When Consumers Are Fascinated by Brand-New Models: A Case of US Golf Drivers Market *

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Abstract

This study sets up a dynamic model of demand to identify consumers' preferences for "newness" of products in a new durable goods market, namely golf drivers market. Forward-looking heterogenous consumers with preferences for newness of products decide when and what to purchase. The model also accounts for the fact that the market is highly subject to seasonal fluctuations. Using the aggregated data from the US golf drivers market the model succeeds at identifying consumers' preference for newness of products when the seasonality and quality differences are controlled for. Experiments with different assumptions are performed to confirm the robustness of the model. Finally, a counterfactual analysis of a merger scenario is carried out to see the effect of consumers' preferences for newness on the volume of sales.

Keywords: Consumer dynamics, preference for newness, consumer heterogeneity, seasonality, golf drivers

JEL Classifications: D12, D22, L11, L68.

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1 Introduction

The market in this study, the golf drivers market, is highly subject to seasonal fluctuations. Another stylized fact of the golf drivers market is that the consumers seem to have strong preferences for "newness" of products. This study attempts to identify consumers' preferences for newness and measure the amount of newness premium when the seasonality and quality difference are controlled for.

Then, what is newness? The definition we use in this study is the status of being the latest model among its own brand.[1] It is distinguished from the age of a product defined as the time elapsed from the model's first inception in the market. Consumers do not prefer a product just launched last month to one released two months ago simply because the former is introduced a month later than the latter. Rather they compare all the latest models of several brands available in the market if they care about new models much. In many circumstances, the newness of a product does not necessarily mean a better quality, e.g. moving manufacturing site from US to China for cost reduction that can yield lower quality. Moreover, the best seller is not always the best product.

Strong preference for the newness of a product can be explained by the prestige and image effect. As in Stigler and Becker (1977) and Becker and Murphy (1993) we can consider the prestige effects of consuming a new good. As Becker and Murphy suggested we think of the effect of introducing a new model in a characteristic sense. Having preferences for search and experience characteristics as described in Stigler (1961), consumers also have preferences for "introducing characteristics" and subsequently "newness characteristics" including when was the last time the brand launched a new model and how frequently a brand introduces new models. Beyond the prestige effect, to a small degree, the snob effect and the Veblen effect contribute to the strong preference for newness. Observing fairly fast drops in price over time, they play a role in explaining why consumers, or early adopters, want to purchase the just launched drivers even though they are relatively expensive, instead of waiting until the price falls sufficiently. Consumers prefer to use newer driver models because they are different from those commonly used/preferred, e.g. your golf buddies envy your new driver's exclusive look. Some consumers buy a new model because they think it serves as a means of attaining or maintaining their social status.

[1]Throughout the study, we use firm and brand interchangeably. They are considered identical but are used to represent the circumstances appropriately.

Golf drivers have rich taste aspects in a horizontal sense. Almost all observable characteristics are taste characteristics including bona fide taste characteristics, e.g. hitting sound, loft of head, length and stiffness of shaft, and feel of grip, as well as many other characteristics inherently having trade-offs between them, e.g. distance the driver carries a ball, accuracy, and forgiveness[2]. A difference in quality among products still exists at least over time, a challenge to an econometrician that requests to find an observable and discernable (to the econometrician) quality measure in a vertical sense.[3]

For the time frame of data, 2005-2009, head size of a driver can serve as an effective quality measure: it is observable for all models and it generally grows over time encompassing overall performance improvement and raised cost. Most importantly, it lets the consumers' preference for newness be identified in the model by absorbing all aspects of quality.[4]

In dealing with durable goods, recent literature extends models with demand-side dynamics to explore consumers' optimal timing problem. Consumers face intertemptoral trade-offs: they compare the value of purchasing a product today to what it is expected later. Initiated by Melnikov (2001), a stream of literature adopt a logit specification to derive the expected utility of product choice in a simple closed form including Song and Chintagunta (2003), Gowrisankaran and Rysman (2011), Carranza (2007), Zhao (2008), and Conlon (2010). Many of studies analyze high-tech industries including digital cameras, video games, and LCD TVs. A stylized fact in these industries is a declining price path over time, which motivates a dynamic modeling of demand.

On the supply side, however, firms' dynamic pricing decisions are not fully exploited except Nair (2007), Zhao (2008), and Conlon (2010) among others. Nair models a serially correlated price process of forward-looking firms, Zhao deals with a dynamic Euler equation approach originated in Berry and Pakes (2000) to derive the optimality condition for pricing, and Conlon sets up forward-looking firms' pricing in response to demand state. However, they all rely on assumptions that eliminates the inter-temporal influences between competitors to simplify the complicated problem with strategic behaviors of firms.

[2]Forgiveness is a rough measure of golf clubs representing how good of a shot a golfer will get when she misses. Due to the manufacturing reasons, it is well-known that the more forgiving a club is, the less the distance is obtained.

[3]Handbags and shoes of luxury brands have same features as described. Markets of automobiles or TVs share many facets with the golf drivers market but the quality of products is easily observable and rated both by consumers and an econometrician. A Universal Serial Bus (USB) flash drive is an example of goods with opposite traits. It has well-established grade of quality, i.e. storage capacity, has negligible prestige effect, and little preference on the newness of products. Consumers generally care about the specification of product only.

[4]See the Appendix for a detailed explanation as to why almost all observable characteristics of a driver are viewed in a horizontal sense, and why the size of each model's head can serve as a quality measure in the time frame of dataset analyzed: 2005-2009.

The model in this study extends approaches in previous studies mentioned above. It is distinguished from them by explicitly modeling consumers' preference for newness of products which impact firms' pricing and introducing decision. Observed dynamic behavior of the market, this study models uniquely the transition of cyclical seasonality. In the model, consumers are forward-looking and heterogenous.

The remainder of the article is organized as follows. Section 2 describes the market for golf drivers to emphasize the stylized fact of consumers' preference for newness of products. Section 3 presents the model for dynamic demand designed to explain the market behavior when consumers strongly appreciate the newness of products. Section 4 discusses how to estimate the model with simulations. Section 5 discusses the estimation results, experiments, and a counterfactual analysis. Finally, section 6 is devoted to conclusions.

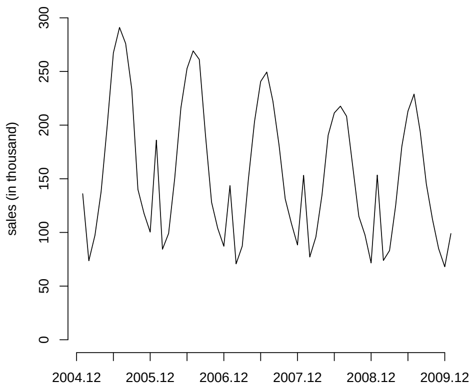
2 Golf Drivers Market and Preference for Newness

In this section, we discuss the observed dynamic behavior of the market and address empirical questions in regard to consumers' strong preferences for newness of products.

