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

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Abstract

Unlike frequent price promotions, a publicly announced permanent price cut is more likely to cause consumers to strategically shift their decision rules to adapt to the new pricing regime. Research is needed to (1) study whether permanent price cuts cause consumer preference to shift over time; (2) examine how the price cuts affect consumer choices in the short and long run; (3) examine the differential and dynamic effect of price cuts on different consumers. We study these issues in the context of Marlboro’s permanent price cut taken by Phillip Morris in 1993 to stop its market-share erosion caused by generic brands, an event often referred to as Marlboro Friday.

We develop a dynamic structural brand choice model with learning and time-varying coefficients to investigate how a permanent shift of pricing policy affects consumer decisions. Using a unique consumer panel data on cigarette purchases before and after this event, we show that consumers adjust their preference to adapt to the new pricing policy. Given the addictive nature of the product, a permanent price cut was effective in encouraging consumers to break their purchase habits and experiment with unfamiliar brands. The newly established consumer preference helps alleviate erosion of Marlboro’s market share. Overall, our analysis indicates that the action taken by Philip Morris was a necessary and effective strategy for preserving Marlboro’s brand equity.

This is the first empirical study that evaluates the new pricing policy announced on Marlboro Friday, an important historical event with good representation of companies adopting new pricing policy.

Key words: Marlboro Friday; permanent price cut; time-varying coefficient; Lucas critique; quality uncertainty; consumer learning; risk aversion; consumer migration.
1. Introduction

The past two decades or so have seen a tremendous growth in discount brands such as private labels and generics. Traditionally, consumers viewed these products as poor substitutes for the branded goods and were willing to pay a price premium to avoid the quality uncertainty associated with an unknown brand. As the quality of discount brands improved and they started to gain market share, several manufacturers raised their prices to maintain the lost revenues. An increasing price gap further reinforced opportunities for generic brands to exploit price-sensitive consumer segments, and by the early 1990’s, generic brands had risen from being a marginal force to leading the dynamics of the marketplace across many industries. National brand manufacturers have tried to counter the growth of discount brands via traditional marketing tools such as increase in promotion and advertising budgets, new product introductions, product-line management, and aggressive temporary price promotions (see Hoch 1996). While these attempts worked for some national brands, for others they failed to counter the gains made by discount brands. With the continuing growth of generic brands, analysts argued that it would become increasingly difficult to woo consumers back to premium brands. On April 2, 1993, one of the most famous and valuable brands in the world – Marlboro – announced it would permanently reduce its prices by 20% to cope with the growing threat from generic brands.

Marlboro Friday (as the event came to be known) was heralded as a milestone in marketing history. The competitive pricing strategy initiated by Philip Morris (PM hereafter), the parent company of Marlboro, has been a topic of contention and intense debate for several reasons. Foremost, the announcement of the price cut was widely interpreted as representing a watershed event in brand marketing, and Marlboro Friday saw the stock prices of Philip Morris fall 23% knocking off billions of dollars in market value. In addition, several other major household brands including Heinz, Coca-Cola, Quaker Oats, and P&G, collectively lost $50 billion in value on the same day. The rationale was that if the Marlboro Man had crashed, then brand equity had crashed as well because major brands were forced to compete with the growing threat from generics on prices. Second, the fallout from the event spread far beyond the tobacco industry. Other manufacturers including Proctor & Gamble, have taken similar initiatives to substitute everyday low prices for a myriad of promotions and coupon offers. A similar pattern has emerged at the
downstream retail level with a systematic growth in EDLP operators offering everyday low prices instead of frequent deep promotions (Bell and Latin 1998). Finally, the event was significant because it touched off an extended debate concerning the wisdom and long-term implications of Philip Morris' drastic actions, with several commentators criticizing the objectives, execution, and timing of the strategy. Philip Morris described it as a decisive action to increase market share and grow long-term profitability in a highly price-sensitive market environment.

Despite its historical significance, the event has received little attention in the academic literature. Existing marketing literature has focused on the short-term price promotions for frequently-purchased packaged goods (Blattberg and Neslin 1989). It has been well documented that short-term frequent promotions are an effective strategy for combating threat from generics because national brands are able to draw greater market share away from discount brands due to promotions than vice versa (Blattberg and Wisniewski 1989, Allenby and Rossi 1991, Bronnenberg and Wathieu 1996). However, cigarette consumption differs from other product categories due to its addictive nature, and is characterized by high inertia and solidified brand loyalties (Arcidiacono, Siege, and Sloan 2005). For instance, Siegel et al. (1996) found that of the 4,651 consumer 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.

The addictive nature of the product implies that temporary price promotions may not be the most effective way to defend the market share of Marlboro and other premium brands for (at least) two reasons: First, consumers could be more risk averse regarding tobacco consumption, and their cost of switching to unfamiliar brands is likely to be higher. Second, given the significant price premium charged by Marlboro, consumers may realize higher long-term financial commitment once addicted to premium brands. These two factors lower the benefit of experimenting with the promoted premium brands. Indeed, despite the historical increase in spending in temporary price promotions by cigarette manufacturers (from 1.5 million dollars to 4.5 million dollars between 1986 and 1992), premium cigarette brands steadily lost market share to generic alternatives whose share rose from negligible to 30% by 1992 (Philip Morris: Marlboro Friday (A), HBS 9-596-001). By the early 1990s, the high price premium charged by national brands coupled with the addictive nature of tobacco consumption had resulted in a fragmented market in which each brand had a group of “sticky” consumers who were unlikely to be swayed to switch brands due to short-term promotions.
The strategy adopted by Phillip Morris in 1993 denotes a permanent strategic shift of pricing policy. It is featured by a one-time permanent price cut that is publicly announced. According to Lucas (1976), a publicly announced permanent price cut can lead consumers to strategically shift their preference to adapt to the new pricing regime. In other words, consumer preference structure can shift in response to announced changes of policies. There is little known on the impact of permanent and publicly announced price (and in general the permanent change of marketing decisions) on consumer purchase behavior.\(^2\) Several questions have persisted about the effectiveness of publicly the announced price cut represented by Marlboro’s event. For instance, did the actions taken by Philip Morris represent a necessary and effective strategy for preserving Marlboro’s brand equity? How did the strategic shift of Marlboro’s pricing policy change consumer purchase behavior? What were the implications on Marlboro’s eroding market share?

In this paper, we study consumer choice decisions in the context of Marlboro’s permanent price cut in 1993. Using a unique panel dataset that includes consumers purchase behavior before and after this event, we investigate the immediate and permanent impact of Marlboro’s pricing strategy on consumer purchase behavior. We develop a dynamic structural brand choice model with learning and time-varying coefficients. To capture the “sticky” nature of the product demand, the model assumes that consumers have uncertainty about different brands but can learn through use experience over time. To study the impact of Marlboro’s permanent pricing cut, we allow consumers’ preference structures to change by adopting a hidden Markov model. The modeling approach allows us to examine: (1) whether permanent price cuts cause consumer preference to shift over time; (2) how the price cuts affect consumer choices in the short and long run; (3) whether there is a differential and dynamic effect of permanent price cuts on different segments of consumers. We draw implications on market share and evaluate the effectiveness of Marlboro’s event on the brand competition between Marlboro and the uprising generic brands.

We found that the permanent price cut makes consumer to transit from the habit-persistent state to the variety seeking state, which results in change of consumer preference for price and quality. The transition path implies three regimes surrounding the Marlboro Event: pre-Marlboro event, experimentation regime (short-term), and post-Marlboro event (long-term). Consumers in

\(^2\) According to Mela et al. (1997), there is a difference between long-term effects and 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. Conversely, 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 strategy change. We focus on the latter.
the first regime (pre-Marlboro event) are characterized by the sticky purchase behavior and low brand-switching rates for the reasons discussed above. Following Marlboro’s publicly announced permanent price cut, consumers were found to shift to a more “adventurous” state by adjusting their preference for risk, price, and quality to adapt to the new pricing strategy. The adjusted preference structure allows consumers to break their purchase habits to experiment with other previously unfamiliar brands. This is especially true for the consumers who used to be price sensitive. The price-induced experimentation effectively reduces the price-quality gap vis-à-vis the discounted brands. When preferences stabilize, the better-informed consumers are found to increase their chances of purchasing Marlboro because of the increased quality sensitivity and lower uncertainty. In short, our results indicate that the drastic and permanent price cut was a necessary and effective step for Phillip Morris to combat the uprising generic brands.

