice behavior of cigarettes using scanner panel data in the context of Marlboro Friday.

The rest of this article is structured as follows: In the next section, we provide a brief description of the cigarette industry and the events surrounding Marlboro Friday. We also discuss the data we use in the empirical application. In §3, we propose a dynamic brand choice model with forward looking, uncertainty, and habit formation and, in §4, provide the empirical results. We conclude in §5 with a discussion of some limitations and directions for further research.

2. Industry Background and Data Description

2.1. Marlboro Friday[4]

The American tobacco industry is highly concentrated. The top two players, PM and R.J. Reynolds (RJR), capture almost 75% of the market. At the brand level, Marlboro arguably has been one of the most recognized brands in the world and is a very profitable product for PM. However, despite its historic strength, when in the late 1980s and early 1990s the U.S. economy experienced a recession, discount brands like GPC (Brown and Williamson), Basic (PM), and Doral (RJR) made major inroads and captured more than one-fourth of the market. The trend toward discounted brands was particularly troublesome for the premium-intensive manufacturer PM. In addition, with growing concern over smoking risks, per capita consumption of cigarettes had declined steadily in the United States, falling from 3,746 cigarettes per adult in 1983 to 2,640 cigarettes per adult in 1992, a 21% drop. Furthermore, the cigarette industry faced (and continues to face) increasing product liability issues and strong government regulations on its marketing activities.

With the upswing in generic brands, slower category demand, and government regulations, Marlboro saw its market share shrink from a high of 30% to 24% by 1992. On April 2, 1993, after years of watching discounted brands make steady gains in market share, PM adopted an elaborate program of consumer and retail promotions, of unspecified

[4] This section is drawn from several business press articles surrounding this event. Interested readers should also refer to a Harvard Business School case study on the issue (Silk and Isaacson 1995).

duration, that slashed the retail price of its premium-priced Marlboro by 20% in the U.S. market. At the same time, PM raised the list price of its low-tier brand, Basic, by 20%. Two months after the announcement, the company made the price cuts permanent by converting the price promotion into an equivalent list-price reduction, which also applied to PM's other premium and mid-tier brands, such as Parliament and Virginia Slims. Smokers were notified of the new prices through a large-scale direct mail campaign, advertising, display signs, catalog distribution, and the "Adventure Team" Expedition program. As the senior vice president at PM stated, "We understand there will be some short-term pain in terms of our profitability. But this is an investment in the future" (Silk and Isaacson 1995). According to the 1993 PM annual report (*Philip Morris* 1994), the actions begun on Marlboro Friday were intended to rebuild the company's premium cigarette brands:

> Our new pricing strategy and actions had a simple objective: to narrow the price gap between our premium product and discount competitors to a point where consumers would once again base their purchases on brand quality, imagery, and preference, rather than on price alone. Our goal was to recover the lost premium brand share, and thereby to protect the long-term profit and cash-generating power of these strong brands.

Within the cigarette industry, the publicly announced event gave a clear signal to competitors that PM was willing to take drastic steps to protect the market share of its flagship brand. Major competitors such as RJR reacted by matching the price cuts for their premium and mid-tier brands and the price increase for their discounted brands within two to three months after Marlboro's new pricing became effective.

2.2. Data Description

The data for this study come from ACNielsen's Wand panel on cigarette purchases. Our data consist of detailed purchase histories for 247 regular smokers in the United States who made 33,112 purchases during the 118 weeks from January 1993 to August 1995. On average, each consumer engaged in 134 purchases in the data set, which includes 4 months of purchase history before Marlboro's event and approximately 18 months after the event. Thus, we have sufficiently long purchase histories for each panelist before and after Marlboro's price cut. The purchase histories are also fairly complete; consumers' purchases are recorded from all outlets, including convenience stores and gas stations. This broad inclusion is particularly important because, unlike the product categories often studied in the literature, i.e., those primarily sold in supermarkets, smaller retail outlets account for a significant proportion of sales of cigarettes.

The cigarette category contains several hundred distinct products with variants in terms of strength (regular/light), size (e.g., 100s), and flavor (e.g., menthol). However, each of these products can be categorized broadly into three quality tiers. To keep our study manageable, we classify all products into 10 brand/tier product aggregates according to manufacturer and quality levels.[5] These include premium, middle, and low tiers from PM, RJR, and other manufacturers, where "other" is an aggregation of brands of several manufacturers other than PM and RJR. We treat Marlboro as a separate brand to examine Marlboro Friday specifically.

In Table 1(a), we provide sample descriptive statistics about selected product aggregates, including the average market shares and prices per pack for the respective products before and after Marlboro Friday. At the brand level, Marlboro is the clear market leader, capturing approximately 16% of the total market before the event and 20% after. According to the change in prices in Table 1(a), the average price of Marlboro and other premium brands for all manufacturers dropped by approximately 15% because of the actions taken by PM, whereas the price of discount brands of PM and RJR increased. We also note the significant price gap between Marlboro and discount brands prior to Marlboro Friday. For example, the discount brands cost approximately \$0.83 less than Marlboro. For a moderate smoker (i.e., consumes one pack per day), this discount amounts to approximately \$303 in annual savings by switching from Marlboro to a discount brand; these savings would be significantly higher for heavy smokers. The action taken by PM significantly reduced the price gap between premium and discount brands from \$0.83 to about \$0.41, which would reduce the annual savings in our example to \$150. Average category consumption stays quite stable before and after the event (11.7 packs per week before the event and 11.9 packs after), indicating that the permanent price cut does not significantly increase category demand and that

[5] To avoid possible aggregation bias, for each choice aggregate used in the empirical estimation we run correlations of prices for the selected universal product codes within each manufacturer/price/quality tier to ensure the prices tend to move together over time. The grouping of the products does not affect the operation of the price variables because we do not aggregate the prices from the product level to the choice level. We use the prices at the product level and consider the prices of each product as observed in the data. Similarly, when replacing missing prices for unpurchased products, we follow the standard steps and use the price of the same product (not choice) paid by other consumers in the same store and on the same day, by other consumers in the same store and in the same week, and then average prices paid by other consumers in the same store in the adjacent periods.

Table 1(a) Market Share and Average Prices

Brand choice	Average market shares Before	Average market shares After	Average prices per pack Before	Average prices per pack After
Marlboro	16.28	20.18	1.83	1.54
Premium tier				
Philip Morris	6.36	6.74	1.86	1.58
RJR	17.15	16.56	1.82	1.51
Others	8.19	7.14	1.86	1.53
Mid-tier				
Philip Morris	11.99	11.40	1.54	1.36
RJR	8.18	7.64	1.33	1.15
Others	9.29	9.07	1.63	1.37
Lower tier				
Philip Morris	1.05	1.02	1.00	1.13
RJR	8.39	9.07	1.02	1.09
Others	13.13	11.18	1.27	1.18

Table 1(b) Brand-Switching Matrix

	Marlboro	Premium	Mid	Low
6 weeks before permanent price cut				
Marlboro	0.80	0.10	0.06	0.04
Premium	0.06	0.84	0.07	0.03
Mid	0.02	0.05	0.87	0.06
Low	0.02	0.05	0.13	0.80
6 weeks right after permanent price cut				
Marlboro	0.84	0.06	0.08	0.03
Premium	0.09	0.83	0.04	0.03
Mid	0.03	0.05	0.83	0.09
Low	0.06	0.05	0.12	0.77
6 weeks before the end of observation				
Marlboro	0.83	0.06	0.08	0.03
Premium	0.08	0.84	0.05	0.03
Mid	0.01	0.09	0.82	0.07
Low	0.05	0.04	0.14	0.77

the major source for sales increases comes from brand switching.

In Table 1(b), we report the switching matrix among Marlboro, other premium brands, mid-tier brands, and generic brands during six weeks before the event, six weeks right after the event, and six weeks before the end of our observation period. More specifically, we calculate the average percentages of tier choices given consumer choices of the previous period. The diagonal elements represent consumer loyalty to a particular choice over time. Consumer loyalty for all tier choices is quite high, even for the discounted brands, which supports our conjecture of a fragmented market before the event. Shortly after the price cut, consumer loyalty for all tiers except Marlboro remains smaller, indicating that consumers switch to Marlboro in response to the permanent price cut. The off-diagonal elements show that most of the switches are from other brands (especially generic brands) to Marlboro. This data pattern suggests that Marlboro's permanent price cut attracted consumers to switch from other brands to Marlboro.