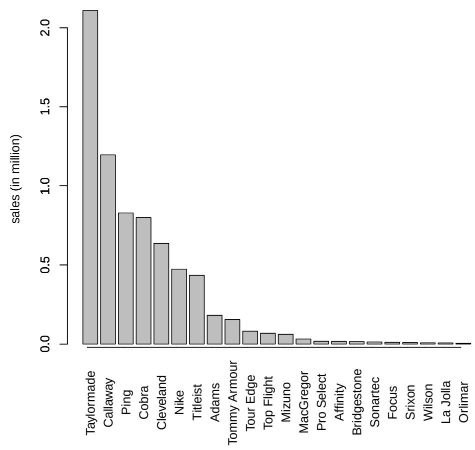
Figure 1 (a) exhibits the time path of total sales of drivers in US market from 2005 to 2009.[5] Apparently, strong seasonality in the volume of sales exists. Each summer shows high volume of sales as it is the high season for playing golf. December depicts a small but sharp peak in each year. It mainly comes from low price by big year-end sale as described below. The figure also depicts a downward long-term trend of sales throughout the five-year span, suggesting evidence of the US economy going slow toward the late-2000s. Figure 1 (b) is each brand's total sales ordered by volume of sales. Seven major brands occupy 90.5 percent of total sales in this period, where top two players take 48 percent of the total. The fact that leading brands dominate the market sales suggests that the brand-related prestige effect exits in this market. Hence we will focus on seven dominant brands when we deal with brand-specific valuation of consumers.

Figure 2 plots the Herfindahl-Hirschman index during the sample period to show the level of market concentration. Although it seems that the market is concentrated to a few top selling firms

[5]Monthly model-by-model sales data are obtained from a market research company specializing in golf industry. They collect actual sales data from approximately 600 green grass pro shops and 250 off-course shops, including stores from national chains, national franchises, individual owners with multiple locations and individual owner single-unit stores.



(a) Monthly Total Sales



(b) Total Sales by Brand

Figure 1. Total Sales of Drivers: 2005-2009

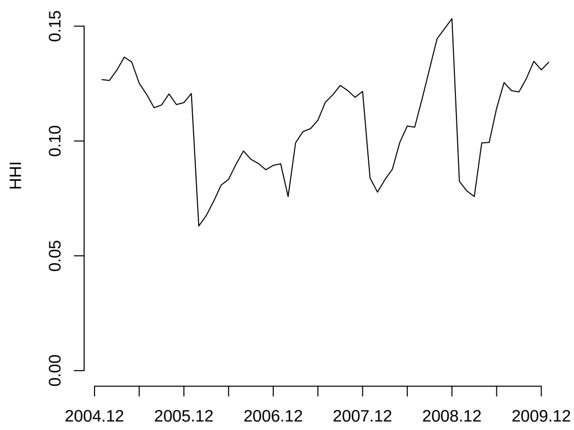


Figure 2. Herfindahl-Hirschman index: 2005-2009

in Figure 1 (b), the US golf drivers market in this period is either unconcentrated or moderately concentrated.

Figure 3 is the average price of all drivers available in the US market, weighted by their sales.[6] Generally, prices are high during the golf season (in the summer) and lower in the winter, around December in particular. The high average price in the summer is obtained because companies launch

[6]Average price data are collected from various sources. Due to confidentiality, annual model-by-model average point-of-sales prices and monthly total average price over all available driver models in each month are provided by the company that allowed to use sales data. Collected prices are validated to match comparably what the company provided.

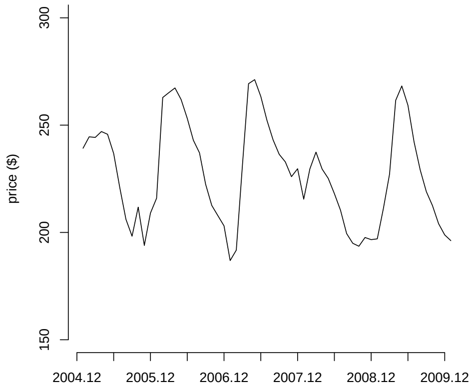


Figure 3. Monthly Average Price of Drivers

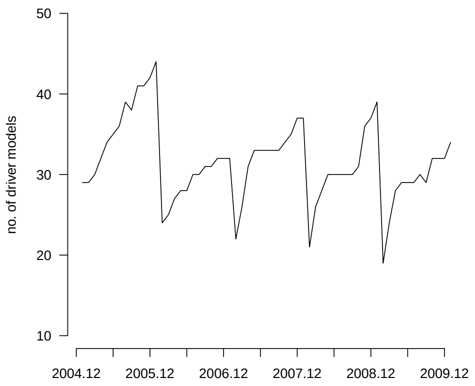


Figure 4. Number of Models Available in a Month

new models in the beginning of the golf season. On the other hand, the low average price in December accounts for the year-end discount and sale, which leads to high volume of sales in December. Figure 4 plots the number of available models in each month. The number of models typically grows within each year, reflecting the fact that new models are launched in the middle of each year.

As a caveat, truncation issues exist in the data. First, the number of models seems lower than what exists in reality. It is because we only consider models identified in the data. Other models in the market are not traced since they exhibit too low sales, they are clone golf drivers, and so forth. However, we consider second-hand markets are separated from the new golf drivers market and hence clone and used drivers are not in our interest. Second, once time hits the end of each year, the number of models drops in Figure 4. It is because the data for some models available in a year are no longer collected in the following year, when they are not successful in particular. The feature of the market, however, curtails the effect of truncation. Every year major brands launch new models and the older models' sales drop fast in response. Moreover, the data are collected across years for the same model when they have sufficient sales. Consequently, the data show small sales values at the end tails of models on which the tracking stopped before the end of sample period. See Figure 5 to find the low tail values of model R1 and model R2.

Figure 5 is a representative time trend of sales of drivers launched by a company. Model names are ordered by their launching date. While the seasonality shown in Figure 1 withstands, it shows an evidence of a cannibalization effect: when a new product is introduced, sales of older models are adversely affected and sales of the latest one drops fast in particular. Putting cannibalizing behavior

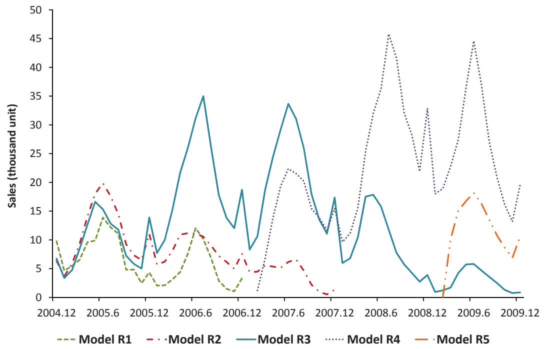


Figure 5. Sales of Drivers Launched by a Company

Figure 6. Average Price and Sales

aside, we also observe a downward movement of sales even without the interference of introductions, i.e. the aging effect. Together with fast declining price path of each driver, the intertemporal competition between new and old models poses an interesting empirical question: do consumers have strong preferences for a driver's newness?