The rest of the paper is structured as follows. In the next section we provide an overview of the industry and available data. In Section 3 we propose a consumer brand choice model under uncertainty, and Section 4 provides the empirical results. We conclude in Section 5 with a discussion of the limitations of the current paper and directions for future research.

2. Industry Background and Data Description
In this section we provide a brief description of the cigarette industry and the events surrounding Marlboro Friday. We also discuss the data used in the empirical application.

2.1 Marlboro Friday
The American tobacco industry is highly concentrated, with the top two players, Philip Morris (PM) and RJ Reynolds (RJR) capturing almost 75% of the market. At the brand level, Marlboro has been, arguably, one of the most recognized brands in the world and a very profitable product for PM. However, despite its historic strength, things started to change in the late 1980s and early 1990s. With the U.S economy experiencing a recessionary period, discount brands like GPC (Brown and Williamson), Basic (PM), and Doral (RJR) made major inroads and captured more than one-fourth of the market by 1993. The trend towards discounted brands was troublesome for the premium-intensive manufacturer PM. In addition, with growing concern over smoking risks,

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3 This section is drawn from several business press-articles surrounding this event. Interested readers are also referred to a Harvard Business School case study on the issue, “Philip Morris: Marlboro Friday (A)” (9-596-001).
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 marketing activities.

Prompted by 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, Philip Morris announced a plan for an elaborate program of consumer and retail promotions of unspecified duration that effectively slashed the retail price of its premium-priced Marlboro by 20% in the U.S. market. At the same time, Philip Morris raised the list price of its low-tier brand, Basic, by 20%. Two months after the announcement, these price cuts were made permanent by converting the price promotion into an equivalent list-price reduction (which we refer to as the Marlboro Event hereafter), which was also applied to Philip Morris’ other premium and mid-tier brands such as Parliament and Virginia Slims. Smokers were notified of the new prices via a large-scale direct mail campaign, advertising, display signs, catalog distribution, and the “Adventure Team” Expedition program. As the senior vice president at Philip Morris said, “We understand there will be some short-term pain in terms of our profitability. But this is an investment in the future.”

According to the 1993 Philip Morris annual report, the actions started 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 all competitors that PM was willing to take drastic steps in order to protect the market share for its flagship brand. Major competitors such as RJR reacted to PM by matching the price cuts for premium and mid-tier brands and the price increase for discounted brands within two or three months after Marlboro’s new pricing became effective.
2.2 Data Description

The data for this study comes from AC Nielsen’s Wand panel on cigarette purchases. Our data consists of detailed purchase histories for 247 randomly selected panelists who made 33,112 purchases during the 118 weeks from January 1993 to August 1995. On average, each household has 134 purchases in our dataset, which includes five months of purchase history before Marlboro’s event and about one and half years after the event. Thus, we have sufficiently long purchase histories on each panelist before and after Marlboro’s price cut. The purchase history is also fairly complete because consumer’s purchases are recorded from all outlets, including convenience stores and gas stations. This is particularly important because, unlike the typical product categories studied in the literature that are primarily sold in supermarkets, smaller retail outlets account for a significant proportion of sales in cigarettes.

The cigarette category contains several hundred distinct products with several variants of each brand that differ in terms of strength (tar and flavor), size (e.g., 100s), and flavor (e.g., menthol). However, each of these products can be broadly categorized into three quality tiers. To keep things manageable, we classify all the products in the category into 10 brand-quality-tier product aggregates according to the manufacturer and quality levels. These include Marlboro, and premium, mid, 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 for the purpose of examining Marlboro event4.

[Insert Table 1 about Here]

Descriptive statistics on selected product aggregates are provided in Table 1. We report the average market shares and prices per pack for respective products before and after the Marlboro Event. At the brand level, Marlboro is the clear market leader, capturing approximately 16% of the total market before the event in our dataset. The market share of Marlboro increases to 20% after the event. Looking at the change in prices in Table 1, we find that the average price of Marlboro and other premium brands for all manufacturers dropped by approximately 15% in our dataset due to the actions taken by PM, while the price of discount brands increased by approximately the same proportion. It is interesting to note the significant price gap between the Marlboro and

4 We ignore the low tier of PM in the empirical application due to its negligible market share.
discount brands prior to Marlboro Friday. For instance, the discount brands are approximately $0.83 cheaper than Marlboro. For a moderate smoker (consuming one pack a day), this amounts to approximately $303 in annual saving by switching from Marlboro to a discount brand. The savings are of course significantly higher for heavy smokers. The action taken by PM significantly reduces the price gap between the premium and discount brands from $0.83 to about $0.40 (reducing the annual saving to $150 in our previous example).

[Insert Figure 1A and Figure 1B About Here]

In Figure 1A, we plot the time series of prices of Marlboro, premium-tier products, medium-tier products and low-tier products. Marlboro Event happens in Week 21. It can be seen that competitors reacted fairly quickly by lowering the prices of their premium and mid tier brands between Week 21 and Week 30, which is within two or three months after the Marlboro Event. In Figure 1B, we trace the change of market shares of Marlboro and the three quality-tiers. It shows that Marlboro and other premium products experienced a noticeable decrease of market share before the Marlboro Event, a significant increase right after the event, and then a slow but steady increase a few months after the event. An interesting aspect of this share increase for Marlboro is that the majority of increases came from mid- and low-tier brands. While this aspect may reflect that Marlboro is cannibalizing sales from lower-tier brands, including its own brand such as Basic, this is not all bad news for PM because the profit margins tend to be almost 10 times higher on premium versus discount brands.5

3. Model

Van Heerde et al. (2005) listed two types of marketing choice models to account for change of optimal consumer decision rule under policy change: dynamic structural models and time-varying coefficient models. Dynamic structural models have been developed to allow forward-looking consumers to form an expectation of future promotions and to strategically shift their purchase timing, quantity, and consumption decisions to coincide with the frequent, temporary, and unexpected price promotions (e.g. stockpiling and consumption decisions as in Gonul and
Srinivasan 1996, Sun, et al. 2003, and Sun 2005). As stated by Van Heerde, et al. (2005) that “in the event of (an expected and permanent) large magnitude policy changes, economic agents would probably adapt their strategies, leading to changes in parameters, which are typically not accommodated in the (existing) dynamic structural models”, and that “the key outcome of the Lucas critique is that response parameters change as a function of policy changes.”

We develop a dynamic structural model with forward-looking consumers and quality uncertainty to capture the sticky nature of consumer demand. Consumers are allowed to learn about each product and reduce uncertainty from (the price-cut induced) use experience. To accommodate the possible shift of consumer preference in response to the permanent price cut, we allow consumers to reside in different states at any time by adopting a hidden Markov model (HMM).

We assume that there are \( i=1,\ldots,I \) consumers who makes periodic choice decisions \( D_{ijt} \) among choice alternatives \( j=0,\ldots,J \) at time periods \( t=1,\ldots,T \). Choice \( j=0 \) represents no purchase decisions. Let the indicator variable \( D_{ijt} \) represent choice of brand \( j \) made by consumer \( i \) at time \( t \):

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

The shift of consumer preference is captured by a hidden Markov process where we assume that there are \( s=1,\ldots,S \) latent states in which a consumer can resides.