In Figure 1(a), we plot the time-series data pertaining to prices of Marlboro and premium-, mid-, and low-tier products. Marlboro Friday occurred around week 13. The price cut was executed around week 19. Competitors reacted fairly quickly by matching the same price changes during weeks 33 and 40. In Figure 1(b), we trace the change in market shares and find that Marlboro experienced a significant increase right after the permanent price cut and then a slow but steady increase after week 33 (shortly after other premium brands matched the permanent price cut). The majority of the share increase for Marlboro came at the expense of mid- and low-tier brands. Although this finding may suggest Marlboro cannibalized sales from lower-tier brands, including its own brand Basic, PM may not mind such an effect because profit margins tend to be almost 10 times higher on premium versus discount brands (Shapiro 1993). We next describe our modeling approach, which incorporates several aspects of cigarette consumption discussed previously.

3. Model

We assume there are $i = 1, \ldots, I$ consumers who make periodic choice decisions D_{ijt} among choice alternatives $j = 0, \ldots, J$ at time periods $t = 1, \ldots, T$.[6] Choice $j = 0$ represents a no purchase decision. The indicator variable D_{ijt} represents the choice of brand j made by consumer i at time t; that is:

$$D_{ijt} = \begin{cases} 1, & \text{if choice } j \text{ is chosen,} \\ 0, & \text{otherwise.} \end{cases} \tag{1}$$

3.1. Utility Function and Quality Uncertainty

We assume consumer brand choice decisions are based on product quality, prices, and addiction. As argued by both psychologists (e.g., Fishbein 1967) and economists (e.g., Lancaster 1966), consumers perceive products as bundles of attributes and develop perceptions about where different brands lie along the dimension of each attribute relative to other brands.

[6] Our data show that consumer category consumption remains stable before and after the event. We tested this at an aggregate as well as for each individual in our sample where we find that over 80% of consumers did not alter purchase quantity significantly. Because our research attempts to draw implications about whether Marlboro Friday was effective in defending its market share, we focus on brand switching behavior without modeling purchase or consumption decisions. Treating quantity as exogenous is a simplification to reduce the computation burden, and it may lead to biases in situations where a policy such as price cut alters the primary demand. In such situations, quantity decisions can be made endogenous as in Erdem et al. (2003), Hendel and Nevo (2005), and Sun (2005).

Figure 1(a) Change of Prices

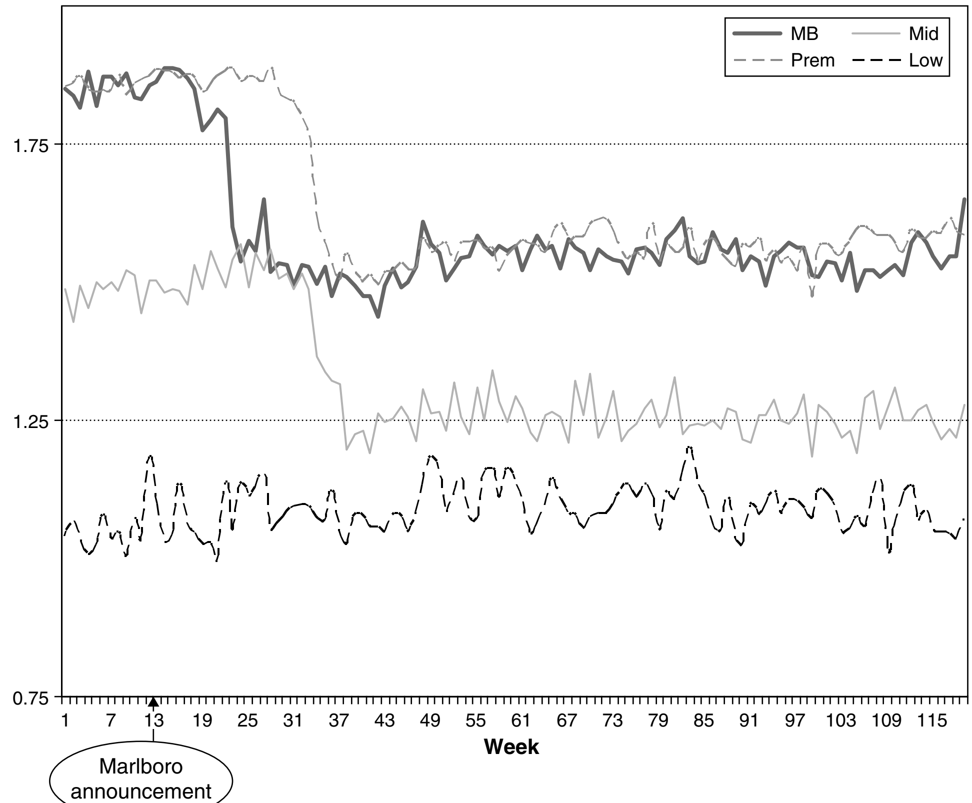
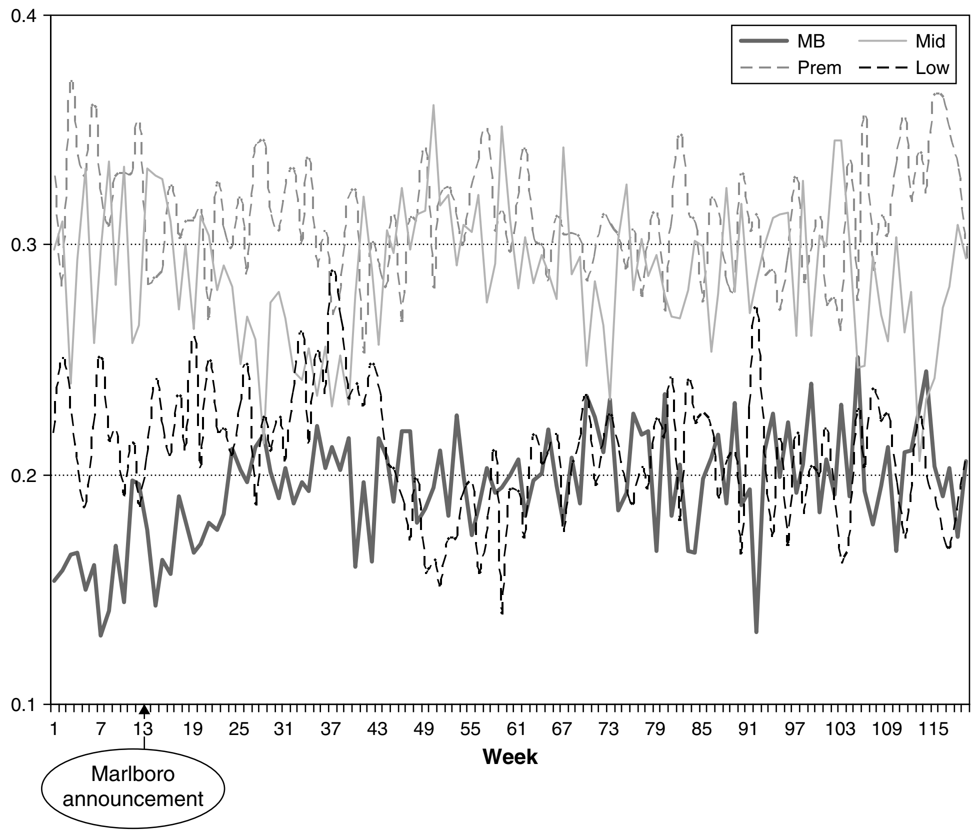


Figure 1(b) Change of Market Shares



Following previous literature on brand choice under uncertainty (e.g., Erdem 1998, Erdem et al. 2004, Erdem and Swait 2004), we use the term "quality" as a summary statistic that reflects both tangible and intangible product attributes. Quality thus labels the general perceived location of the product in the multidimensional product space.