Another empirical question to verify is if consumers depreciate a product over time or not. Figure 6 displays the time paths of average price and average sales since the inception of each model. The declining price path shows a typical dynamic behavior of a new durable goods market. Data show that the price of a model drops over time with varying rate depending on how the model is appreciated in the market. Generally, the price path declines fast in response to sluggish sales in early periods after introduction, and vice versa. The time path of sales also demonstrates a typical pattern of a new durable goods market: sales increase initially and decline generally as time elapses. Observing dynamic behavior of price and sales, many of previous literature deal with a product's age, defined as the time elapsed from the product's first inception in the market, in modeling demand. The assumption behind using the age as a product characteristic is that consumers feel a product less attractive as time elapsed from its first appearance in the market, leading to the significant drop in price and sales over time. Refer to Hui (2004) and Hitsch (2006) for recent applications that are close to our model.

Finally, Table 1 displays the estimation results of hedonic regression. The dependent variable is the price in log scale. The explanatory variables, newness and age are as defined above. The quality measure, head size, is in cc divided by 460. The dummy for golf season has value 1 for May-September and 0 for the rest of the year. Also, the premium of seven major brands are considered. With all highly significant estimated coefficients the hedonic regression results suggest consumers' do have preferences for newness. Moreover, the results suggest that it is worth while to examine the aging effect, products' quality difference, seasonality in demand, and heterogenous brand premium.

Table 1. Hedonic Estimation Results

Variable	Coefficient	Std. Err.
(constant)	4.406	0.151
newness	0.116	0.022
age	-0.040	0.001
head size	1.201	0.151
season	0.023	0.021
Taylormade	0.474	0.029
Callaway	0.279	0.029
Ping	0.155	0.038
Cobra	-0.102	0.037
Cleveland	-0.131	0.037
Nike	0.220	0.034
Titleist	0.312	0.044

Note: The dependent variable is the price ($) in log scale. Newness variable is defined as an indicator that has value 1 if a product is the latest model of its brand, and 0 otherwise. Age is the time elapsed since the model is first introduced in the market, in year scale. Head size is in cc divided by 460.

The findings from the market suggest a dynamic modeling of demand. Consumers have intertemporal trade-offs when they make a purchasing decision. Consumers seem to care about newness of products when they make a purchase, an incentive to purchase a new product promptly. On the other hand, expecting price drops in the future and introduction of a new model that can fit better her taste, each consumer has an incentive to wait until the next period instead of paying more at this period.

3 The Model

3.1 Demand

We denote each product as j and its brand as b. Let $\mathcal{J}_t^b$ and $\mathcal{B}_t$ be the set of available products of brand b at time t and available brands at time t, respectively. Denote all available products in the market, regardless of their brands, at time t as $\mathcal{J}_t$ so that $\mathcal{J}_t = \cup_{b \in \mathcal{B}_t} \mathcal{J}_t^b$. We introduce the "outside" product, an option for each consumer not to buy any of available products. Without loss of generality, denote the outside brand and product to be $b = j = 0$.

Consumers make an intertemporal choice: purchasing decision is not only what to choose but when to buy. During each period, consumers who have not purchased a product decide whether to buy one or not among those available in the market. They get the chance to make a same decision in the following period if they decide not to buy any. If they buy one, they leave the market. This assumption is reasonable for a short sample period in a durable goods market: once they buy a durable good they use it for several periods. Returning a purchased product within a term is considered as non-purchase of a product. The benefit of this assumption exceeds the loss of omitting possibilities of repeated purchases: the utility obtained from purchasing a product is maintained throughout the lifetime, and consumers' behavior other than intertemporal purchasing decision is ruled out, e.g. upgrading a driver and reselling the purchased driver in a secondary used market. Even though the possibility of upgrading a driver is ruled out, we allow golfers' skill level or taste may vary over time. For example, a golfer generally prefers a driver with sharper accuracy to one with higher forgiveness as the skill level increases.

Consumers are aware of all available products' characteristics including specifications, prices, brand names, ages, and whether they are the brand's latest model or not. Consumers compare all available models based on their own taste, i.e. golfers test drivers and choose the one that meets their needs best.

Let Ω_{it} denote the set of all state variables affecting consumer i's purchase decisions at time t. Then we let $U(\Omega_{it})$ be the value function for a consumer i at state Ω_{it} that contains all relevant information regarding purchasing and timing decision. Also, let u_{ijt} be her lifetime utility given by product j purchased at time t. A consumer who has not purchased any product faces the decision problem according to the following value function:

$$U(\Omega_{it}) = \max\left\{ \max_{j \in \mathcal{J}_t} u_{ijt}, \;\; u_{i0t} + \beta \mathbb{E}[U(\Omega_{i,t+1})|\Omega_{it}] \right\}, \tag{1}$$

where β is the common discount factor shared by all consumers. So the consumer who has not owned a product chooses to purchase product j if and only if both the following conditions hold: 1) the expected overall lifetime utility she would get at time t by purchasing product j is the maximum of all those from $j' \in \mathcal{J}_t$, and 2) it is higher than a reservation value, $\beta \mathbb{E}[U(\Omega_{i,t+1})|\Omega_{it}]$, plus the utility generated from buying no product denoted as u_{i0t}.

Let d_{ijt} be the choice variable of consumer i having value 1 if she chooses product j at time t, and 0 otherwise. Accordingly, if $d_{ijt} = 1$ then $d_{ij't} = 0$ for all available $j' \neq j$ including the outside good. From the setting we have in the value function (1), if $d_{ijt} = 1$ for $j \neq 0$, consumer i receives u_{ijt} and leaves the market at time t. If $d_{i0t} = 1$, consumer i has another chance to make a purchasing decision at time $t + 1$. We then can rewrite the value function of consumer i as follows:

$$U(\Omega_{it}) = \max_{j \in \mathcal{J}_t \cup \{0\}} L_j U(\Omega_{it}), \tag{2}$$

where L_j is the alternative-specific operator defined by

$$\begin{aligned} L_j U(\Omega_{it}) &= u_{ijt}, \qquad \text{for all } j = 1, \ldots, |\mathcal{J}_t|, \\ L_0 U(\Omega_{it}) &= u_{i0t} + \beta \mathbb{E}[U(\Omega_{i,t+1}) | \Omega_{it}, d_{i0t} = 1]. \end{aligned} \tag{3}$$

It is well-known that if a solution to the problem (2) exists then it is unique, e.g. Rust (1994).

The unobservable (to an econometrician) characteristics of products are separated into two groups: vertical and horizontal characteristics, denoted as ξ_{jt} and ζ_{jt}, respectively. The vertical characteristics summarize quality-related characteristics of a product, e.g. durability and maintenance cost. The horizontal characteristics include all features dependent upon consumers' taste: due to consumers' diverse taste or skill level most of product characteristics falls in this category, e.g. hitting distance, forgiveness, and controllability of a driver. In a horizontal manner, each consumer has her own optimal taste on products, denoted as ζ_{it} in a same taste space that ζ_{jt} lies on. Here ζ_{it} is unobservable to an econometrician as well. Let $d(\zeta_{it}, \zeta_{jt})$ be the economic distance between consumer i's optimal taste and product j's taste characteristics. Then $\varepsilon_{ijt} := h(d(\zeta_{it}, \zeta_{jt}))$ is a decreasing function of $d(\zeta_{it}, \zeta_{jt})$ such that $h(0) = \infty$ and $h(\infty) = -\infty$. This setup allows us to transform consumers' heterogeneity in taste into a vertical measure in a Hotelling sense: each consumer pays the traveling cost which is proportional to the distance from her location, i.e. her optimal taste, to a shop, i.e. a product's characteristics.