3.1. Utility Function and Perceived Quality

We assume that consumer purchase decisions are based on product quality and prices. As argued

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6 In the context of choice model, literature has documented a few ways to allow for time-varying parameters for purposes other than examining the effect of a permanent price cut on consumer choices. Papatla and Krishnamurthi (1996) used a probit model which allows marketing-mix responsiveness to be a linear function of long-term promotion exposure variables. Mela, Gupta, and Lehmann (1997), Mela, Gupta and Jedidi (1998), and Mela, Jadidi and Bowman (1998) used a two-stage model. In the first stage, parameters are estimated separately for each quarter. In the second stage, the quarterly specific first derivative of market share derived from the first-stage estimation results with respect to price is regressed on price and other marketing-mix variables. Using a rolling three-period window (e.g., parameters estimates for Quarters 1, 2 and 3 to represent Quarter 2), the authors obtain time-varying coefficients. Kim, Menzefericke and Feinberg (2005) propose a Bayesian dynamic logit model, in which the parameters are assumed to follow a VAR(p) model. They establish that ignoring changing preferences results in biased estimation of state-dependence. Recently, Montgomery, Li, Srinivasan, Liechty (2004) and Netzer, Lattin and Srinivasan (2005) develop a latent Markovian chain model to allow consumer preference to differ across states to capture the abrupt changes in Web-browsing behavior (searching versus purchasing and relationship campaign).
by psychologists (Fishbein 1967) and economists (Lancaster 1966), consumers perceive products as bundles of multiple attributes and develop perceptions about where different brands lie along the dimension of each attribute relative to other brands. Following previous literature on brand choice under uncertainty (e.g., Erdem 1998; Erdem, et al. 2004), we use the term “quality” as a summary statistic that reflects both tangible and intangible attributes of a product. The quality labels the general “perceived” location of the product in the multidimensional product space.

Let $U_{ijs}(s)$ represent the utility obtained by consumer $i$ from purchasing brand $j$ when she is in state $s$:

$$U_{ijs}(s) = \alpha_i(s)Q_{E_{ij}} + \alpha_i(s)r_i(s)Q_{E_{ij}}^2 + \beta_i(s)P_{ij} + e_{ijs}(s)$$

where $Q_{E_{ij}}$ is the experienced quality of product $j$. We also include a squared term of experienced quality $Q_{E_{ij}}^2$ to take into account consumer risk preference. $P_{ij}$ refers to the price of brand $j$ faced by individual $i$ at time $t$. The parameter $\alpha_i(s)$ captures the utility weight that consumer $i$ places on quality, while $r_i(s)$ measures consumer $i$’s degree of risk aversion regarding uncertainty in quality perception. The parameter $\beta_i(s)$ is the weight that consumer $i$ places on price. As we will elaborate on later, we allow all parameters to change across state $s$ to capture whether consumer preferences shift over time. The error term $e_{ijs}(s)$ includes all the random shocks known to the consumer but unobservable to the econometrician.

Note that what is included in the utility function is the experienced quality, not unobservable true quality. Usually, consumers do not have perfect information on the location of the product along the multidimensional product attributes space. However, consumers can learn about product position or perception of true quality based on available information. Literature has shown that consumers can rely on advertising, price, and use experience to form quality perception (Erdem, Keane and Sun 2005). We focus on use experience as an information source because the permanent price cut can induce consumers to break their addictive purchase habit and experiment with premium brands. This price-induced use experience is likely to serve as the most important source of information to reduce quality uncertainty in the tobacco industry. Indeed, as shown by Erdem, Keane and Sun (2005), use experience provides more dominant and the most precise
information on product quality than do advertising and price. We do not include advertising and price in the information set because advertising is highly regulated by government, and consumers are less likely to rely on a one-time price cut as a repetitive information source. Let \( I_{it} = \{Q_{E_{jt}}, \tau = 1, ..., t-1, j = 1, ..., J\} \) denote the information set available to consumer \( i \) before making purchase decision at time \( t \). Facing uncertainty, consumers are assumed to behave as Bayesian learners, who update their expectations of quality based on \( I_{it} \).

Let \( Q_j \) represent the intrinsic quality of product \( j \). At \( t=0 \), we assume all consumers have prior information on the true quality of product \( j \). Define \( \mu_{Q_{jt}} \) as the prior expectation of the quality and \( \sigma_{Q_{jt}}^2 \) as the prior variance for brand \( j \) at time \( t=0 \). It is normally distributed according to

\[
Q_j \sim N(\mu_{Q_{jt}}, \sigma_{Q_{jt}}^2)
\]

where the mean and variance of initial quality are allowed to differ across brands.

Starting from period \( t=1 \), consumer \( i \) starts to update their quality expectation based on the previous purchase experience. As consumers get more experienced with product \( j \), they learn more about \( Q_j \). However, use experience cannot fully reveal the true quality of a brand. We assume that each use experience provides a noisy but unbiased signal of true quality, according to

\[
Q_{E_{jt}} = Q_j + \xi_{ijt} \quad \text{and} \quad \xi_{ijt} \sim N(0, \sigma_{ijt}^2).
\]

where \( \xi_{ijt} \) is the idiosyncratic component of the experienced quality and \( \sigma_{ijt}^2 \) is the experience variability capturing the noise of information contained in use experience of product \( j \) for consumer \( i \). The noise could be caused either by inherent variability of true product quality or the context-dependent nature of the consumer’s experience. We assume \( \xi_{ijt} \) follows a normal distribution and is independent across consumers, brands, and time periods. Then \( 1/\sigma_{ijt}^2 \) is the precision of information contained in a use-experience signal in Bayesian updating. The higher the variability, the less diagnostic each use experience is in resolving uncertainty about quality levels.

Define consumer \( i \)’s expectation of brand \( j \)’s true quality at time \( t \) as \( \mu_{Q_{jt}} = E[Q_j \mid I_{it}] \) and
variance of expected quality as \( \sigma_{Q_{jt}}^2 = \text{var}[Q_j | I_t] = E[(Q_j - \mu_{Q_{jt}})^2 | I_t] \). The variance \( \sigma_{Q_{jt}}^2 \) reflects the variance of the consumer’s quality beliefs and represents perceived risk to consumers. A nonzero variance means consumers cannot perfectly observe product quality. If brand \( j \) is used at time \( t-1 \), the perceived quality is updated according to,

\[
\mu_{Q_{jt}} = \mu_{Q_{jt-1}} + D_{jt-1}(Q_{E_{jt-1}} - \mu_{Q_{jt-1}}) \times \left( \frac{\sigma_{Q_{jt-1}}^2}{\sigma_{Q_{jt-1}}^2 + \sigma_{ij}^2} \right)
\]

Intuitively, whenever a consumer experiences brand \( j \) during time \( t-1 \) (as denoted by \( D_{jt-1} = 1 \)), her perceived quality of product \( j \) is updated by new information \( (Q_{E_{jt-1}} - \mu_{Q_{jt-1}}) \) weighted by information precision \( \frac{\sigma_{Q_{jt-1}}^2}{\sigma_{Q_{jt-1}}^2 + \sigma_{ij}^2} \). The new information \( Q_{E_{jt-1}} - \mu_{Q_{jt-1}} \) is the difference between expected quality and use-experience quality revealed during period \( t-1 \). The precision of information obtained from use experience is given by the Kalman gain coefficient obtained from the Kalman filtering algorithm \( \frac{\sigma_{Q_{jt-1}}^2}{\sigma_{Q_{jt-1}}^2 + \sigma_{ij}^2} \). Accordingly, the updating of the variance of perceived quality is given by

\[
\sigma_{Q_{jt}}^2 = \sigma_{Q_{jt-1}}^2 - D_{jt-1} \frac{(\sigma_{Q_{jt-1}}^2)^2}{\sigma_{Q_{jt-1}}^2 + \sigma_{ij}^2}
\]

Thus, consumers’ quality perception is updated based on use experience. All else equal, the higher the number of use experience, the more precise is the consumer’s quality belief about the true quality. If premium brands deliver more consistent quality over time (or \( \sigma_{ij}^2 \) is smaller), consumers obtain more precise information from use experience, and thereby decrease their perceived risk faster for this brand than they do for other brands.

Note that we do not directly model brand loyalty or habit formation because brand persistency or habit formation is endogenously captured by the updating of quality belief. Even though consumers have identical priors, their perceptions of brand quality can diverge over time as they have different paths of use experience. Brand preference heterogeneity arises endogenously
over time for a priori identical consumers. In addition, consumer’s perceived variance of the quality of a brand is determined entirely by the amount of information that the consumer has received about the brands. When consumers are risk averse with respect to quality, consumers may choose to repeatedly purchase the same brand with lower quality uncertainty.