Let $U_{ijt}(s)$ represent the utility obtained by consumer i from choosing brand j,

$$U_{ijt} = \alpha_{0i} Q_{E_{ijt}} + \alpha_{0i} r_i Q^2_{E_{ijt}} + \alpha_{1i} P_{ijt} + \alpha_{2i} A_{ijt} + \alpha_{3i} A_{ijt} Q_{E_{ijt}} + \alpha_{4i} A_{ijt} Q^2_{E_{ijt}} + e_{ijt}, \tag{2}$$

where $Q_{E_{ijt}}$ is the experienced quality of product j. We also include a squared term of experienced quality $Q^2_{E_{ijt}}$ to allow for increasing or decreasing marginal returns for higher quality. P_{ijt} refers to the price of brand j faced by consumer i at time t. A_{ijt} is the addiction stock of consumer i for brand j at time t, which evolves according to the following law of motion:

$$A_{ijt} = \phi_j A_{ijt-1} + C_{ijt-1}, \tag{3}$$

where $\phi_j \in (0, 1)$ is the rate of depreciation of the stock, and C_{ijt-1} is consumer i's consumption of brand j cigarette at time $t-1$. Assuming consumers always consume everything before they make the next purchase, we follow Ailawadi and Neslin (1998) and calculate consumption C_{ijt-1} as the total quantity purchased during the last purchase occasion divided by the total number of periods elapsed between two consecutive purchase occasions. The definition of the stock of addiction follows Stigler and Becker (1977) and Becker and Murphy (1988) and summarizes the cumulative effect of past consumption. We also include the interaction term between quality and addiction, as well as its squared term, to allow for the possibility that addiction changes consumers' sensitivity to quality. Note that, other than some reduced form tests of how addiction affects consumption, to our knowledge, no empirical research models how addiction affects consumer brand choice using scanner panel data. We allow the stock of addiction to be brand specific to capture its differential effect on brand choice. We also make the rate of depreciation differ across brands to allow for the possibility that addiction may build up faster with past accumulative consumption for some brands. The inclusion of consumer i's stock of addiction for brand j allows us to take into account the possible effect of brand-level habit persistence on brand choice.[7]

Included in the utility function is experienced quality, not unobservable true quality. When consumers do not have perfect information about the location of the product along the multidimensional product attribute space, they can learn about product position or improve their perception of true quality based on available information. As demonstrated by Erdem et al. (2008), usage experience provides more dominant and precise information about product quality than advertising or prices.[8] Therefore, let $I_{it} = \{Q_{E_{ij\tau}}, \tau = 1, \ldots, t-1, j = 1, \ldots, J\}$ denote the information set available to consumer i before he or she makes a purchase decision at time t. Facing uncertainty, consumers are assumed to behave as Bayesian learners who update their expectations of quality based on I_{it} using their usage experience.

Let Q_j represent the intrinsic quality of product j. At $t = 0$, we assume all consumers have prior information about the true quality of product j. We define $\mu_{Q_{j0}}$ as the prior expectation of quality and $\sigma^2_{Q_{j0}}$ as the prior variance for brand j at time $t = 0$. It is assumed to be normally distributed according to

$$Q_j \sim N(\mu_{Q_{j0}}, \sigma^2_{Q_{j0}}), \tag{4}$$

where the mean and variance of initial quality are allowed to differ across brands. Starting from period $t = 1$, consumer i begins to learn more about Q_j based on previous purchase experiences. However, usage experience cannot fully reveal the true quality of a brand. We assume that each usage experience provides a noisy but unbiased signal of true quality, according to

$$Q_{E_{ijt}} = Q_j + \xi_{ijt} \quad \text{and} \quad \xi_{ijt} \sim N(0, \sigma^2_{\xi_j}), \tag{5}$$

where ξ_{ijt} is the idiosyncratic component of experienced quality, and $\sigma^2_{\xi_j}$ is the experience variability that captures the noise of information contained in the usage experience. The noise could stem from either the inherent variability of the true product quality or the context-dependent nature of the consumer's experience. We assume ξ_{ijt} follows a normal distribution and is independent across consumers, brands, and time periods. Thus, $1/\sigma^2_{\xi_j}$ is the precision of information contained in a usage experience signal for Bayesian updating.

Define consumer i's expectation of brand j's true quality at time t as $\mu_{Q_{ijt}} = \mathrm{E}[Q_j \mid I_{it}]$ and the variance of expected quality as

$$\sigma^2_{Q_{ijt}} = \mathrm{var}[Q_j \mid I_{it}] = \mathrm{E}[(Q_j - \mu_{Q_{ijt}})^2 \mid I_{it}].$$

[7] Most existing economics literature that models cigarette addiction is analytical in nature. Assuming consumption is observable, these articles interact addiction level with consumer category consumption to derive a theory of consumer rational behavior. The analytical framework of rational addiction at the category level cannot be borrowed directly to study consumer brand choices.

[8] We do not include advertising or price in the information set because advertising is highly regulated by the government, and consumers are less likely to rely on a one-time price cut as a repetitive information source.

Then, $\sigma^2_{Q_{ijt}}$ reflects the variance of the consumer's quality beliefs and represents perceived risk to the consumer. If brand j is used at time $t-1$, the perceived quality is updated according to

$$\mu_{Q_{ijt}} = \mu_{Q_{ij,t-1}} + D_{ij,t-1}(Q_{E_{ij,t-1}} - \mu_{Q_{ij,t-1}}) * \left(\frac{\sigma^2_{Q_{ij,t-1}}}{\sigma^2_{Q_{ij,t-1}} + \sigma^2_{\xi_j}}\right). \tag{6}$$

Intuitively, whenever a consumer experiences brand j during time $t-1$ (as denoted by $D_{ij,t-1} = 1$), his or her perceived quality of product j is updated by new information $(Q_{E_{ij,t-1}} - \mu_{Q_{ij,t-1}})$, weighted by information precision $\sigma^2_{Q_{ij,t-1}}/(\sigma^2_{Q_{ij,t-1}} + \sigma^2_{\xi_j})$. Accordingly, updating the variance of perceived quality is given by

$$\sigma^2_{Q_{ijt}} = \sigma^2_{Q_{ij,t-1}} - D_{ij,t-1}\frac{(\sigma^2_{Q_{ij,t-1}})^2}{\sigma^2_{Q_{ij,t-1}} + \sigma^2_{\xi_j}}. \tag{7}$$

Thus, consumers' quality perceptions are updated based on usage experience. All else being equal, the higher the number of usage experiences, the more precise the consumer's belief about true quality. If premium brands deliver more consistent quality over time (i.e., $\sigma^2_{\xi_j}$ is smaller), consumers obtain more precise information from their usage experience and thereby decrease their perceived risk faster for the focal brand than for other brands.

Given the assumption that usage experience provides unbiased signals, we determine $\mathrm{E}[Q_{E_{ijt}} \mid I_{it}] = \mu_{Q_{ijt}}$, and therefore, $Q_{E_{ijt}} = \mu_{Q_{ijt}} + (Q_j - \mu_{Q_{ijt}}) + \xi_{ijt}$. With quality uncertainty, consumers form expectations about product quality and make purchase decisions based on the expected utility they derive from consuming a brand. Thus, the expected utility for consumer i of purchasing brand j at time t, given the information set, can be written as

$$\begin{aligned}
&\mathrm{E}[U_{ijt} \mid I_{it}] \\
&= \mathrm{E}\big[\alpha_{0i}Q_{E_{ijt}} + \alpha_{0i}r_iQ^2_{E_{ijt}} + \alpha_{1i}P_{ijt} + \alpha_{2i}A_{ijt} \\
&\qquad + \alpha_{3i}A_{ijt}Q_{E_{ijt}} + \alpha_{3i}A_{ijt}Q^2_{E_{ijt}} + e_{ijt} \mid I_{it}\big] \\
&= \alpha_{0i}\mu_{Q_{ijt}} + \alpha_{0i}r_i\mu^2_{Q_{ijt}} + \alpha_{0i}r_i\mathrm{E}\big[(Q_j - \mu_{Q_{ijt}})^2 \mid I_{it}\big] \\
&\quad + \alpha_{0i}r_i\sigma^2_{\xi_j} + \alpha_{1i}P_{ijt} + \alpha_{2i}A_{ijt} + \alpha_{3i}A_{ijt}\mu_{Q_{ijt}} \\
&\quad + \alpha_{4i}A_{ijt}\mathrm{E}\big[(Q_j - \mu_{Q_{ijt}})^2 \mid I_{it}\big] + e_{ijt} \\
&= (\alpha_{0i} + \alpha_{3i}A_{ijt})\mu_{Q_{ijt}} + (\alpha_{0i}r_i + \alpha_{4i}A_{ijt})\mu^2_{Q_{ijt}} \\
&\quad + (\alpha_{0i}r_i + \alpha_{4i}A_{ijt})\big(\sigma^2_{Q_{ijt}} + \sigma^2_{\xi_j}\big) + \alpha_{1i}P_{ijt} + \alpha_{2i}A_{ijt} + e_{ijt}.
\end{aligned} \tag{8}$$

The parameter α_{0i} captures the utility weight that consumer i places on quality; r_i is the coefficient of the uncertainty in consumer perceptions and can be interpreted as the consumer risk attitude (Erdem and Keane 1996). If α_{0i} is estimated as positive and r_i negative, consumers are risk averse, avoid uncertainty, and are less likely to choose a brand with which they are unfamiliar. The parameter α_{1i} is the weight that consumer i places on the price, α_{2i} measures the effect of habit persistence created by the past consumption of brand j on the consumer's propensity of choosing brand j, α_{3i} measures whether addiction changes the consumer's sensitivity to quality, and α_{4i} measures whether addiction increases the consumer's risk attitude. We use vector α_i to represent all the α_is appearing in the expected utility function. Finally, the error term e_{ijt} includes all random shocks known to the consumer but unobservable to the econometrician.