We define the newness of product j at time t, denoted as n_{jt}, as an indicator variable equal to 1 if product j is the brand's latest model at time t and 0 otherwise. It is distinguished from a product's age: even though a model was launched long ago, it may still be the latest model made by its brand,

and vice versa. We assume the lifetime utility generated by purchasing product j to be as follows:

$$u_{ijt}(x_{jt}, n_{jt}, p_{jt}, Z_t, \xi_{jt}, \varepsilon_{ijt}; \theta^d)$$
$$= \alpha_0 + x_{jt}\alpha_{xi} + \lambda_i n_{jt} + \alpha_{si} Z_t - \alpha_{pi} \log p_{jt} + \xi_{jt} + \varepsilon_{ijt}, \qquad \text{for all } i, j, t. \tag{4}$$

Here, x_{jt} is a length-K (row) vector of observed characteristics of product j at time t, p_{jt} is the price of product j at time t, Z_t is the marketwise seasonality variable that accounts for golf season, and ε_{ijt} is a stochastic term for taste characteristics defined as above. All the parameters on demand side are summarized in θ^d, including α and λ. Verifying if $\lambda_i > 0$ is an important empirical question of this study. A positive estimate of λ_i represents the estimated amount of prestige effect that newness of a product brings to consumer i.

The way n_{jt} is set up (being independent of rivals' launching behavior in particular) resembles how consumers really choose the right driver for them. Many golfers are only interested in the latest models of all (or several) brands. They do not prefer a driver launched by brand A last month to one introduced by brand B three months ago simply because that was launched two months later. Within brand umbrella, however, consumers do take the newness into account.

Following Berry, Levinsohn, and Pakes (1995), hereafter BLP, we introduce the random utility setting:

$$u_{ijt}(x_{jt}, n_{jt}, p_{jt}, Z_t, \xi_{jt}, \varepsilon_{ijt}; \theta^d)$$
$$= \alpha_0 + x_{jt}\alpha_x + \lambda n_{jt} + \alpha_s Z_t - \alpha_p \log p_{jt} + \xi_{jt} +$$
$$\sum_{k=1}^{K} \sigma_{\alpha_x k}\nu_{\alpha_x ik} x_{jkt} + \sigma_\lambda \nu_{\lambda i} n_{jt} + \sigma_{\alpha_s}\nu_{\alpha_s i} Z_t - \sigma_{\alpha_p}\nu_{\alpha_p i} \log p_{jt} + \varepsilon_{ijt}, \tag{5}$$

such that

$$\alpha_{xi}^k = \alpha_x^k + \sigma_{\alpha_x}^k \nu_{\alpha_x i}^k \quad \text{for all } k = 1, \dots, K, \; \alpha_{si} = \alpha_s + \sigma_{\alpha_s}\nu_{\alpha_s i}, \; \alpha_{pi} = \alpha_p + \sigma_{\alpha_p}\nu_{\alpha_p i} \quad \text{and} \quad \lambda_i = \lambda + \sigma_\lambda \nu_{\lambda i},$$

where $(\nu_{\alpha_x i1}, \dots, \nu_{\alpha_x iK}, \nu_{\alpha_s i}, \nu_{\alpha_p i}, \nu_{\lambda i})$ are unobserved consumer heterogeneity. The utility from not buying any of the products, u_{i0t}, is similarly given by

$$u_{i0t} = \sigma_0 \nu_{0i} + \varepsilon_{i0t}, \qquad \text{for all } i, t. \tag{6}$$

We set $\sigma_0 = 0$, which is equivalent to normalizing the utility from the outside good to zero.

Let us decompose the lifetime utility into two parts: one is the same for all consumers (mean utility, δ_{jt}) and the other is consumer-specific term varying by consumers' taste (μ_{ijt}.) Then we can rewrite the random utility setup in formula (5) as

$$u_{ijt} = \delta_{jt}(x_{jt}, n_{jt}, Z_t, p_{jt}; \theta_1^d) + \mu_{ijt}(x_{jt}, n_{jt}, Z_t, p_{jt}; \theta_2^d) + \varepsilon_{ijt}, \tag{7}$$

where

$$\delta_{jt} := \alpha_0 + x_{jt}\alpha_x + \lambda n_{jt} + \alpha_s Z_t - \alpha_p \log p_{jt} + \xi_{jt}$$

and

$$\mu_{ijt} := \sum_{k=1}^{K} \sigma_{\alpha_x k}\nu_{\alpha_x ik}x_{jkt} + \sigma_\lambda \nu_{\lambda i} n_{jt} + \sigma_{\alpha_s}\nu_{\alpha_s i} Z_t - \sigma_{\alpha_p}\nu_{\alpha_p i}\log p_{jt}.$$

Accordingly, the parameters in demand side θ^d are also decomposed into two parts: the product-specific demand parameters along with seasonality, $\theta_1^d = (\alpha, \lambda)$, and the consumer-specific ones, $\theta_2^d = (\sigma_\alpha, \sigma_\lambda)$.

To separate out the effect of the seasonality, we consider another decomposition of life time utility.

$$u_{ijt} = \delta_{jt}^0(x_{jt}, n_{jt}, p_{jt}; \theta_1^d) + \mu_{ijt}^0(x_{jt}, n_{jt}, p_{jt}; \theta_2^d) + (\alpha_s + \sigma_{\alpha_s}\nu_{\alpha_s i})Z_t + \varepsilon_{ijt}, \tag{8}$$

where

$$\delta_{jt}^0 := \delta_{jt} - \alpha_s Z_t \qquad \text{and} \qquad \mu_{ijt}^0 := \mu_{ijt} - \sigma_{\alpha_s}\nu_{\alpha_s i} Z_t.$$

Notice that the seasonality affects all available products equally.

Solving the general dynamic programming problem (2) is very difficult. It is almost impossible to solve the transition probability of the state space Ω_{it} precisely if its dimension is big. We therefore assume the followings, to specify the utility in a computationally tractable way:

Assumption 1 (Transformation of Uniform Taste Shocks) *Assume that ζ_{it} and ζ_{jt} are independent and are uniformly distributed on interval (0,1). Let h be a monotone continuous function on (0,1) such that $h(x) = -\log(-\log(1-x)^2)$.*

Assumption 1 gives that ε_{ijt} are distributed *iid* according to Type I extreme value distribution over

i, j.[7] Along with assuming ε_{i0t} follows same distribution as ε_{ijt}, it is well-known that the difference of two ε_{ijt}'s follows the logistic distribution: refer to Anderson, de Palma, and Thisse (1992) pp. 39-40. The logit specification renders the probability that a consumer will purchase any product, or participate in the market, does not depend on which product will be purchased. Rather, it is only determined by the log-sum term also known as the "inclusive value":

$$\begin{aligned} r_{it} &:= \log \sum_{j \in \mathcal{J}_t} \exp(\delta_{jt} + \mu_{ijt}) \\ &= \alpha_{si} Z_t + \log \sum_{j \in \mathcal{J}_t} \exp(\delta^0_{jt} + \mu^0_{ijt}) \\ &= \alpha_{si} Z_t + r^0_{it}, \end{aligned} \tag{9}$$

where $r^0_{it} := \log \sum_{j \in \mathcal{J}_t} \exp(\delta^0_{jt} + \mu^0_{ijt})$.