Given the assumption that use experience provides unbiased signals, we have 

\[ E[Q_{ijt} \mid I_{ijt}] = \mu_{Q_{ijt}} \; \text{; then we have} \; Q_{ijt} = \mu_{Q_{ijt}} + (Q_j - \mu_{Q_{ijt}}) + \xi_{ijt}. \]

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 to consumer \( i \) from purchasing brand \( j \) at time \( t \), given the information set, can be written as,

\[
E[U_{ijt}(s) \mid I_{ijt}) = \alpha_i(s)E[Q_{ijt} \mid I_{ijt}] + \alpha_i(s)\gamma(s)E[Q_j \mid I_{ijt}] + \beta_i(s)P_{ijt} + e_{ijt}(s)
\]

\[
= \alpha_i(s)\mu_{Q_{ijt}} + \alpha_i(s)\gamma(s)\mu_{Q_j} + \alpha_i(s)\gamma(s)E[(Q_j - \mu_{Q_j})^2 \mid I_{ijt}] + \alpha_i(s)\gamma(s)\sigma_{ijt}^2 + \beta_i(s)P_{ijt} + e_{ijt}(s)
\]

\[
= \alpha_i(s)\mu_{Q_{ijt}} + \alpha_i(s)\gamma(s)\mu_{Q_j} + \alpha_i(s)\gamma(s)(\sigma_{Q_j}^2 + \sigma_{ijt}^2) + \beta_i(s)P_{ijt} + e_{ijt}(s)
\]

There are a few things we need to point out in the expected utility function. First, the expected utility depends on both perceived quality and perceived risk, both of which have been shown to be important components of brand equity (Aaker 1991; Erdem and Swait 1998). When making choice decisions between premium brands and generic brands, consumers need to trade off perceived quality with prices and quality uncertainty. The high prices charged by premium brands prevent consumers from purchasing because the addictive nature of the product implies long-term commitment to pay higher prices. Even if premium brands do not charge a price premium, some consumers still may not choose premium brands because of higher perceived risk stemming from unfamiliarity with these brands. Second, we do not impose any restrictions on the value of risk coefficient. If \( \alpha_i(s) \) is estimated to be positive and \( \gamma(s) \) negative, it means consumers are the risk averse: The increased perceived-quality variance \( \sigma_{Q_j}^2 = E[(Q_j - \mu_{Q_j})^2 \mid I_{ijt}] \) and experience variability \( \sigma_{ijt}^2 \) decreases consumers’ expected utility and lowers brand-choice probability. In other words, risk-averse consumers avoid such deviations and are less likely to choose a brand with which they are unfamiliar. Note that consumers with less experience with a product may have higher uncertainty with that product. Finally, a decrease of \( \gamma(s) \) (in absolute value) implies that consumers become less sensitive to the perceived risk. Compared to the state in which they have a
high risk aversion coefficient, they are in a state in which they are willing to take more risk and experiment with brands with which are less familiar.

### 3.2. Consumer Latent States

Behavioral researchers have shown ample evidence that consumers have different states of mood and emotion and that consumer decisions depend on the states they reside (Ratner, Kahn and Kahneman 1999; Rabin 2000; Lerner, Small and Loewenstein 2004; Hsee and Rottenstreich 2004; Rottenstreich and Hsee 2001; Leith, Pezza and Baumeister 1996). For example, Ratner, Kahn and Kahneman (1999) established that consumers alternate between habit-persistent and variety-seeking states. Instead of assuming that consumers have static preferences for price and quality, we allow for the possibility that consumers may have multiple latent states in which they present different preference structures. This is captured by a hidden Markov process that was introduced to marketing by Montgomery et al. (2004) and Netzer, Lattin and Srinivasan (2005). In HMM, consumers are assumed to have multiple latent states and the transition among these states is governed by a hidden Markov process. The transition of states can be inferred from the observed longitudinal sequence of product choices. Different from the few time-varying coefficient approaches developed for reduced-form models, we capture the possible change of consumer preference in a more structured way by allowing consumers to have the probabilities of residing in multiple latent states, which is more consistent with consumer decision process. Assume there are $S$ latent states in which a consumer can be placed. At each time period, the consumer has $s=1, \ldots, S$ latent states to reside in. They can either stay in the current state or move to other states.

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8 Time-series models have been developed to allow the price coefficient to vary over time to study how promotion policy affects promotion sensitivity. Applied to store-level aggregate sales data, these models impose a VARMA structure as the evolution path for time-varying parameters. For example, Foekens, Leeftang and Wittink (1999), Haauer, Wedel (2001), and Pauwels, Hanssens and Siddarth (2002) used persistence modeling technique to study if the long-term promotion’s effect is transitory or permanent. They found no support for permanent effects. Kopalle, Mela, Marsh (1999) model the parameter dynamics by introducing the long-run exposure of price promotion and found that price promotion has positive immediate effects while having negative future effects. Dekimpe, Hanssens and Silva-risso (1999) use response function to separate evolution time trend and find that brand sales and category sales are mostly stationary. Pauwels and Srinivasan (2004) introduce a structural break unit-root tests to investigate whether store brand entry created structural change to each variable (univariate). Since the analysis is at the aggregate level, this stream of research offers empirical evidence on the change of price sensitivities at the store level without explaining the mechanism causing the shift of individual consumer preference.
We use an $S \times S$ matrix $\Theta_i$ to denote the probabilities for consumer $i$ to transit to another state at time $t$.

\[
\Theta_i = \begin{bmatrix}
\Theta_{i11} & \Theta_{i12} & \cdots & \Theta_{i1S} \\
\Theta_{i21} & \Theta_{i22} & \cdots & \Theta_{i2S} \\
\vdots & \vdots & \ddots & \vdots \\
\Theta_{iS1} & \Theta_{iS2} & \cdots & \Theta_{iSS}
\end{bmatrix}
\]

Each element in the transition matrix represents the probability of transit from state $s$ at $t-1$ to state $r$ at time $t$ for consumer $i$.

To capture the possibility that the consumer propensity for transition can be influenced by product prices available in the market, we define $W_{itS}$ as consumer $i$'s propensity to transit from state $s$ at time $t$. We assume the propensity for transition is a function of prices and unobservable factors to the researcher. The overall propensity for consumer $i$ from state $s$ can be written as

\[
W_{its} = \mu(s) \cdot PGAP_{it} + \zeta_{its}
\]

$PGAP_{it}$ is the vector of price difference between other brands and generic brands. $\mu(s)$ is a vector of coefficients to be estimated that measure the effect of prices on consumer propensity for transition. We assume price gaps have the same coefficients across brands in our estimation. $\zeta_{its}$ represent the unobserved factors that are assumed to be independently and identically extreme value distributed. Thus, the transition probability can be described by an ordered logit model with the thresholds levels $l(s, r)$ from state $s$ to $r$.

\[
\theta_{i1l} = \Pr(\text{transit from } s \text{ to } l) = \frac{\exp(l(s, l) - \mu(s) \cdot PGAP_{it})}{1 + \exp(l(s, l) - \mu(s) \cdot PGAP_{it})}
\]
\[ \theta_{sr} = \text{Pr}(\text{transit from } s \text{ to } r) = \frac{e^{\exp(l(s, r) - \mu(s)^\prime PGAP_\theta)}}{1 + e^{\exp(l(s, r) - \mu(s)^\prime PGAP_\theta)}}, \]

\[ \theta_{ss} = \text{Pr}(\text{transit from } s \text{ to } s) = 1 - \frac{e^{\exp(l(s, S - 1) - \mu(s)^\prime PGAP_\theta)}}{1 + e^{\exp(l(s, S - 1) - \mu(s)^\prime PGAP_\theta)}}, \]

for \( 1 < r < S \).

Define the probabilities of consumer \( i \) residing in state \( s \) for \( s = 1, \ldots, S \) at time \( t \) as a vector \( \Pi_i = (\pi_i(1), \ldots, \pi_i(S))' \). From the transition matrix, we can obtain \( \Pi_{it} \) according to

\[ \Pi_{it} = \Pi_{i,t-1} \Theta_{\theta}. \]

Since the transition matrix is not stationary, we use the stationary distribution at the mean of the time varying covariates prior to the price cut. We assume the initial state distribution \( \Pi_{i0} \) is the solution to the equation \( \Pi_{i0} = \Pi_{i0} \overline{\Theta}_{\theta} \), where \( \overline{\Theta}_{\theta} \) is the transition matrix at the mean of the covariates prior to the Malboro price cut.