Thus, our model allows for both learning and addiction, which have distinctive implications for dynamic consumer choice behavior. By modeling learning, we allow past choice experiences to affect brand choice by reducing consumer uncertainty about a particular product. We conjecture that consumers are risk averse; they may choose to purchase the same brand repeatedly to avoid the negative utility associated with uncertainty. As the mean of quality is updated and variance is reduced, consumers will adjust their brand choice decisions. By modeling addiction, we allow accumulative past consumption levels of brand j to affect consumers' probability of choosing brand j. We suspect that higher addiction makes consumers more likely to purchase the same brand repeatedly. It also leads consumers to be more sensitive to quality and more risk averse, and thus to stick to the brands with higher perceived quality and lower uncertainty. Note that allowing for addiction changes the implications of the standard learning model because switching brands becomes more costly, so consumers may be less likely to experiment with new products (Osborne 2006). Even if the permanent price cut induces consumers to experiment with Marlboro, addiction may mitigate this effect.

3.2. Price Expectation

When making brand choice decisions, consumers do not observe future prices but rather form expectations about future prices. Following the standard practice in the literature (Erdem et al. 2003),[9] we assume consumers can predict the distribution of future prices. More specifically, we specify that the log price of brand j follows the process.

$$\begin{aligned}
\ln P_{ijt} = \lambda^B_{1j} + \lambda^B_2 \ln P_{ijt-1} + \lambda^B_{3j}\frac{1}{J-1}& \\
\cdot \sum_{l\neq j} \ln P_{ijt-1} + \lambda^B_4 t + \eta^B_{ijt}&
\end{aligned} \tag{9a}$$

$$\begin{aligned}
\ln P_{ijt} = \lambda^A_{1j} + \lambda^A_2 \ln P_{ijt-1} + \lambda^A_{3j}\frac{1}{J-1}& \\
\cdot \sum_{l\neq j} \ln P_{ijt-1} + \lambda^A_4 t + \eta^A_{ijt}.&
\end{aligned} \tag{9b}$$

[9] See also Hendel and Nevo (2005), Sun (2005), Sriram et al. (2006), and Wierenga (2006).

To accommodate the possibility that price process may differ before and after the event, we estimate the price processes separately before and after the permanent price changes. λs are coefficients (λ^B representing the coefficients before the cut and λ^A representing those after the cut), and P_{ijt-1} is the past price paid by consumer i for brand j at time $t-1$. By including the mean log price of all competing brands $((1/(J-1))\sum_{l\neq j}\ln P_{ijt-1})$ in the price process, we take into account price competition. The inclusion of t captures the time trend of the price process. The variable η_{ijt} is the random shock of brand j at time t. We assume that the random shocks in prices of all J brands, η_{it}, follow a multivariate normal distribution:

$$\eta_{it} = N(0, \Sigma_\eta). \tag{9c}$$

The diagonal elements denote the corresponding variance of η_{ijt}, and the off-diagonal elements denote the covariance between the prices of different brands. Allowing random shocks to be correlated can further capture the comovement of prices of the competing brands. Before the announcement, consumers form expectations about future prices according to Equation (9a) because they do not know prices will be cheaper in the future. After the announcement, their price expectations are given by Equation (9a) for periods before the permanent price cut and (9b) for periods after the cut.

The price process parameters are estimated using the price data prior to the estimation of the model (before solving and estimating the dynamic optimization problem). When we solve the consumer's dynamic optimization problem, we treat the price expectation process as known and draw future prices according to its distribution. The expected future price is randomly drawn for 100 times and random error is integrated over the simulation. This follows the standard literature as in Erdem and Keane (1996). Because most of the price changes are at the tier level (as we discussed before), we assume the coefficients of brands in the same quality/tier to be the same and estimate the coefficients for Marlboro, premium, mid-tier, and generic brands.

3.3. Forward-Looking Consumers

We model consumers as forward-looking decision makers who maximize the sum of their discounted future expected utilities. Thus,

$$\max_{D_{ijt}} \left\{ \mathrm{E}_t \sum_{\tau=t}^{\infty} \delta_i^{\tau-t} \mathrm{E}_t[U_{ij\tau} \mid I_{it}] \right\}, \tag{10}$$

where δ is the discounting factor that measures the relative importance of the current and future expected utilities. The operator $\mathrm{E}_t[\cdot]$ stands for the conditional expectation, given the consumer's information set at time t, and $\mathrm{E}_t[U_{ij\tau} \mid I_{it}]$ is the state-dependent, per-period utility function as defined in Equation (8). We follow the convention and set the utility discount rate at 0.995 (Gönül and Srinivasan 1996, Erdem and Keane 1996). In our paper, consumers are forward looking in the sense that they engage in strategic sampling—taking into account the information value of the choices they make. Given the addictive nature of cigarette consumption, we specify the dynamic programming problem over an infinite horizon. However, we find convergence of the backward induction process when T is twice the number of sample periods.

Given a one-period utility function, we obtain the following Bellman equation:

$$V_{ijt}(I_{it}) = \mathrm{E}[U_{ijt} \mid I_{it}] + \delta \mathrm{E}\Big[\max_{D_{ij(t+1)}} \sum_j D_{ij(t+1)} V_{ij(t+1)}(I_{ij(t+1)}) | I_{it}\Big]. \tag{11}$$

Equation (11) thus captures the notion that consumers may not choose the brand that gives the highest expected time t utility because they also consider how the time t decision affects I_{it+1} and therefore their expected utility in future periods. The optimal choice is given by

$$D^*_{ijt} = \arg\max_{D_{ijt}} \sum_j D_{ijt} V_{ijt}(I_{ijt}). \tag{12}$$

According to this setup, the decision variable is brand choice, and the endogenous state variables are the mean and variance of experienced quality of each product as well as the stock of addiction of each product. Price expectations serve as the exogenous state variable. When consumers adjust their brand choices in response to the change of prices, their quality belief, associated uncertainty, and addiction levels are also endogenously adjusted.

The setup of the dynamic programming problem is as follows: At the beginning of time t, consumers form expectations about future prices. Given their current beliefs about quality and uncertainty, they trade off quality, financial payments, and addiction to make a sequence of optimal brand choices that maximizes long-term utilities. This decision process implies that (if the coefficients are estimated as expected) when price cuts are made permanent for Marlboro, forward-looking consumers realize the significantly reduced long-term financial commitment and are motivated strategically to try Marlboro despite the mitigating effect of addiction. They sacrifice current utility by choosing an unfamiliar brand to learn and benefit from reducing uncertainty in the future. However, this effect is likely to be weaker for temporary price promotions.

3.4. Heterogeneity and Log-Likelihood Function

It is established in marketing literature that ignoring consumer heterogeneity leads to biased estimates of state dependence. We use a latent-class approach developed by Kamakura and Russell (1989) to control for unobserved consumer heterogeneity. Suppose there are $m = 1, \ldots, M$ segments of consumers, and each consumer has a probability $0 \leq \pi(m) \leq 1$ of belonging to segment m. Let $\Psi = \{\alpha(m), r(m), Q_{j0}, \sigma_{Q_{j0}}, \sigma_{\xi_j}, \pi(m)\}$ denote a vector of coefficients to be estimated for all m and j. Again, Q_{j0} is the expected initial quality for each brand j, $\sigma_{Q_{j0}}$ is the standard deviation of the prior perceptions of each brand, and σ_{ξ_j} is the standard deviation of the usage experience variability.

Define $V^*_{ijt} = V_{ijt} - e_{ijt}$ as the deterministic part of the utility function in Equation (8). Assuming the error term e_{ijt} is independently and identically extreme value distributed, we obtain the probability that consumer i at time t will purchase brand j conditional on Ψ,

$$\text{Prob}(D_{ijt} = 1 \mid \Psi) = \sum_{m=1}^{M} \pi(m) \frac{e^{\text{E}[V^*_{ijt}(m)]}}{\sum_{j=1}^{J} e^{\text{E}[V^*_{ijt}(m)]}}. \tag{13}$$

Thus, the log-likelihood function to be maximized is

$$\log L(\Psi) = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j=1}^{J} D_{ijt} \log[\text{Prob}(D_{ijt} = 1 \mid \Psi)]. \tag{14}$$

Because the state variables are continuous, we encounter the problem of a large state space. We adopt the interpolation method developed by Keane and Wolpin (1994) and calculate the value functions, and then use these values to estimate the coefficients of an interpolation regression. More specifically, we draw 1,000 state-space points and adopt a linear interpolation function of the state variables. Next, we use the interpolation regression function to provide values for the expected maxima at any other state points for which values are needed in the backward recursion solution process.[10]

[10] The interpolation method was developed by Keane and Wolpin (1994) for approximating discrete-choice dynamic programming problems. It significantly reduces the computation burden by calculating the expected maxima of the value functions for only a subset of state points. Then, these simulated expected maxima are used to fit an interpolating regression that provides values for the expected maxima at the other points, as needed in the backward solution process when solving a dynamic programming problem. See Keane and Wolpin (1994) for a detailed discussion. Our dynamic programming problem involves four continuous state variables: addiction stock, mean belief about quality, variance of belief about quality, and prices for each j. The adoption of interpolation method significantly reduces the computation burden.