As discussed in Rust (1994), we assume the well-known conditional independence to make the transition probability of each consumer's state space, $\mathbb{P}(\Omega_{i,t+1}|\Omega_{it})$, computationally tractable by reducing the dimension of Ω_{it}:

Assumption 2 (Conditional Independence) *Assume that the demand-side state space is partitioned into observable and unobservable components, $\Omega_{it} = (r_{it}, \epsilon_{it})$, and the unobserved state variable is time specific and does not affect future states.*

In Assumption 2, ϵ_{it} denotes the state variable observed by consumer i but unobserved by an

[7] The sketch of proof is as follows: Let $\Xi_{(1)} := \min\{\zeta_{it}, \zeta_{jt}\}$ and $\Xi_{(2)} := \max\{\zeta_{it}, \zeta_{jt}\}$ where ζ_{it} and ζ_{jt} are independent and uniformly distributed in (0,1). Also, let the distance between ζ_{it} and ζ_{jt} be $D := |\zeta_{it} - \zeta_{jt}| = \Xi_{(2)} - \Xi_{(1)}$. Then the density for joint order statistic is obtained as

$$f_{\Xi_{(1)}, \Xi_{(2)}}(x_1, x_2) = 2.$$

See Casella and Berger (2001) pp.233-234 for the proof of above joint density. To find the probability of having $\Xi_{(1)}$ and $\Xi_{(2)}$ within some interval d, we need to integrate over all (permissible) starting positions of x_1. The density for D is then given by

$$f_D(d) = \int_0^{1-d} f_{\Xi_{(1)}, \Xi_{(2)}}(x_1, x_1 + d) dx_1 = 2(1-d).$$

Since $d = 1 - \exp\left(-\frac{1}{2}\exp(-x)\right)$ where $x = h(d)$, we obtain the density for ε_{ijt} using the change of variable technique,

$$\begin{aligned} f(x) &= f_D(h^{-1}(d)) \left| \frac{1}{h'(h^{-1}(d))} \right| \\ &= 2\exp\left(-\frac{1}{2}\exp(-x)\right) \left| \frac{1}{2}\exp(-x)\exp\left(-\frac{1}{2}\exp(-x)\right) \right| \\ &= \exp(-x)\exp(-\exp(-x)) \end{aligned}$$

which is the density of standard Type I extreme value distribution.

econometrician. We then have

$$\mathbb{P}(\Omega_{i,t+1}|\Omega_{it}) = \mathbb{P}(r_{i,t+1}, \epsilon_{i,t+1}|r_{it}, \epsilon_{it}) = \mathbb{P}(r_{i,t+1}|r_{it}) \cdot \mathbb{P}(\epsilon_{i,t+1}). \tag{10}$$

Song and Chintagunta (2003), for example, rely on the same assumption in dealing with new product adoption of heterogenous and forward-looking consumers. Using the relation between the (overall) inclusive value, r_{it}, and the inclusive value net of seasonality, r^0_{it}, in (9), we can rewrite the transition probability (10) as

$$\mathbb{P}(\Omega_{i,t+1}|\Omega_{it}) = \mathbb{P}(r^0_{it+1}, Z_{t+1}|r^0_{it}, Z_t) \cdot \mathbb{P}(\epsilon_{it+1}) = \mathbb{P}(r^0_{it+1}|r^0_{it}) \cdot \mathbb{P}(Z_{t+1}|Z_t) \cdot \mathbb{P}(\epsilon_{it+1}). \tag{11}$$

We assume that the transition of seasonality $\mathbb{P}(Z_{t+1}|Z_t)$ is given deterministically to all consumers. Then what remains to understand is the transition of the observable inclusive value net of seasonality r^0_{it} over time. To facilitate the computation, we make an assumption on the transition of inclusive value proposed by Melnikov (2001):

Assumption 3 (Markov Property) *The inclusive value net of seasonality r^0_{it} follows a 1st-order Markov process.*

Assumption 3 makes r^0_{it} the sufficient statistic for the distribution of $r^0_{i,t+1}$: the distribution of future inclusive value $r^0_{i,t+1}$ depends only on the current value r^0_{it} and does not depend on any past values of r^0_{is} for all $s < t$. Assumption 3 is rationalized when many products are available in the market. When there are sufficiently large number of products in the market, the effect of an individual firm's pricing and introducing decision on the inclusive value is negligible. Many previous studies in dynamic demand models rely on this type of assumption in reducing computational burden: see Hendel and Nevo (2006), Carranza (2007), Zhao (2008), Gowrisankaran and Rysman (2011), and Conlon (2010) for applications.

Under Assumptions 2 and 3, an active consumer who is still in the market does not have to keep track of all past behaviors in the market. Rather, she makes a purchasing decision based on the realized current inclusive value since $\Omega_{it} \equiv r_{it}$. (see Aguirregabiria and Mira, 2010, for details.)[8] The

[8] A more realistic assumption would be consumers update their beliefs on the probability of introduction and product characteristics of future models in a Bayesian manner, e.g. Jiang, Manchandab, and Rossi (2009). Bayesian approach, however, is not within the scope of this study. Furthermore, Bayesian updating may not be reliable with fairly short sample periods.

unobservable state variable ϵ_{it} that does not contribute to the transition of state can be handled in a time specific manner. Denote the expected continuation value as

$$
\begin{aligned}
\mathbb{U}^0_{i,t+1}(\Omega_{it}) &:= \mathbb{E}[U(\Omega_{i,t+1})|\Omega_{it}, d_{i0t} = 1] \\
&= \mathbb{E}[U(r_{i,t+1})|r_{it}, d_{i0t} = 1] = \mathbb{U}^0_{i,t+1}(r_{it}).
\end{aligned} \tag{12}
$$

By virtue of the extreme value specification, we have the solution to the dynamic programming problem (2) in a closed form as follows:

$$
\begin{aligned}
&\mathbb{U}^0_{i,t+1}(r_{it}) \\
&\quad = \mathbb{E}[U(r_{i,t+1})|r_{it}, d_{i0t} = 1] \\
&\quad = \mathbb{E}\left[\max_{j \in \mathcal{J}_t \cup \{0\}} L_j U(r_{i,t+1}) \middle| r_{it}, d_{i0t} = 1 \right] \\
&\quad = \sum_{j \in \mathcal{J}_t} \left(\delta_{j,t+1} + \mu_{ij,t+1} + \mathbb{E}[\varepsilon_{ij,t+1}|r_{it}, d_{i0t} = 1]\right) \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&\qquad + \left(\beta \mathbb{E}[U(r_{i,t+2})|r_{it}, d_{i0,t+1} = 1] + \mathbb{E}[\varepsilon_{i0,t+1}|r_{it}, d_{i0t} = 1]\right) \mathbb{P}(d_{i0,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&\quad = \sum_{j \in \mathcal{J}_t} \left(\delta_{j,t+1} + \mu_{ij,t+1} + \gamma - \log \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1)\right) \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&\qquad + \left(\beta \mathbb{E}[U(r_{i,t+2})|r_{it}, d_{i0,t+1} = 1] + \gamma - \log \mathbb{P}(d_{i0,t+1} = 1|r_{it}, d_{i0t} = 1)\right) \mathbb{P}(d_{i0,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&\quad = \gamma + \sum_{j \in \mathcal{J}_t} \left(\delta_{j,t+1} + \mu_{ij,t+1} - \log \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1)\right) \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&\qquad + \left(\beta \mathbb{E}[U(r_{i,t+2})|r_{it}, d_{i0,t+1} = 1] - \log \mathbb{P}(d_{i0,t+1} = 1|r_{it}, d_{i0t} = 1)\right) \mathbb{P}(d_{i0,t+1} = 1|r_{it}, d_{i0t} = 1)
\end{aligned} \tag{13}
$$