### 3.3 Forward Looking Consumers

Recent economics literature has established that forward-looking behavior explains the observed patterns of heavy drinking and smoking better than myopic models (Arcidiacono et al. 2005) due to the addictive nature of tobacco consumption. To be consistent, we model consumers as forward-looking decision makers who maximize the sum of their discounted future expected utilities. Given the permanent price change is public announced, we assume consumers do not have uncertainty about the new pricing policy.

\[ \max_{D_{ij}} \left\{ E_i \sum_{\tau = 1}^{T} \delta_i^{\tau - 1} E_i[U_{ij} \tau(s)|I_{ij}] \right\} \]
where \( \delta \) is the discounting factor measuring the trade-off between current and future expected utilities. The operator \( E_t[.] \) stands for the conditional expectation given the consumer's information set at time \( t \). \( E_t[U_{ijt}(s) \mid I_{it}] \) is the state-dependent per-period utility function as defined in Equation (7). We follow the convention and set the utility discount rate to be 0.995.

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

\[
V_{ijt}(s \mid I_{it}) = E[U_{ijt}(s) \mid I_{it}] + \delta E[\max_{D_{ijt+1}} V_{ijt+1}(s)(I_{it+1}) \mid I_{it}]
\]

Equation (13) captures the notion that consumers may not choose the brand that gives the highest expected time \( t \) utility, since they also consider how the time \( t \) decision affects \( I_{it+1} \) and therefore expected utility in future periods. The optimal choice is given by

\[
D_{ijt} = \arg \max_{D_{ijt}} \{ D_{ijt} V(I_{it}) \}
\]

In the above set-up of the model, the decision variable is brand choice and the endogenous state variables are mean and variance of experienced quality of each product.

### 3.4. Log Likelihood Function

Let \( \Psi = \{\alpha(s), \gamma(s), \beta(s), Q_{j0}, \sigma_{Q_{j0}}, \sigma_{\xi_j}, l(s, r), \mu(s)\} \) for all \( s \) denote a vector of coefficients to be estimated. More specifically, we estimate the following coefficients: (1) quality coefficient \( \alpha(s) \); (2) risk-aversion coefficient \( \gamma(s) \); (3) price coefficient \( \beta(s) \); (4) expected initial quality for each brand \( j Q_{j0} \); (4) standard deviation of the prior perceptions of each brand \( \sigma_{Q_{j0}} \); (5) standard deviation of the use-experience variabilities \( \sigma_{\xi_j} \); (6) thresholds of transition \( l(s, r) \); (7) price coefficients in transition equation \( \mu(s) \). These parameters are estimated for each state \( s=1, \ldots, S \).

Define \( V_{ijt}^*(s) = V_{ijt}(s) - e_{ijt}(s) \) as the deterministic part of the utility function in Equation (7). Assuming the error term \( e_{ijt}(s) \) is independently and identically extreme value distributed, we can obtain the probability of a consumer at time \( t \) purchasing brand \( j \) conditional upon \( \Psi \),
Thus the log-likelihood function to be maximized is

\[
\log L(\Psi) = \sum_{i=1}^I \sum_{t=1}^T \sum_{j=1}^J D_{ijt} \log[\Pr(\text{ob}(D_{ijt} = 1 | \Psi)]
\]

To estimate the model, we use simulated maximum likelihood, which employs Monte Carlo methods to simulate the integrals rather than evaluating them numerically (McFadden 1989, Keane 1993). Since state variables are continuous, we have the problem of a large state-space. We adopt the interpolation method developed by Keane and Wolpin (1994) by calculating the value functions for a few state space points and using these to estimate the coefficients of an interpolation regression. Then the interpolation regression function is used to provide values for the expected maxima at any other state points for which values are needed in the backwards recursion solution process.

### 3.5. Initial Values and Identification

For identification purposes, we have \( \sum_{j=1}^J Q_j = 0 \). Since absolute quality levels have no meaning, the quality level for one brand must be fixed to normalize the scale. This avoids the identification problem of adding a constant to quality levels leads to no uniqueness of the price, quality and risk coefficients. We set \( Q_6 = 0 \), meaning we normalize the discount brand of RJR to have a quality level of 0 and measure quality of other brands relative to this brand. We also normalize the use-experience variability of premium brands \( \sigma_{\xi_j} \) to be a constant 5.

Since the first observation period does not coincide with the start of a household’s choice process, we follow Erdem, Keane and Sun (2005) and assume the consumer’s prior variance on the
quality level of brand $j$ at the start of our estimation period is given by \( \ln \sigma_{Q_{ij}} = \ln \sigma_{Q_{ij}} - k \sum_{\tau=-5}^{0} D_{ij\tau} \),

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 will have lower uncertainty on brand $j$.

To reduce the number of parameters, we estimate variance of the initial quality and experience variability \( \sigma_{Q_{ij}}, \sigma_{\tilde{x}_{ij}} \) at the quality-tier level. In other words, we group brands within the same quality tier and estimate these variables for premium brands, mid-tier brands, and generic brands.

4. Empirical Results
4.1 Model Comparison

In Table 2, we report and compare the model fit statistics of several competing models. To demonstrate whether our proposed model better explains the data than existing models, we estimate two benchmark models. The first model is our proposed model without forward-looking, learning, or time-varying coefficient. It is similar to most existing static heterogeneous logit models. The second model is our proposed model with forward-looking, and consumer learning, but without the time-varying coefficient. This model is similar to most existing dynamic structural models that are proposed to study consumer purchase and consumption behavior under promotion uncertainty, in which consumer preference is assumed to be fixed over time (Erdem and Keane 1996; Gonul and Srinivasan 1996; Sun, Neslin and Srinivasan 2003; Sun 2005). The third model is our proposed dynamic structural model with both learning and time-varying coefficients.

Since the three models have either intra- or inter- consumer heterogeneity, we need to determine how many states or how many segments best fit the data. To address this empirical question, we estimate the three competing models for various segments and states. The results indicate that Model 1 with four segments, Model 2 with four segments, and Model 3 with three states are the best-fitting models. It is interesting to find that without allowing for time-varying coefficients, Models 1 and 2 find four segments. Thus the intra-consumer heterogeneity is
captured by inter-consumer heterogeneity. This is because HMM approach allows for dynamic segmentation, which nests the static latent class approach. We report in Table 2 the model fit statistics of the three competing models with the chosen numbers of states or segments.

The comparison of model-fitting statistics shows that our proposed model significantly outperforms Models 1 and 2, suggesting that it is important to allow for forward-looking, time-varying coefficients as well as learning to reduce uncertainty in our application. Since our proposed model is the best-fitting model, our following discussion will focus on Model 3.

4.2. Estimates of Parameters in the Utility Function

Now we discuss the parameter estimates in the utility function listed in Table 3. All the coefficients are significant with expected signs with the only exception of price coefficient in state 3. In general, the price coefficients in all three states are low indicating consumers are not very price sensitive. This may be due to the highly addictive nature of tobacco consumption, which prevents consumers from being responsive to price changes. It is consistent with the findings of the American Lung Association that average consumers have low sensitivity to cigarette price (for every 10% increase in cigarette prices, the demand reduces by only 4%).

Comparing the changes of price, risk aversion, and quality coefficients across the three states, we notice that the first consumer state is characterized by high risk aversion coefficient (-1.11) while the other two states are featured by low risk aversion coefficients (-0.45 and -0.41). Based on this observation, we label consumer state 1 as the “habit-persistent state,” and states 2 and 3 as the “variety-seeking states.” This confirms the findings of Ratner, Kahn and Kahneman (1999). Interestingly, within the two variety-seeking states, state two is featured by high price sensitivity (-0.16 versus -0.01) and state three is identified by high quality sensitivity (0.97 versus 3.71). Thus, when consumers are in variety-seeking states 2 and 3, their variety seeking behavior are driven by either price or quality.

4.3 Transition of Latent States
The price gaps between premium and mid-tier brands and generic brands is shown to have a negative effect on the transition probabilities for consumers to switch from the habit-persistent state to the variety-seeking states, and positive effect for them to switch out of price-driven variety-seeking state, and negative effect for them to switch out of quality-driven variety-seeking states. Thus, the lower the listed price of Marlboro, the higher the probabilities for consumers to be adventurous, the lower the probabilities to try lower priced unfamiliar brands, but the higher the probabilities to explore unfamiliar brands with higher quality. This is because the lower prices make forward-looking consumers realize the reduced long-term financial cost. They are encouraged to be less guarded on uncertainty, focus more on quality and less on price, and experiment unfamiliar brands.