Table 2 Model Comparison

	Model 1 (Without forward looking, learning, or addiction)	Model 2 (Without addiction)	Model 3 (Without learning)	Model 4 Proposed model 1 Seg	Model 4 Proposed model 2 Seg	Model 4 Proposed model 3 Seg
−LL	25,147.0	24,595.2	24,124.5	24,539.9	23,715.4	23,682.3
AIC	25,176.0	24,624.2	24,141.5	24,565.9	23,748.4	23,722.3
BIC	25,297.8	24,645.9	24,212.9	24,675.2	23,887.3	23,890.5

3.5. Initial Values and Identification

Because absolute quality levels have no meaning, the quality level for one brand must be fixed to normalize the scale to avoid the identification problem of adding a constant to the quality levels, which can lead to a lack of uniqueness in the quality, risk, price, and addiction coefficients. We set $Q_6 = 0.1$, meaning that we normalize the RJR discount brand at a quality level of 0.1 and measure the quality of other brands relative to it. We also normalize the usage experience variability of premium brands σ_{ξ_j} to be a constant 5.[11]

Because the first observation period does not coincide with the start of a household's choice process, we follow Erdem et al. (2005) and assume that the consumer's prior variance on the quality level of brand j at the start of our estimation period is given by $\ln \sigma_{Q_{ij0}} = \ln \sigma_{Q_{j0}} - k \sum_{\tau=-5}^{0} D_{ij\tau}$, where k is a parameter to be estimated. Thus, consumers with more prior experience with brand j during the five weeks before the start of our estimation period have lower uncertainty about brand j. Finally, to reduce the number of parameters, we estimate the variance of initial quality and experience variability $(\sigma_{Q_{j0}}, \sigma_{\xi_j})$ at the quality/tier level. In other words, we group brands within the same quality tier and estimate the variables for premium (Marlboro is treated as one of the premium tier), mid-tier, and generic brands.

4. Empirical Results

4.1. Model Comparison

In Table 2, we report and compare the model fit statistics with three benchmark models. The first benchmark model is our proposed model without forward looking, learning, or addiction. It is similar to most existing myopic brand choice models. The second benchmark model adds forward-looking and learning components but no addiction and is similar to some existing dynamic structural models that have been proposed to study consumer choice behavior under promotion uncertainty (Erdem and Keane 1996, Gönül and Srinivasan 1996, Sun et al. 2003, Sun 2005).

[11] For a detailed discussion on the identification of quality and uncertainty, see Erdem et al. (2005).

The third benchmark model adds forward-looking and addiction components but no learning. Model 4 is our proposed model.

Because model fitting statistics show that the two-segment model fits the data best for all four competing models, we only report the two-segment results in Table 2. Our proposed model outperforms the three benchmark models without learning, addiction, and/or forward looking, which implies that allowing for uncertainty and forward looking is important to capture consumer decision processes for addictive products. Because our proposed model is the best fit, the next discussion focuses on Model 4.

4.2. Parameter Estimates

In Table 3(a), we report the estimates in the price process. The positive and significant coefficients on the lagged price indicate that if prices are higher in the previous period, they are also likely to be higher this period. For Marlboro, the coefficient of the average of the competitors' prices are insignificant, indicating Marlboro's pricing decisions are independent of competitors' pricing. For the mid- and lower tier, the coefficients of the average of competitors' prices are positive and significant, implying that these brands increase prices if the average last period price of competitors is higher. In the variance–covariance matrix, many off-diagonal elements are significant and positive, indicating a tendency for the price shocks to move in the same direction.

Table 3(a) Estimation Results of the Price Process

	Before permanent price cut	After permanent price cut
Brand constant		
Marlboro	0.98 (0.14)**	1.08 (0.05)**
Premium tier	0.83 (0.14)**	0.93 (0.05)**
Mid-tier	0.38 (0.14)**	0.67 (0.05)**
Lower tier	−0.12 (0.16)	0.52 (0.05)**
Lagged price	0.45 (0.05)**	0.33 (0.02)**
Avg. competitor lagged prices		
Marlboro	0.01 (0.10)	0.01 (0.01)
Premium tier	0.12 (0.08)	0.12 (0.04)**
Mid-tier	0.28 (0.10)**	0.19 (0.04)**
Lower tier	0.45 (0.12)**	0.20 (0.04)**
Time trend	−0.0007 (0.0009)	−0.0008 (0.0001)**
Variance covariance matrix Σ_η		
11	0.0222 (0.0005)**	0.0228 (0.0002)**
12	0.0028 (0.0001)**	0.0038 (0.0001)**
13	0.0051 (0.0001)**	0.0059 (0.0001)**
14	0.0052 (0.0001)**	0.0069 (0.0001)**
22	0.0043 (0.0001)**	0.0081 (0.0001)**
23	0.0023 (0.0001)**	0.0048 (0.0001)**
24	0.0021 (0.0001)**	0.0023 (0.0001)**
33	0.0123 (0.0002)**	0.0127 (0.0002)**
34	0.0063 (0.0001)**	0.0066 (0.0001)**
44	0.0220 (0.0005)**	0.0195 (0.0002)**

**Significant at 0.05 level.

Table 3(b) Estimation Results of the Proposed Model

Parameters	Segment 1	Segment 2
Utility function		
Quality	2.87 (0.04)**	0.93 (0.02)**
Uncertainty	−0.43 (0.01)**	−0.39 (0.01)**
Price	−0.04 (0.01)**	−0.12 (0.01)**
Addiction	0.15 (0.01)**	0.10 (0.01)**
Addiction * Quality	0.001 (0.001)	0.001 (0.0003)**
Addiction * Uncertainty	−0.001 (0.001)	−0.001 (0.0003)**
Depreciation of addiction		
Marlboro	0.65 (0.02)**	
Premium tier	0.65 (0.02)**	
Mid tier	0.61 (0.03)**	
Lower tier	0.59 (0.02)**	
Quality Q_j		
Marlboro	1.84 (0.02)**	
Premium tier		
Philip Morris	1.86 (0.04)**	
RJR	1.96 (0.03)**	
Others	1.92 (0.04)**	
Mid-tier		
Philip Morris	1.57 (0.03)**	
RJR	1.36 (0.04)**	
Others	1.51 (0.03)**	
Lower tier		
Philip Morris	0.61 (0.05)**	
RJR	0.10 (fixed)	
Others	0.97 (0.03)**	
Quality variance σ_{j0}^2		
Premium	7.72 (0.18)**	
Mid	7.78 (0.28)**	
Low	8.51 (0.31)**	
UE variability $\sigma_{\xi_j}^2$		
Premium	5 (fixed)	
Mid	5.41 (0.04)**	
Low	5.46 (0.04)**	
k	0.03 (0.01)**	

Notes. We report standard errors in parentheses. UE represents use experience.
**Significant at 0.05 level.

We now discuss the parameter estimates in the utility function listed in Table 3(b). Most coefficients are significant and have the expected signs. All else being equal, consumers are more likely to choose brands with higher perceived quality levels, lower uncertainty, lower prices, and higher addiction. In addition, the higher the addiction level, the higher consumers' sensitivity to quality and uncertainty. Therefore, consumers with higher addiction are more likely to purchase their preferred and familiar brands, a claim consistent with the intuition that, compared with occasional smokers, highly addicted smokers are more likely to consume their preferred brand and avoid unfamiliar products. We estimate ϕ_{ij} as slightly higher for Marlboro and other premium brands to indicate that past accumulative consumption of these brands contributes more to the addiction stock. Therefore, given an equal amount of past accumulative consumption, consumers develop more addiction from consuming premium brands than from generic brands.