where $\gamma \simeq 0.5772$ is Euler's constant, see for example Eckstein and Wolpin (1989) and Ali (2008) for related discussions. The transition probability for $j \neq 0$ is

$$
\begin{aligned}
\mathbb{P}(d_{ij,t+1} = 1|\Omega_{it}, d_{i0t} = 1) &= \mathbb{P}(d_{ij,t+1} = 1|r_{it}, d_{i0t} = 1) \\
&= \left(\frac{\exp(\widetilde{r}_{i,t+1})}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})} \right) \left(\frac{\exp(\delta_{j,t+1} + \mu_{ij,t+1})}{\exp(\widetilde{r}_{i,t+1})} \right) \\
&= \frac{\exp(\delta_{j,t+1} + \mu_{ij,t+1})}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})}
\end{aligned} \tag{14}
$$

whereas the transition probability for the outside good is

$$\mathbb{P}(d_{i0,t+1} = 1|\Omega_{it}, d_{i0t} = 1) = \frac{\exp(\beta \mathbb{U}^0_{i,t+2})}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})}, \tag{15}$$

where $\widetilde{r}_{i,t+1}$ is the predicted inclusive value of consumer i after she observed the realized inclusive value at time t, r_{it}. The realized $r_{i,t+1}$ and the conjectured $\widetilde{r}_{i,t+1}$ are not necessarily equal. In particular, they are different when new models are introduced and/or old models are discontinued at time $t+1$, i.e.

$$\begin{aligned}
\widetilde{r}_{i,t+1} &= \log\Bigg(\sum_{j \in \mathcal{J}_t \cap \mathcal{J}_{t+1}} \exp(\delta_{j,t+1} + \mu_{ij,t+1}) + \sum_{j \in \mathcal{J}_t \setminus \mathcal{J}_{t+1}} \exp(\delta_{j,t+1} + \mu_{ij,t+1}) \Bigg) \\
&\neq \log\Bigg(\sum_{j \in \mathcal{J}_t \cap \mathcal{J}_{t+1}} \exp(\delta_{j,t+1} + \mu_{ij,t+1}) + \sum_{j \in \mathcal{J}_{t+1} \setminus \mathcal{J}_t} \exp(\delta_{j,t+1} + \mu_{ij,t+1}) \Bigg) = r_{i,t+1},
\end{aligned}$$

if $\mathcal{J}_t \setminus \mathcal{J}_{t+1} \neq \emptyset$ and/or $\mathcal{J}_{t+1} \setminus \mathcal{J}_t \neq \emptyset$.

Then we have

$$\begin{aligned}
\mathbb{U}^0_{i,t+1} &= \gamma + \sum_{j \in \mathcal{J}_t} \left(\log\left[\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right] \right) \frac{\exp(\delta_{j,t+1} + \mu_{ij,t+1})}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})} \\
&\qquad + \left(\log\left[\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right] \right) \frac{\exp(\beta \mathbb{U}^0_{i,t+2})}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})} \\
&= \gamma + \frac{\log\left[\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right]}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})} \left(\sum_{j \in \mathcal{J}_t} \exp(\delta_{j,t+1} + \mu_{ij,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right) \\
&= \gamma + \frac{\log\left[\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right]}{\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2})} \left(\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right) \\
&= \gamma + \log\left[\exp(\widetilde{r}_{i,t+1}) + \exp(\beta \mathbb{U}^0_{i,t+2}) \right].
\end{aligned} \tag{16}$$

From the specification we made, the market share of product j at time t is obtained by aggregating the individual probability of choices such that

$$\begin{aligned}
s_{jt} &= \int \mathbb{P}(d_{ijt} = 1|r_t) dG^{\nu}_i(\nu) \\
&= \int \left(\frac{\exp(\delta_{jt} + \mu_{ijt})}{\exp(r_{it}) + \exp(\beta \mathbb{U}^0_{i,t+1})} \right) dG^{\nu}_i(\nu),
\end{aligned} \tag{17}$$

where G_i^ν denotes the distribution of ν_i. Accordingly, the demand for product j at time t is obtained by

$$q_{jt}\big(x_{jt}, \xi_{jt}, p_{jt}; \theta^d\big) = M_t s_{jt} = M_t \int \mathbb{P}(d_{ijt} = 1 | r_t) dG_i^\nu(\nu), \tag{18}$$

where M_t is the total number of active consumers in the market who have not purchased a product. It is obtained by taking the exogenous number of potential consumers, namely M_t^0, and subtracting those who have purchased at least a product in all previous periods.

3.2 Remarks on supply

We do not present the model for firms in this study. However, a few remarks are in order. First, firms' decisions relevant to our demand model includes pricing and introduction decision. Without firms' explicit introduction decisions, the model would not be able to perform a counterfactual analysis in view of the pace of model changes. Second, strategic behavior of firms has to be incorporated in the model. In making pricing and introducing decisions firms take rivals' decisions into account. In order to avoid complexity in dynamic modeling, previous literature rely on rather controversial assumptions that result in static and/or monopolistic pricing. Incorporating firms' heterogeneity and forward-looking behavior, assumptions in recent literature are still limited to depend solely on demand states, e.g. Zhao (2008) and Conlon (2010). Third, the challenges in modeling firms' dynamic behavior also includes the unknown cost structure. In most cases, cost information is not available to researchers and it is to be recovered. Dealing with both pricing and introduction decisions, the supply model should explain both marginal and introduction costs. Fourth, the choice of product characteristics is also an important issue in regard to firms' introduction decision.

4 Estimation

4.1 Seasonality

Let m_t be an indicator variable that has value 1 if t is a month in golf season, and 0 otherwise. In this study, the golf season is set from May to September. The seasonality variable is then the present discounted value of all future m_t's since u_{ijt} is the lifetime utility. For example, the present discounted value of all future m_t's in May is obtained as

$$\begin{aligned} Z_t &= \sum_{\tau=t}^{\infty} \beta^{\tau-t} m_\tau \\ &= m_t + \beta m_{t+1} + \beta^2 m_{t+2} + \beta^3 m_{t+3} + \ldots \\ &= (1 + \beta + \beta^2 + \beta^3 + \beta^4) + (\beta^{12} + \beta^{13} + \beta^{14} + \beta^{15} + \beta^{16}) + \ldots \\ &= (1 + \beta + \beta^2 + \beta^3 + \beta^4) + \beta^{12}(1 + \beta + \beta^2 + \beta^3 + \beta^4) + \ldots \\ &= (1 + \beta + \beta^2 + \beta^3 + \beta^4)(1 + \beta^{12} + (\beta^{12})^2 + \ldots) \\ &= \frac{1 + \beta + \beta^2 + \beta^3 + \beta^4}{1 - \beta^{12}} =: B \end{aligned} \tag{19}$$

Similarly, one can easily calculate Z_t for all other months and the results are shown in Table 2. The months in bold represent the golf season.