[Insert Figure 2A, 2B, 2C, and 2D About Here]

Based on the parameter estimates in the transition probability function, we calculate the periodical transition probabilities according to Equations (10) and the resulting probabilities of residing in each state according to Equation (11). In Figure 2A, we show how average probabilities of being in the three states change over time. Based on the general trend of how these probabilities change over time, we observe that the whole observation period can be separated into three regimes. The first regime is from the beginning of the observation period to Week 30. The second regime covers Week 31 to Week 69, followed by the third regime. The figure shows that during the regime before the Marlboro event, consumers have high but stable probabilities of residing in the habit-persistent state. During the second regime, consumers significantly decrease their probabilities of residing in the habit-persistent state. They become much more adventurous. In the remaining weeks, the probabilities of residing in the habit-persistent state stabilize again with a slight decreasing trend. In general, the average probabilities of residing in the habit-persistent state are much lower during the third regime than that in the first regime.

The change of transition probabilities causes a change of population preference for quality, risk, and price. We calculate the population preference for quality, risk, and price and trace the change of these variables over time in Figure 2B, 2C, and 2D, respectively. We observe that consumer preferences are relative stable before Marlboro event. This supports the non time-varying coefficients approach commonly adopted in marketing literature to study consumer
response to temporary price promotions. However, when there is a publicly announced new price policy, consumer preferences are shifted, which suggests a long-lasting effect of permanent price cut on consumer decision process. The preferences slowly stabilized during the third regime. Comparing to pre-event regime, consumers become more quality sensitive, less risk averse, and less price sensitive and thus their purchase decisions are more driven by quality and less by price in the long-run.

4.4 Experimentation and Learning

As mentioned before, the transition to the variety-seeking state and the resulting shift of consumer preference allows consumers to experiment with unfamiliar brands after the permanent price cut. We now discuss consumer learning of product quality, which is implied by the quality estimates in Table 3. Recall that our measure of quality is a summary statistic of perceived multidimensional product attributes, and uncertainty of product quality can be caused by less experience with the product. It is not surprising to find that the estimates of mean quality, \( Q_j \), are estimated to be higher for premium brands than for generic brands. The nonzero estimates of initial quality variance \( \sigma^2_{Q_0} \) are 7.89, 7.92, and 7.72 for premium, mid-, and low-tier, respectively. These initial variances indicate that consumers have uncertainty with regards to various brands. Interestingly, the initial variances of Marlboro and the premium brands are not very different from those of the generic brands. Unlike other product categories, for which premium brands demonstrate lower initial quality uncertainty, smokers have high quality uncertainty even for premium brands such as Marlboro at the beginning of our observation period. The high price premium charged by national brands, coupled with the addictive nature of tobacco consumption, results in a fragmented market. Given that consumers are found to be risk averse, the unfamiliarity with Marlboro prevents forward-looking consumers from purchasing this brand, which contributes to the erosion of market shares.

The experience variability parameters \( \sigma^2_{\xi_j} \) are estimated to be 5.05 and 5.12 for mid- and low-tier brands, with that of premium brands normalized to be 5. This indicates that use experience provides noisy information. The experience variability is slightly higher for low-tier brands than for premium brands. This could be due to the fact that premium brands usually deliver
more consistent quality levels than generics do. Consumers can derive more accurate information from consumption experience of premium brands. The same amount of use experience is more effective in reducing quality uncertainty for premium brands than for generic brands.

To illustrate how use experiences help consumers learn about product quality, in Figure 3A, we plot the evolution of average quality variance \( \sigma_{\theta}^2 \) for Marlboro, premium, mid-, and low-tier brands over the observation regime. During the first regime, the variances of premium, and mid-tier brands stay quite constant, indicating a fragmented market before the Marlboro event. The products of each quality tier are purchased by their loyal consumers, who are already familiar with these brands, and additional consumption does not contribute much to the decrease of quality uncertainty. During the second regime, the quality variances of premium brands drop quickly as the permanent price cut encourages consumers to experiment with these brands. Since use experience serves as the only information channel in our model, consumers learn about Marlboro and significantly reduce their quality uncertainty. Although the quality uncertainty of generic brands also drops, the rate of drop is slower than in the first regime. This is because the price cut induces consumers to switch from generic brands to premium brands, and thus reduce the use experience with generic brands. During the third regime, we observe slower but more steady decrease of uncertainty regarding premium brands. After extensive experimentation, consumers become much more informed about Marlboro and the learning slows down. However, the overall reduction of quality uncertainty increases consumer propensity for purchasing premium brands. This leads to a more noticeable steady decrease of quality uncertainty during the third regime than during the first regime, when consumers are less informed and the market was highly fragmented. Overall, we find that the permanent price cut induces consumers to shift preference, which facilitates them to experiment unfamiliar brands. The experimentation effectively reduces uncertainty, breaks consumer’s sticky consumption behavior, and mitigates market fragmentation.

In Figure 3B, we draw the price-adjusted perceived quality for the four quality tiers. In the first regime, we observe a big gap between the price-adjusted quality of Marlboro and generic brands. Even though the premium brands are perceived to be of higher quality, the quality difference does not seem to justify the price premium charged by these brands. The generic brands
are more attractive to consumers because of the higher price-quality ratio. The significant difference in price-adjusted perceived quality coupled with the high uncertainty shown above explains the erosion of market share of Marlboro before the Marlboro Event. During the second regime, the price cut of Marlboro immediately decreases the price-adjusted quality gap. In addition, the price induced trials reduce the variance of perceived quality while increasing the mean perceived quality, which further closes the gap. At the third regime, the gap continues to close slowly but steadily. During the last 20 weeks of our observation period, the average gap becomes 33% smaller than the average gap before Marlboro event. However, we should note that the price-adjusted perceived quality of Marlboro is still higher than that of the discounted brands, suggesting that Marlboro still faces the pressure of losing consumers to generic brands, albeit on a smaller scale.

As we discussed before, Equation (7) indicates that consumers trade off higher perceived quality with higher prices and quality uncertainty when making choices between premium and generic brands. Before the Marlboro event, the high price premium charged by Marlboro resulted in a fragmented market in which consumers did not respond to temporary price promotions to switch from generics to Marlboro (and other premium brands). The permanent price cut of Marlboro was needed to close the price gap and induce consumers to experiment with Marlboro. The new price charged by Marlboro is more aligned with the improved perceived quality with significantly reduced uncertainty. This makes Marlboro more attractive and increases consumer propensity for purchasing Marlboro. Since brand loyalty is endogenized in the learning process, lower quality uncertainty actually increases consumer’s loyalty to Marlboro. This is particularly true among those consumers who experimented extensively Marlboro.

4.5 Three Regimes and Impact on Market Shares

According to the above discussion, our results indicate that the permanent price cut shift consumer preference for price, quality, as well as risk attitude. Before the Marlboro event, when high price premiums were charged by Marlboro, risk-averse consumers stayed in their habit-persistent state and were less likely to switch brands given the addictive nature of tobacco consumption. This resulted in a fragmented market in which each brand had a group of “sticky” consumers. Consumers have better knowledge of the products they frequently consume and significant
uncertainty for those that they are not addicted to, including premium brands. After the price cut, realizing it is permanently cheaper to consume Marlboro (and other premium brands), forward-looking consumers shift their preference structure, which allows them to loosen up their well-established habit persistence and experiment with unfamiliar brands. After a few month of experimentation, the more informed consumers establish a preference structure that are more quality focused and less price emphasized.