With regard to the quality estimates, recall that our measure of quality is a summary statistic of perceived multidimensional product attributes, and that uncertainty about product quality may be caused by less experience with the product. Therefore, it is not surprising to find that the estimates of mean quality, Q_j, are higher for premium brands than for generic brands. The nonzero estimates of initial quality variance σ_{j0}^2 are 7.72, 7.78, and 8.51 for premium-, mid-, and low-tier brands, respectively. These initial variances indicate consumer uncertainty with regard to various brands. Interestingly, the initial variances of Marlboro and premium brands are not very different from those of the generic brands. Consumers have high quality uncertainty even for premium brands such as Marlboro at the beginning of the observation period because the high price charged by premium brands before the event, reinforced by the addictive nature of tobacco consumption, makes forward-looking consumers realize the higher long-term financial commitment. Thus they are discouraged to respond to (temporary) promotions to experiment with Marlboro and other unfamiliar brands. This situation leads to a fragmented market before the permanent price cut, in which consumers remain loyal to a particular brand and seldom explore unfamiliar brands. This description explains why consumers have almost equally high uncertainty for Marlboro as for generic brands.

The experience variability parameters $\sigma_{\xi_j}^2$ are estimated to be 5.41 and 5.46 for mid- and low-tier brands, with that of premium brands normalized to 5. Therefore, usage experience provides noisy information. The experience variability is slightly higher for low-tier brands than for premium brands possibly because premium brands usually deliver more consistent quality levels than generics. Because consumers derive more accurate information from their consumption experience with premium brands, the same amount of usage experience is more effective in reducing quality uncertainty for premium brands than for generics.

Comparing the coefficients across the two segments, we notice that consumers in the first segment are characterized by higher sensitivity to quality and uncertainty, lower sensitivity to price, and higher sensitivity to addiction. By contrast, those in the second segment have lower sensitivities to quality, uncertainty, and addiction, but higher sensitivity to price. Therefore, consumers in the second segment are more likely to respond to price changes and experiment with unfamiliar brands. The permanent price cut seems more attractive to these price-sensitive consumers.

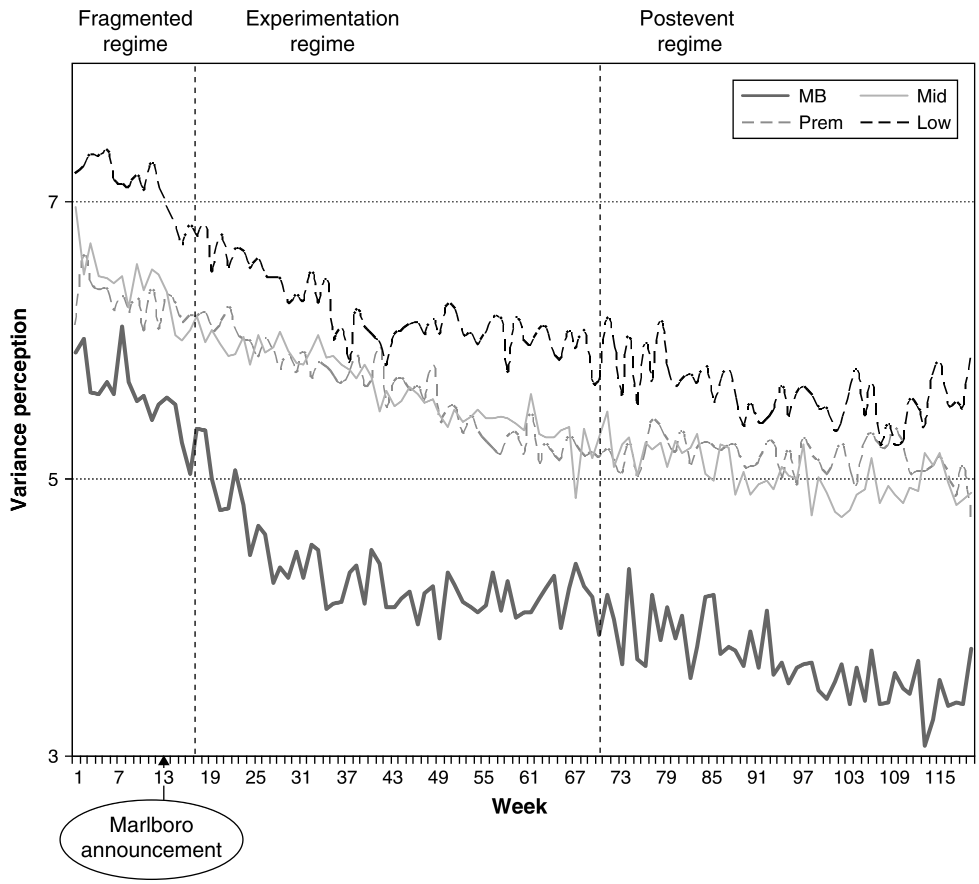
4.3. Experimentation and Learning

We next illustrate whether the permanent price cut is effective in encouraging consumer experimentation and whether the price-induced usage experience helps Marlboro disrupt consumer inertia. closer to the actual figure. In Figure 2(a), we plot the evolution of the average quality variance ($\sigma_{Q_{ijt}}^2$) for Marlboro, premium-, mid-, and low-tier brands over the observation period. Following Kitagawa and Akaike (1978), we run piecewise AR(1) model on the average variance of Marlboro (MB) to test for structural breaks. Based on Akaike information criterion (AIC), we found two break points at week 19, and week 71 best fits the data. Thus, the whole observation period can be separated into three regimes. The first starts at the beginning of the observation period and ends in week 18. The second covers weeks 19–70, and the third starts around week 71.

During the first regime, the variances of premium and mid-tier brands remain fairly stable. Although PM offers frequent price promotions, consumers do not respond by switching to Marlboro. The products of each quality tier are purchased by loyal consumers, who are already familiar with these brands; additional consumption does not contribute much to the decrease in quality uncertainty. This pattern confirms our previous conjecture that consumers are less likely to switch brands in response to temporary price promotions offered on addictive goods. During the second regime, when the temporary price promotion is announced as a permanent reduction of prices, the quality variances of premium brands drop quickly as the significant reduction of long-term financial payment encourages forward-looking consumers to experiment with Marlboro. The experimentation significantly reduces their quality uncertainty and builds their addiction to Marlboro. Most of the reduction of uncertainty for Marlboro happens between weeks 19 and 33 before the other premium manufacturers matched Marlboro's permanent price cut, which demonstrates Marlboro's first-mover advantage in this setting. During the third regime, we observe a slower but more steady decrease of uncertainty about Marlboro and other premium brands. After extensive experimentation, consumers become more informed about Marlboro, and the learning process slows.

On the basis of this discussion, we term the three regimes "fragmented regime," "experimentation regime," and "postevent regime." The second regime starts around week 19, indicating a noticeable delay after Marlboro Friday. This delay might have been

Figure 2(a) **Change of Variance of Perceived Quality**



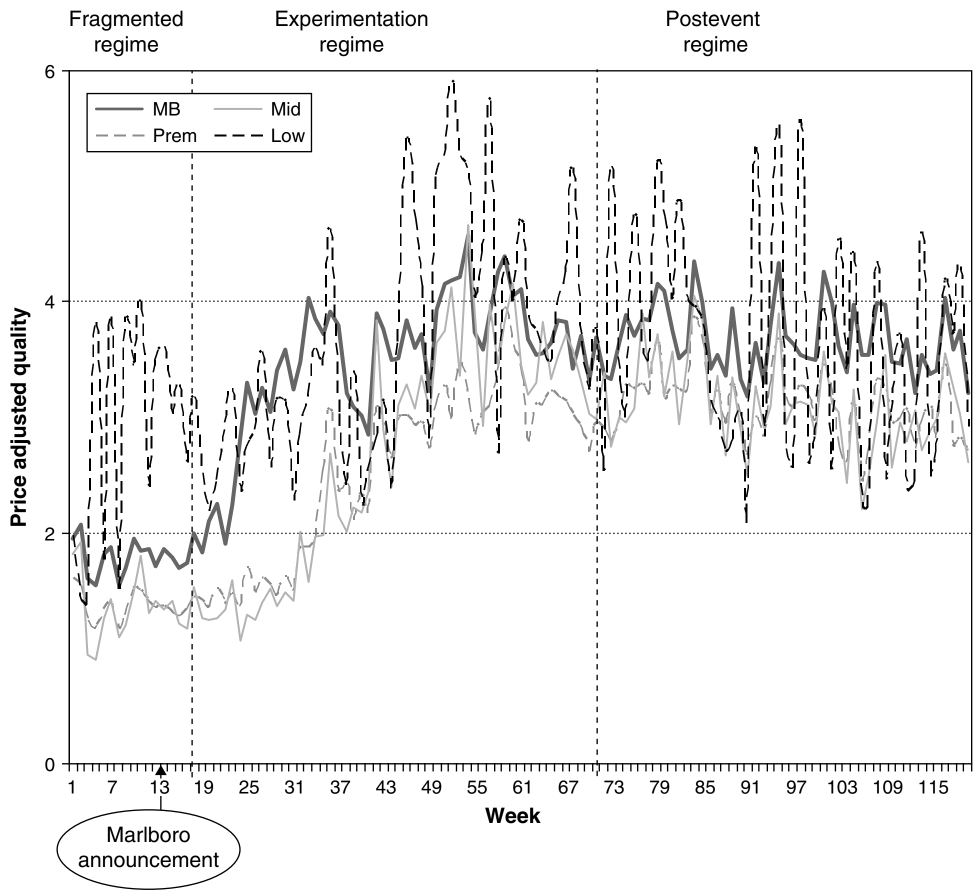
caused by a few factors. First, the price change was initially announced as a price promotion in week 13 before being converted to a permanent price cut, and therefore consumers did not respond. This supports our conjecture that consumers are less likely to react to price promotions but do react to permanent price cuts. Second, even though Marlboro publicly announced its new pricing policy, it took time for retailers to adjust prices to reflect the new listed price.