Table 2. The Present Discounted Value of Seasonality

month	Z_t	month	Z_t	month	Z_t
January	$\beta^4 B$	**May**	B	**September**	$1 + \beta^8 B$
February	$\beta^3 B$	**June**	$(1 + \beta + \beta^2 + \beta^3) + \beta^{11} B$	October	$\beta^7 B$
March	$\beta^2 B$	**July**	$(1 + \beta + \beta^2) + \beta^{10} B$	November	$\beta^6 B$
April	βB	**August**	$(1 + \beta) + \beta^9 B$	December	$\beta^5 B$

Note: Months in bold indicate the golf season. Z_t is the marketwise seasonality and β is the monthly discount factor same across all consumers. B is solely dependent to β. See equation (19) for its derivation.

Of course, we can think of another setup that depicts a small peak in each December in Figure 1 (a). However, the baseline model assumes the above to demonstrate the effect of golf season on seasonality. An experiment is performed in Section 5 that accommodates the year-end high demand to the seasonality.

4.2 Markov process of r_{it}^0

Under Assumption 4, we introduce the AR(1) model, i.e. a Markov process, to specify the transition of the inclusive value net of seasonality as follows:

$$r_{i,t+1}^0 = \eta_{0i} + \eta_{1i} r_{it}^0 + \epsilon_{it}, \qquad \text{where } \epsilon \sim \mathcal{N}(0, \sigma_r^2). \tag{20}$$

Then as $t \to t+1$ the seasonality value is updated while $\widetilde{r}^0_{i,t+1} = \mathbb{E}_{it} r^0_{i,t+1}$ is obtained from (20), i.e.

$$\widetilde{r}_{i,t+1} = \eta_{0i} + \eta_{1i} r^0_{it} + (Z_{t+1} - Z_t)(\alpha_s + \sigma_s \nu_{is}). \tag{21}$$

4.3 Triple layers of estimation loops

To make the integration in (17) tractable, we take the simulation approach: we draw $(\nu_i^1, \ldots, \nu_i^K, \nu_{\lambda i}, \nu_{\alpha i})$, $i = 1, \ldots, N$ from the standard multivariate normal distribution. The approximated market share is then given by

$$\widetilde{s}_{jt}\big(x_{jt}, \xi_{jt}, Z_t, p_{jt}\big) = \frac{1}{N} \sum_{i=1}^{N} \varphi_{it} \left(\frac{\exp\left(\delta_{jt} + \mu_{ijt}\right)}{\exp(r_{it}) + \exp\left(\beta \mathbb{U}^0_{i,t+1}\right)} \right) \tag{22}$$

where φ_{it} is the "density" of consumer i at time t. At $t = 1$, $\varphi_{i1} = 1$ and for $t > 1$ each consumer leaves the market with probability $\left(\frac{1}{1+\exp(\beta \mathbb{U}^0_{i,t+1} - r_{it})}\right)$ and thus $\varphi_{it} = \varphi_{i,t-1} \left(\frac{\exp(\beta \mathbb{U}^0_{i,t+1} - r_{it})}{1+\exp(\beta \mathbb{U}^0_{i,t+1} - r_{it})}\right)$.

For estimating demand, we adopt an algorithm similar to that used in BLP. The difference to BLP is that the demand equation (18) accounts for a nonconstant continuation values and a time-varying distribution of consumers' characteristics. The estimation algorithm has three loops to converge. 1) Given a pre-specified θ^d, the continuation value at steady state $\mathbb{U}^0_{i\infty}$ is obtained. Then all previous continuation values, $\mathbb{U}^0_{i,t+1}$, $t = 1, \ldots, T$, are successively obtained from (16) and (21). 2) Using the obtained continuation values $\mathbb{U}^0_{i,t+1}$, $t = 1, \ldots, T$, we calculate the simulated market share and match it with observed market share. 3) Finally, a new set of values of θ^d is searched. These three loops are run until they all converge. Below is the detailed descriptions of each estimation loop.

[***Outer-loop***] Since we do not have information beyond the sample period, we assume that $\mathbb{U}^0_{i,T+1} = \mathbb{U}^0_{i,T+2} = \ldots = \mathbb{U}^0_{i\infty}$. Given a pre-specified θ^d, we can obtain the stationary continuation value using

$$\begin{aligned} \mathbb{U}^0_{i\infty} &= \gamma + \log\left[\exp(\widetilde{r}_{i,T+1}) + \exp(\beta \mathbb{U}^0_{i\infty})\right] \\ &= \gamma + \log\left[\exp(\eta_{0i} + \eta_{1i} r^0_{iT} + (Z_{T+1} - Z_T)(\alpha_s + \sigma_s \nu_{is})) + \exp(\beta \mathbb{U}^0_{i\infty})\right]. \end{aligned} \tag{23}$$

Using (16) and (21), all previous continuation values are successively calculated from $\mathbb{U}^0_{i,T+1} = \mathbb{U}^0_{i\infty}$. With the pre-specified θ^d and obtained $\mathbb{U}^0_{i,t+1}$ for $t = 1, \ldots, T$, the simulated market share (22) is calculated.

[***Middle-loop***] Given the predicted (or simulated) market share (22) with the pre-specified values of the demand parameters θ^d, each of implied mean utility level δ_{jt} is numerically obtained using the fixed point algorithm proposed in BLP. At each iteration *(iter)*, the value of the mean utility at time t $\delta_{jt}^{(iter)}$ is updated by

$$\delta_{jt}^{(iter+1)} = \delta_{jt}^{(iter)} + \log s_{jt}^{obs} - \log \widetilde{s}_{jt}(\delta_{jt}^{(iter)}; \theta^d) \tag{24}$$

where s_{jt}^{obs} is the observed market share whereas $\widetilde{s}_{jt}$ is the simulated share as specified in the equation (22). Under a certain regularity condition, the algorithm guarantees a unique solution by the contraction mapping theorem. Carranza (2007) shows $0 \leq \partial\beta\mathbb{U}_{it}^0/\partial r_{it} < 1$ is a sufficient condition for the regularity conditions to guarantee the algorithm has a unique interior fixed point.

[***Inner-loop***] After the middle-loop converges, the new values of parameters θ^d are searched by matching the new simulated share value $\widetilde{s}_{jt}(\delta_{jt}^{(iter+1)}; \theta^d)$ with the observed market share s_{jt}^0. In this step, efficient and consistent estimates are obtained by the two-step GMM method. To control the endogeneity of price, the product-specific demand parameters θ_1^d is estimated by 2SLS using adequate instruments including the average age of rivals' models and the average head size of them. The iterations are repeated until all three loops converge.