According to the above discussion, we label the three states as “pre-event” regime, “experimentation” regime, and “post event” regime. Note that the three regimes implied by the transition probabilities in Figure 2 are roughly consistent with the change of quality uncertainty shown in Figure 3A. Interestingly, the second regime starts in Week 31. There is a noticeable three months delay after Marlboro made the announcement for average consumers to shift their preference. This delay may be caused by several factors: First, when the price change was announced as price promotion (Marlboro Friday), consumers are found not to respond by shifting their preference structure. This confirms our previous conjecture that consumers do not react to price promotion, but to a permanent price cut, by shifting their preference. Second, even though Marlboro publicly announced its new pricing policy, it usually took a while to reach the average consumers. Third, as shown by Figure 1A, it took about two or three months for RJR and other premium brands to follow suit, which may have caused the delay of the average consumer’s changing of decision rule.

We next address the fundamental question leading up to the event: Did a permanent price cut help mitigate the eroding market share of Marlboro? In Table 4, we report the change of average probabilities of residing in variety-seeking states and of purchasing Marlboro over the three regimes. To study the differential impact of permanent price cut on different consumers, we separate consumers into price segment and quality segment based on their average probabilities of residing in state 2 during the pre-event regime (since consumers have high price sensitivity in this state). If consumers’ average probabilities of staying in state 2 dominate those in state 1 and 3, we classify them in the price segment. Otherwise, they are classified in the quality segment.

We observe that the average probabilities of both residing in variety-seeking states and
purchasing Marlboro increase from the first regime to the post-event regime. However, the permanently reduced price has a differential impact on consumers who are *a priori* price and quality driven consumers. Comparing to those in the quality segment, consumers in the price segment seem to be influenced much more by the permanent price cut as their probabilities of residing in variety-seeking states are increased more. Also, comparing to the 17% increase of purchase probabilities for consumers in the quality segment, the increase is about 44% among those in the price segment. This is because being price sensitive to begin with, these consumers are more likely to respond to the permanent price cut and experiment with Marlboro. In addition, given that they are more likely to be sticky to generic brands before the event, there is more room for them to improve their knowledge of Marlboro through use experience. Overall market shares of Marlboro increased by 4%, constituting a 25.3% increase in sales. This is particularly significant as it reversed the trend of the previous few years of share losses, and given the fact that major competitors matched the permanent price change.

### 4.6 Promotion Elasticities

We now study how the Marlboro event changes Marlboro’s competitiveness relative to competing brands in situations when temporary price promotions are offered. In Table 5, we report the switching matrix among Marlboro, premium brands, mid-tier brands, and discounted brands before and after the event. The switching matrix is obtained by reducing the price of each brand by 10% in a randomly chosen week and simulating the percentage changes of purchase probabilities of all the four quality tiers. All the self- and cross- elasticities decrease in the post-event period. This is because the permanent price cut makes consumers less price sensitive and this change of consumer preference also applies to their purchase behavior towards other brands. If consumers don’t respond to promotion due to uncertainty before the event, they become less responsive to promotion due to their shift of emphasis from price to quality after the event. This changes works better for Marlboro. When discounted brands offer temporary promotions, the cross-elasticity of Marlboro decreases the most from the pre-event period to the post-event period. This suggests that the promotions offered by generic brands are less likely to attract consumers from Marlboro.
Marlboro becomes less vulnerable to promotions of discounted brands. When Marlboro offers a price cut in the post-event regime, it draws more purchases from mid-tier brands than from other premium brands and lower-tier brands as in the pre-event regime. To some extent, the strategic step undertaken by Marlboro makes it more competitive and less vulnerable to discounted brands.

4.7 Summary

To better summarize the empirical findings, we graphically demonstrate the effect of a permanent price cut on consumer choices and purchase propensity of Marlboro in Figure 5. When a permanent price cut is publicly announced, consumers realize that it is permanently cheaper to consume premium brands. As predicted by Lucas, the new pricing regime results in the change of consumer overall preference. They break out from their purchase habits and go through an experimenting period to learn about the other brands. The experimentation in turn reduces the uncertainty with regards to previously unfamiliar brands. In the long run, consumers place lower emphasis on price and higher emphasis on quality. From Marlboro’s perspective, the newly established preference implies that, on average, consumers are more likely to purchase and remain loyal to Marlboro for the following reasons: First, the price of Marlboro is permanently lower, which directly increases the utility of purchasing Marlboro. Second, consumers who went through the experimentation phase reduced their quality uncertainty of Marlboro, which increases their purchase probabilities and brand loyalty for Marlboro. Third, consumers emphasize more on quality. As a result, market share of Marlboro increases.

We want to point out that the well-documented mechanism of how frequent price promotions increase consumer price sensitivities (e.g., Kim and Lehmann 1993; Papatla and Krishnamurthi 1996; Mela, Gupta and Lehmann 1997) is different from that of how a permanent price cut shifts consumer preference for price and quality. Under price promotions that are the frequent, temporary, and unexpected price shocks, consumers “are trained” or “react” to be more price sensitive because repeatedly observed frequent promotions make consumers change their reference price and expected future price, which affects consumer utility, and hence choices. On the contrary, the publicly announced permanent price cut directly affects population preference to change because consumers are induced to switch out of habit-persistent state to experiment with
unfamiliar brands. Furthermore, the increase of price sensitivity because of price promotion may hurt brand equity. However, through the non-intuitive mechanism described in Figure 4, PM’s permanent price cut increases its market share and (in some sense) preserves brand equity.

Here is a summary of our major findings regarding how the Marlboro event changed consumer purchase behavior.

- Consumers are found to reside in “habit persistent” and “variety seeking” states. The price cut induce consumers to transit to the variety-seeking states.
- The new pricing policy shifts consumer preference in the long-run. Consumers become more quality sensitive and less price sensitive.
- The shift of consumer preference allows consumers to experiment with unfamiliar premium brands, which translates into gradual reduction of quality uncertainty.
- The new pricing policy has a bigger impact on the a priori price-sensitive consumers.
- Consumers are more likely to purchase Marlboro because of higher quality sensitivity, lower quality uncertainty, and permanently lowered prices.

From the empirical evidence, we draw the following implications regarding the evaluation of Marlboro’s pricing policy. Before the permanent price cut, Marlboro was vulnerable to the discounted brands. A drastic and publicly announced price cut was necessary to break consumer inertia. Marlboro’s policy was effective in increasing its market share. Marlboro achieved its intention of making consumers focus on quality. The strategic price shift of Marlboro increases the effectives of temporary price promotions as well as competitiveness of Marlboro to generic brands. These changes imply long-term profit and cash-generating power. It seems to be a necessary and effective strategy to combat the uprising generic brands, and to some extent the overall results seem to fall into the management’s expectation.

5. Conclusion, Limitation, and Future Research

Unlike most price promotions studied by the existing marketing literature, Marlboro’s new pricing policy was a publicly announced permanent price cut. This policy has been followed by other manufacturers of premium consumer products to combat their losing market share to generic
brands. According to Lucas, consumers who are informed of the permanent price change are more likely to strategically shift their decision rules to adapt to the new pricing policy. To our knowledge, this is the first paper to explicitly examine the impact of PM’s pricing strategy on consumer choice behavior and to evaluate the effectiveness of these policy changes. Our objective in this paper was to (1) study whether permanent price cuts cause consumer preference to shift over time; (2) examine how the price cuts affect consumer choices in an immediate and permanent way; (3) examine the differential and dynamic effect of price cuts on consumers; (4) evaluate the immediate and long-term impacts of a permanent price shift on market share.

We develop a dynamic structural brand-choice model with consumer learning and time-varying coefficients to study how a permanent shift of pricing policy affects consumer decisions. Applying our model to purchase history data of cigarettes around Marlboro Friday, we evaluate the immediate and permanent impact of Marlboro’s event on its market share and draw implications on the brand competition between Marlboro and uprising generic brands. Results show that consumers adjust their preference structure to adapt to the new pricing regime. A permanent price cut is needed to encourage consumers to experiment premium brands. Reduced uncertainty of premium brands coupled with newly established consumer preference helped alleviate erosion of Marlboro’s market share and increase the loyalty among consumers who prefer Marlboro. As a result, Marlboro is better positioned and less vulnerable to discounted brands.

Substantively, this is the first empirical study that explicitly examines how consumers react to a permanent shift of marketing variable and draw implications on whether such a drastic strategy is necessary and effective to combat uprising generic brands. Methodologically, it is the first attempt to empirically model the coexistence of the consumer “habit persistent” and “variety seeking” states in the framework of a forward-looking model with consumer learning. The proposed model avoids the “Lucas Critique” by allowing for both forward-looking and time-varying preference. Although we take Marlboro Friday as an example to demonstrate how a permanent price change affects consumer choice behavior, a modified methodology can be applied to other similar situations, such as P&G’s move from high-low pricing to everyday low pricing and co-branding of major brand manufacturers.