In addition to quality uncertainty, perceived qualities also change over time. It is insightful to address how the relative attractiveness of premium brands and generic brands adjust over time. We use the ratio between perceived quality and price, calculated as $\mu_{Q_{ijt}}/P_{ijt}$ (where $\mu_{Q_{ijt}}$ is the calculated mean of perceived quality at time t), to summarize the relative changes of quality perceptions and prices. This measurement roughly approximates the commonly used value–price ratio that consumers use when making choices. In Figure 2(b), we plot and compare these ratios across the four tier choices. In the first regime, we observe a big gap between the ratios of Marlboro and generic brands. Even though the premium brands are perceived to have higher quality, the quality difference does not seem to be enough to justify the price premium they charge. The generic brands seem more attractive. The significant difference in the quality and price ratio, coupled with high uncertainty, explains the erosion of Marlboro's market share before the permanent price cut. During the second regime, the price cut immediately decreases the gap. In addition, the price-induced trials reduce the variance of perceived quality while increasing the mean perceived quality, which increasingly closes the gap. In the third regime, the gap continues to close slowly but steadily as experimentation slows down. During the last 20 weeks of our observation period, the average gap becomes 39% smaller than before the event. However, the price and quality ratio of Marlboro remains slightly higher than those of the discounted brands, suggesting that Marlboro may still face the pressure of losing consumers to generic brands, albeit on a smaller scale.

4.4. Impact on Market Shares

We next address the fundamental question leading up to the event: Did a permanent price cut help mitigate Marlboro's eroding market share? In Table 4, we report the changes in the average probabilities of purchasing Marlboro over the three regimes. The average probability of purchasing Marlboro for all

Figure 2(b) Change of Perceived Quality and Price Ratio



consumers increases from the fragmented regime to the postevent regime. The overall purchase probability of Marlboro is increased by 3%, a 20% increase in sales. This increase is particularly significant because it reversed the trend of the previous years of share losses and because major competitors matched the permanent price change.

As we discussed previously, before Marlboro Friday, the high premium price charged by Marlboro implies significantly higher financial payment in the long run, which prevents addictive consumers from responding to temporary price promotions and switching from generics to Marlboro (or other premium brands). The price cut permanently lowers consumers' total financial burden for consuming the addictive product and is effective in inducing consumers to experiment with Marlboro during the experimentation regime. The extensive experimentation significantly reduces the uncertainty and builds addictions associated with Marlboro. The permanently lowered price, improved perceived quality, reduced uncertainty, and accumulated addiction thus make Marlboro more attractive. All these factors contribute to the increasing consumer propensity for purchasing Marlboro during the postevent regime. Overall, we find that the price reduction implemented as a publicly announced permanent price cut is effective in helping Marlboro stop the share erosion by inducing consumers to break their sticky choice behavior and experiment with unfamiliar brands. However, this is less likely to happen under the temporary price promotions adopted as the dominant strategy for PM to defend its market share before Marlboro Friday.

To study what type of consumers contribute more to the increase in Marlboro's market share, we examine the differential impact of the permanent price cut on the two segments of consumers. Comparing the average purchase probabilities, we find that the permanently reduced price has a higher impact on

Table 4 Change of Consumers' Purchase Probabilities and Marlboro's Market Share

		Average purchase probability of Marlboro		
Segment	Percentage of consumers	Fragmented regime	Experimentation regime	Post-event regime
All consumers	100	16.3	19.0	19.4
Segment 1	39.3	27.1	28.3	27.8
Segment 2	60.7	11.4	13.5	14.5

consumers from the second segment, in that their probabilities of purchasing Marlboro increase more. Recall that consumers in the second segment are characterized by a lower risk aversion coefficient, lower sensitivity to quality, lower sensitivity to addiction, and higher sensitivity to price. Being more price sensitive to begin with, this segment of consumers is more likely to be induced by the permanently lowered prices of Marlboro. In addition, as evidenced by the significantly lower probability of purchasing Marlboro before the event, this segment of consumers may be less familiar with and have higher uncertainty about Marlboro. The long-term benefit for them to experiment with Marlboro is higher, and they are more likely to respond to the permanent price cut by trying Marlboro. In addition to lowering uncertainty among these consumers, the experimental consumption builds an addiction to Marlboro, given Marlboro's higher carry-over coefficient in the addiction updating equation. Compared with the 3.1% increase of purchase probabilities for segment one consumers, the increase is approximately 27.2% among segment two consumers. Thus, the increase of market share can largely be attributed to price-sensitive consumers who are infrequent purchasers of Marlboro.

4.5. Long-Term Implications

Recall that the brand switching matrix in Table 1(b) implies that consumer loyalty to Marlboro improves from the fragmented regime to the postevent regime. This is because intensive experimentation reduces uncertainty and accumulates addiction, which increases the utility of choosing Marlboro. Because the reduction of uncertainty and accumulation of addiction are long lasting, consumers are likely to remain loyal to Marlboro during the relative long term. Given that the impact of the permanent price cut is stronger among consumers in the second segment, the increase in brand loyalty is also likely to occur among these consumers, who are more price sensitive and were less loyal to Marlboro before the event.

To examine whether Marlboro Friday changed Marlboro's competitiveness relative to the competing brands, in Table 5, we report short-term brand switching elasticities for Marlboro, premium brands, mid-tier brands, and discounted brands when each of the four tiers offers temporary price promotions. The promotion elasticities compared between the fragmented regime and the postevent regime show whether a permanent price cut changes the competitiveness among these quality tiers when temporary promotions are offered. We obtain the elasticity matrix by reducing the price of each brand by 10% in a randomly chosen week and simulating the percent changes of purchase probabilities for all four quality tiers during the same

Table 5 Promotion Elasticities

	Marlboro	Premium	Mid	Low
Fragmented regime				
Marlboro	0.22	−0.07	−0.05	−0.04
Premium	−0.03	0.21	−0.02	−0.02
Mid	−0.03	−0.01	0.19	−0.03
Low	−0.03	−0.01	−0.02	0.18
Postevent regime				
Marlboro	0.18	−0.05	−0.04	−0.06
Premium	−0.01	0.14	−0.02	−0.02
Mid	−0.02	−0.01	0.18	−0.03
Low	−0.01	−0.01	−0.02	0.18

time period. First, we notice that all the promotion elasticities are quite small compared with the −1 to −2 range reported in a meta-analysis by Tellis (1988) and by Van Heerde et al. (2003) for other frequently purchased packaged goods.[12] As we discussed previously, this difference reflects the addictive nature of tobacco consumption; when consumers have developed a habit for a particular product, a temporary price cut cannot lower the long-term financial payment and does not increase the attractiveness of the promoted brand. Thus, consumers are less likely to respond to temporary price promotions by switching brands. The elasticities are consistent with the low elasticities (range of −0.2 to −0.3) reported in economics literature for the consumption of tobacco and liquor (Baltagi and Levin 1986, Baltagi and Griffin 1995, Evans and Farrelly 1998). Second, most promotion elasticities are smaller during the third regime, indicating that consumers become (even) less likely to respond to promotion. After extensive experimentation, consumer uncertainty for Marlboro is significantly reduced, and the value of a trial is much smaller. Third, comparing the cross-elasticity of Marlboro between the first and the third regime, we find that the promotions offered by generic brands are less likely to attract consumers away from Marlboro. However, when Marlboro offers a price promotion in the postevent regime, it draws more purchases away from discounted brands, compared with the results during the first regime. To some extent, Marlboro has become less vulnerable to discounted brands, but not vice versa.

Thus, the permanent price cut for Marlboro is not only effective in inducing immediate brand switching but also changes consumer choice behavior and reduces head-to-head competition with discounted brands in the relative long term. The result of extensive experimentation is to create a (long-lasting) reduction of uncertainty and accumulation of addiction for Marlboro. These factors attract consumers to

[12] Existing economics literature on addictive goods such as drugs, tobacco, and liquor report consumption elasticities ranging between 0.2 to 0.3.

Table 6 Two Policy Simulations

	Average purchase probability of Marlboro		
Segment	Fragmented regime	Experimentation regime	Postevent regime
Baseline	16.3	19.0	19.4
Without permanent price cut	16.2	15.9	14.8
Reduced uncertainty at the beginning of the observation period	17.8	19.3	19.6

purchase Marlboro repeatedly and build brand loyalty. In addition, this strategic step undertaken by PM makes Marlboro more competitive and less vulnerable to the promotions offered by discounted brands in the relative long term.

Dynamic structural models, such as the one used in this paper, allow us to conduct a variety of contrafactual policy simulations (Chintagunta et al. 2006). To better understand the long-term implications of Marlboro's pricing strategy for market share, we conduct a counterfactual simulation to show the change in Marlboro's market share if it had not cut its price permanently. In particular, assuming there is no permanent price cut and the price processes of all the brands remain the same as before Marlboro Friday (Equation (9a)), we simulate the change of market shares of the four quality tiers over the entire observation period. The results are displayed in Table 6. This what-if analysis shows that without the dramatic price cut, Marlboro's market share falls from an average of 16.2% a few weeks before the permanent price cut to an average of 14.8% near the end of our observation period (whereas the market share of discounted brands increases from 23.3% to about 27%), and this trend appears likely to continue. Without this drastic shift of pricing policy, Marlboro would have continued to lose market share to discounted brands; therefore, the permanent price cut was necessary to regain its dominant status in the long run.

As we discussed before, consumers engage in strategic sampling—they take into account the information value of the choices they make. Higher uncertainty means higher value of information and gives consumers higher incentive to experiment with Marlboro. Another interesting question is how is the effectiveness of a permanent price cut in attracting brand switching affected by the magnitude of consumer uncertainty about Marlboro? To answer this question, we conduct another simulation by reducing the value of initial quality variance by a half. We report the change in Marlboro's market share in Table 6. Market share of Marlboro increases during the fragmented regime because of the reduction of uncertainty, confirming that higher uncertainty (as in the data) prevents consumers from purchasing Marlboro. The reduction in uncertainty reduces the benefit for consumers to sample and learn. The smaller increase in market shares before and after the permanent price cut suggests that consumers are less likely to experiment MB when information becomes less valuable. This result implies that a permanent price cut is more effective in inducing brand switching when the market is more fragmented.

4.6. Summary

To summarize, our results show that PM's permanent price cut was necessary and effective to preserve its market share. A permanent price cut induces forward-looking consumers to break out of their purchase habits and go through an experimental phase to learn about the premium brands. The price-induced experimentation significantly reduces their uncertainty. In the long run, on average, more informed consumers are more likely to purchase and remain loyal to Marlboro because of "permanently" lowered prices, lower uncertainty about Marlboro, and higher addiction level to Marlboro. The new pricing policy has a greater impact on consumers who are more price sensitive and less familiar with Marlboro. As a premium brand, Marlboro is in a unique position to benefit from a permanent price cut because consumers learn faster (as indicated by the lower usage experience variability coefficient) and accumulate addiction faster (as indicated by the higher depreciation of addiction coefficient) than they would for other brands. As the initiator of the permanent price cut, Marlboro also benefited from a first-mover advantage, such that the reduction of uncertainty and increase of addiction resulting from extensive experimentation made it more costly for consumers to switch to other brands when they matched the price cut. We also demonstrate that a consumer model with forward looking, uncertainty, and addiction better explains consumer brand choice decision processes for product categories with addictive natures in the context of a permanent price cut.

From the empirical evidence, we draw several implications about Marlboro's pricing policy. Before the permanent price cut, Marlboro was vulnerable to discounted brands because of its high price. A drastic and publicly announced price cut was necessary to combat the rising generic brands and effectively build loyalty. Furthermore, the strategic price shift increased the competitiveness of Marlboro as opposed to generic brands with respect to temporary price promotions. Simple calculations show that after the price cut Marlboro saw significant improvement in revenues, but the overall revenue for PM as well as other competitors went down. In particular, the changes in revenues were as follows: Marlboro (+4%), PM (−4%), RJR (−14%), other (−23%). Note that the main reason for the decline in industry revenues was that the primary demand for cigarettes remained stable despite the price cut.[13] Thus, while PM saw a decline in revenues because of the event, the losses incurred by its competitor were significantly higher. From a strategic perspective the event was successful for PM for two reasons: (1) It regained the lost momentum for its premier Marlboro brand, which according to industry reports had higher margins compared to mid- and low-tier brands, and (2) although not observed in our data, the event led to the eventual demise of certain competitors over the long run who were unable to sustain the losses because of the price cut.

To some extent, the overall results seem to match the management's expectations. As stated in the *Financial Times* (Kay 1996, p. 11): "A price war can only pay if its long run result is to change market structure (competitiveness) or market behavior (consumer behavior). Philip Morris succeeded in doing both. The price war largely destroyed the cheap brands, and American Tobacco quit the market altogether." Furthermore, "by 1995, Marlboro had regained its lost market share . . . . The PM share price more than recovered its lost ground."

5. Conclusions, Limitations, and Further Research

Unlike most price promotions studied by existing marketing literature, Marlboro's new pricing policy was a publicly announced, permanent price cut. Research is needed to investigate the impact of permanent and publicly announced price cuts on consumer brand choice decisions and draw implications on the effectiveness of this drastic shift in pricing policy.

We develop a dynamic structural brand choice model with uncertainty, forward looking, and addiction to study how a permanent shift of pricing policy affects consumers' decision process for tobacco, an addictive product category. Applying our model to the purchase history data of cigarettes around Marlboro Friday, we evaluate the immediate and long-term impact of Marlboro's action on its market share and draw implications on consumer brand choice behavior and on the brand competition between Marlboro and generic brands. We find that a permanent price cut encourages consumers to experiment with premium brands. The intensive experimentation significantly reduces uncertainty and increases addiction. The cheaper long-term financial commitment, reduced uncertainty, and stronger addiction increase loyalty among consumers, especially those who were more price sensitive and less loyal to Marlboro. This shift in consumer calculus helped alleviate the erosion of Marlboro's market share and left it better positioned and less vulnerable to competition from discounted brands in the relative long run. This empirical study is the first to examine explicitly how consumers react to a permanent shift of marketing variables and draw implications about whether such a drastic strategy is effective to combat generic brands of an addictive product. Our results imply that for addictive products, permanent price cuts could be more effective than temporary price promotions in inducing brand switching.

Our research is subject to limitations, which also open avenues for future research. First, a more flexible model might be developed to allow for endogenous purchase quantity and consumption decisions to study how consumers strategically adjust their purchase quantity and consumption when the industry price of an addictive product is permanently reduced. From a public policy perspective, a related question of importance would be whether such industry-wide price cuts attract new consumers, particularly young consumers, into the category. It would also be interesting to analyze the impact of drastic price cuts from a competitor's and a downstream retailer's perspectives. As discussed in the data section, it took several months for all retailers and major competitors to adopt the new pricing policy, so it might prove interesting to study how competitors and retailers gradually follow the price cut and adjust their pricing policies. In doing so, price decisions can be endogenized by modeling firms' optimal pricing decisions. In addition, consumers are forward looking in the sense that they engage in active learning—taking into account the information value of the choices they make. Future research can study the difference between active learning and passive learning in the literature. Furthermore, our analysis relates to the context of addictive goods. It would be interesting to examine consumer brand choice behavior for nonaddictive products and compare the implications of the effectiveness of a permanent price cut with that of an addictive product. Finally, further research should investigate how consumers react to drastic changes in other marketing strategies, such as cobranding or a permanent change from high–low pricing to EDLP.

[13] A recent paper by Gordon and Sun (2008) examines this issue more formally to address why consumers do not increase their consumption when the price of the product category is permanently lowered. These authors test consumer behavior theory on "self-control" in the rational expectation framework where purchase quantity and consumption decisions are endogenized. The authors demonstrate that consumers form expectations of the long-term harmful effect of smoking and strategically adjust their purchase and consumption decisions to balance short-term addiction and long-term health effects.

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