Obviously, there are several caveats to our analysis and directions for future research. From a modeling perspective, future research can allow forward-looking consumers to form expectations about the schedule of permanent price cuts of different brands and study how their
expectations affect consumer purchase behavior. Similarly, a more flexible time-varying coefficient model can be developed to allow for the migration of consumers among segments. 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 the retailers and major competitors to adopt the new pricing policy. It would be interesting to study how competitors and retailers gradually follow the price cut and adjust their pricing policies. Finally, it would interesting to study how consumers react to changes in other marketing strategies such as co-branding or a permanent change from HILO to EDLP.
Reference


### Table 1. Market Share and Average Prices

<table>
<thead>
<tr>
<th>Brand Choice</th>
<th>Average Market Shares</th>
<th>Average Prices per Pack</th>
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<sup>1</sup> Due to negligible market share, we do not include lower tier of PM in empirical analysis.

### Table 2. Model Comparison

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<tbody>
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<td>In-Sample:</td>
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<tr>
<td>-LL</td>
<td>24977.0</td>
<td>24445.2</td>
<td>23523.4</td>
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<tr>
<td>AIC</td>
<td>25006.0</td>
<td>24474.2</td>
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<td>BIC</td>
<td>25127.8</td>
<td>24595.9</td>
<td>23689.7</td>
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Table 3. Estimation Results

<table>
<thead>
<tr>
<th>Parameters</th>
<th>State 1</th>
<th>State 2</th>
<th>State 3</th>
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<tbody>
<tr>
<td><strong>Utility Function</strong></td>
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<tr>
<td>Quality</td>
<td>0.32(0.10)(^1)</td>
<td>0.97(0.01)</td>
<td>3.71(0.13)</td>
</tr>
<tr>
<td>Risk Averse</td>
<td>-1.11(0.07)</td>
<td>-0.45(0.01)</td>
<td>-0.41(0.01)</td>
</tr>
<tr>
<td>Price</td>
<td>-0.03(0.01)</td>
<td>-0.16(0.02)</td>
<td>-0.01(0.01)</td>
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<tr>
<td><strong>Transition parameters</strong></td>
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<tr>
<td>Price gap</td>
<td>-0.28(0.36)</td>
<td>0.16(0.28)</td>
<td>-1.68(0.38)</td>
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<tr>
<td>Threshold to higher state</td>
<td>2.87(0.28)</td>
<td>3.66(0.22)</td>
<td>NA</td>
</tr>
<tr>
<td>Threshold to lower state</td>
<td>NA</td>
<td>-3.55(0.23)</td>
<td>-5.03(0.31)</td>
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<tr>
<td><strong>Quality</strong>(Q_j)</td>
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</tr>
<tr>
<td>Marlboro</td>
<td>1.74(0.02)</td>
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<tr>
<td>Premium tier</td>
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<tr>
<td>Philips Morris</td>
<td>1.76(0.04)</td>
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<tr>
<td>RJR</td>
<td>1.86(0.03)</td>
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<tr>
<td>Others</td>
<td>1.82(0.04)</td>
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<tr>
<td>Mid tier</td>
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<td>Philips Morris</td>
<td>1.47(0.03)</td>
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<tr>
<td>RJR</td>
<td>1.26(0.04)</td>
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<tr>
<td>Others</td>
<td>1.41(0.03)</td>
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<tr>
<td>Lower tier</td>
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<tr>
<td>RJR</td>
<td>0 (fixed)</td>
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<tr>
<td>Others</td>
<td>0.87(0.03)</td>
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<tr>
<td><strong>Quality variance</strong>(\sigma_{j0}^2)</td>
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<tr>
<td>Premium</td>
<td>7.89(0.08)</td>
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<td>Mid</td>
<td>7.92(0.09)</td>
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<tr>
<td>Low</td>
<td>7.72(0.11)</td>
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<tr>
<td><strong>UE variability</strong>(\sigma_{\tilde{y}}^2)</td>
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<tr>
<td>Premium</td>
<td>5(fixed)</td>
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<tr>
<td>Mid</td>
<td>5.05(0.29)</td>
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<tr>
<td>Low</td>
<td>5.12(0.57)</td>
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<td>(k)</td>
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<td>3.00(0.09)</td>
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\(^1\) We report standard errors in the parenthesis.
Table 4. Consumers’ Migration Path and Impact on Premium Tier’s Market Share

<table>
<thead>
<tr>
<th>Migration Path</th>
<th>% of Consumers</th>
<th>Average Purchase Probability of Marlboro</th>
<th>Pre-Announcement</th>
<th>Experimentation</th>
<th>After-Announcement</th>
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</thead>
<tbody>
<tr>
<td>A prior Quality Segment</td>
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<tr>
<td>Prob of Residing in VS State</td>
<td>60.3</td>
<td>63.4</td>
<td>65.0</td>
<td>65.6</td>
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<tr>
<td>Prob of Purchasing Marlboro</td>
<td>23.3</td>
<td>26.6</td>
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<td>27.2</td>
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<td>A prior Price Segment</td>
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<tr>
<td>Prob of Residing in VS State</td>
<td>39.7</td>
<td>15.6</td>
<td>27.5</td>
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<td>31.9</td>
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<td>Prob of Purchasing Marlboro</td>
<td>6.8</td>
<td>10.3</td>
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<td>9.8</td>
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<td>Total Market Share of Marlboro</td>
<td>15.8</td>
<td>19.5</td>
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Table 5. Promotion Elasticities

<table>
<thead>
<tr>
<th>Pre-event stage</th>
<th>MB</th>
<th>Prem</th>
<th>Mid</th>
<th>Low</th>
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<tr>
<td>MB</td>
<td>0.838</td>
<td>-0.237</td>
<td>-0.130</td>
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<tr>
<td>Prem</td>
<td>-0.139</td>
<td>0.266</td>
<td>-0.079</td>
<td>-0.039</td>
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<tr>
<td>Mid</td>
<td>-0.094</td>
<td>-0.106</td>
<td>0.211</td>
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<tr>
<td>Low</td>
<td>-0.061</td>
<td>-0.047</td>
<td>-0.118</td>
<td>0.191</td>
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<table>
<thead>
<tr>
<th>After-event Stage</th>
<th>MB</th>
<th>prem</th>
<th>mid</th>
<th>low</th>
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<tr>
<td>MB</td>
<td>0.476</td>
<td>-0.142</td>
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<td>Prem</td>
<td>-0.073</td>
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<td>Mid</td>
<td>-0.052</td>
<td>-0.058</td>
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<td>Low</td>
<td>-0.024</td>
<td>-0.021</td>
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</table>
Figure 1A. Change of Prices

![Figure 1A. Change of Prices](image)

Figure 1B. Change of Market Shares

![Figure 1B. Change of Market Shares](image)
Figure 2A  Probabilities of Residing in Habit-Persistent State

<table>
<thead>
<tr>
<th>Event</th>
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<tr>
<td>Pre-event</td>
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<td>Experimentation</td>
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<tr>
<td>Post-event</td>
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Figure 2B Shift of Preference Parameters

![Graph showing the shift of preference parameters for Quality, Price, and Risk.](figure_2b.png)
Figure 3A. Change of Variance of Perceived Quality

Figure 3B. Change of Price Adjusted Perceived Quality
Figure 5. Graphical Demonstration of How Permanent Cut Affects Marlboro’s Market Share

Experimentation Stage

- Permanent Price Cut
  - Instantaneous Promotion Effect
    - Shift of Preference Structure
      - Migration of Consumers
  - Price-induced Experimentation
    - Increase Perceived Quality of Marlboro
      - Reduce Quality Uncertainty of Marlboro

Post-Event Stage

- Informed consumers (reduce quality uncertainty)
  - Shift of Preference (higher emphasis on quality)
    - Change Composition (better separate quality and price consumers)
  - Increase Market Share (especially among those who experimented MB)
  - Higher Loyalty (especially among quality consumers)