5 Estimation Results and Discussion

5.1 Baseline model

Monthly sales and average price data are collected model-by-model for 61 time periods: December 2004 to December 2009. Prices are in dollar unit and are deflated by the December 2009 Consumer Price Index (CPI) value. Total of 103 driver models across 22 brands are included to constitute total of 1,922 data points. The observed product characteristics are set to be $x_{jt} = (a_{jt}, hsize_j, DB_j)$, where a_{jt} is the age of driver j at time t in year scale, $hsize_j$ is the head size of driver j in cc divided by 460, the maximal size permitted by USGA as discussed in Section 2, and DB_j is a vector of brand dummies. Observed the total sales by brand shown in Figure 1 (b), the brand dummy vector includes top seven brands in sales: Taylormade, Callaway, Ping, Cobra, Cleveland, Nike, and Titleist. The indicator for newness n_{jt} is as defined in Section 3. The monthly discount factor is set at $\beta = 0.992$,

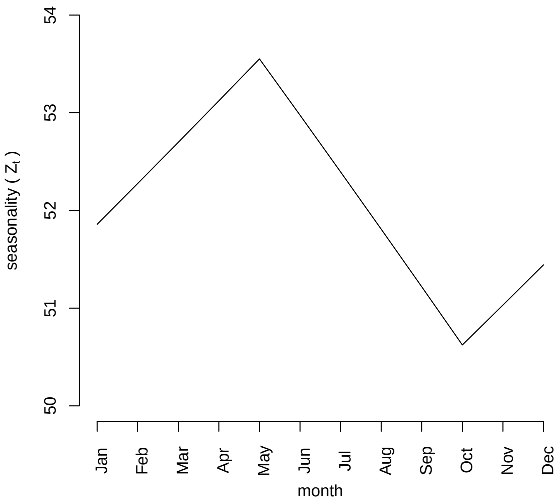


Figure 7. Seasonality in Each Month (Z_t)

Note: Z_t is the marketwise seasonality and the monthly discount factor β is set at 0.992.

Table 3. Descriptive Statistics of Mean Utility Shifters

	Mean	Std. Dev.	Observations
newness (n_{jt})	0.463	0.499	1,922
age (a_{jt})	1.237	0.896	1,922
head size ($hsize_j$)	0.960	0.066	1,922
price (p_{jt})	208.76	118.95	1,922

Note: Newness variable is defined as an indicator that has value 1 if a product is the latest model of its brand, and 0 otherwise. Age is the time elapsed since the model is first introduced in the market, in year scale. Head size is in cc divided by 460. Price is in dollar unit.

which yields the seasonality Z_t in each month as shown in Figure 7.

Table 3 shows the descriptive statistics of product characteristics in x_{jt}. While the head size of drivers are clustered close to 460cc, the newness, age, and price have sufficient variability. Correlation coefficient between newness and age is -0.473 which shows natural negative but not too close correlation between them.

Table 4 displays the estimation results of the baseline model. The simulation of market share is performed by 10,000 random draws. In the mean utility portion of θ_1^d, the estimate for the newness (λ) is of ours special interest and is expected to be significantly positive if consumers have strong

Table 4. Estimation Results: Baseline Model

Variable		Baseline Model Estimate	Std. Err.
Mean Utility (δ)			
(constant)	α_0	6.945	1.677
newness	λ	0.327	0.064
age	α_a	-0.825	0.153
head size	α_h	1.065	0.528
seasonality	α_s	1.452	0.026
Taylormade	$\alpha_b^{taylormade}$	3.177	0.164
Callaway	$\alpha_b^{callaway}$	2.275	0.112
Ping	α_b^{ping}	2.377	0.105
Cobra	α_b^{cobra}	1.682	0.095
Cleveland	$\alpha_b^{cleveland}$	1.641	0.097
Nike	α_b^{nike}	1.630	0.107
Titleist	$\alpha_b^{titleist}$	2.265	0.144
price	α_p	1.450	0.311
Consumer Heterogeneity (μ)			
newness	σ_λ	0.894	0.243
age	σ_a	0.029	0.010
head size	σ_h	0.092	0.043
seasonality	σ_s	0.299	0.127
price	σ_p	0.296	0.036

Note: Mean utility δ_{jt} is same across all consumers. All parameters are expected to have positive signs except age. Consumer heterogeneity is individual-specific variations on variables in the mean utility except brand dummies.

preference for newness, i.e. they are willing to pay more for the latest model over the same brand's outdated ones. We expect the estimate of parameter for age (α_a) to be negative if consumers in fact depreciate a model over time. Also, the parameter for head size (α_h) is anticipated to have a positive estimate when the consumers do observe the bigger driver head as a higher quality. Each estimate of brand dummy parameters (α_b) is expected to have positive values if consumers care and are willing to pay more for the drivers made by a major brand assigned to the dummy. In general they would have some order comparable to the ranking of aggregated sales shown in Figure 1 (b) but not necessarily. Finally, the estimate of price parameter (α_p) has to be positive as the way it is formulated.

The signs of $\widehat{\lambda}$, $\widehat{\alpha}_a$, $\widehat{\alpha}_h$, and $\widehat{\alpha}_p$ are obtained highly significantly as expected. Most importantly, the estimate $\widehat{\lambda}$ measures the amount of prestige effect effectively. The estimated $\widehat{\alpha}_b$'s are overall ordered by the ranking in total sales except Titleist with a comparable value to Callaway. It suggests that the top four brands in the US drivers market are Taylormade, Ping, Callaway, and Titleist in

Table 5. Dollar Values of Characteristics: Baseline Model

Variable		Change in Variable	% Changes in Price
Product Characteristics			
newness	λ	$n_{jt}: 0 \rightarrow 1$	0.2530
age	α_a	$a_{jt}: a \rightarrow a + \frac{1}{12}$	-0.0486
head size	α_h	$hsize_j: h \rightarrow h + \frac{10}{460}$	0.0161
Brand Dummies			
Taylormade	$\alpha_b^{taylormade}$		7.9445
Callaway	$\alpha_b^{callaway}$		3.8017
Ping	α_b^{ping}		4.1516
Cobra	α_b^{cobra}		2.1899
Cleveland	$\alpha_b^{cleveland}$		2.1010
Nike	α_b^{nike}		2.0776
Titleist	$\alpha_b^{titleist}$		3.7687

Note: The numbers in the rightmost column are percent changes in price induced by the change in corresponding variables. Brand values are compared to minor brands with zero values of all brand dummies. In calculating the dollar values, a representative consumer is considered by ignoring consumers' heterogeneity.

the sense of brand premium that consumers recognize. Also, the second tier group consists of Cobra, Cleveland, and Nike in the same sense.

The demand parameters of consumer heterogeneity, θ_2^d, are precisely estimated for drivers' age, head size, newness, and price. The heterogeneity for brand dummies σ_b are not included in estimation. The estimation results with σ_b are obtained almost identical to those in Table 4 while only $\widehat{\sigma}_b$ are all small and insignificant at 5% level, meaning no significant evidence can be found that consumers' heterogenous perception on brand premium is diverse.

Table 5 exhibits the calculated dollar values of product characteristics and brand dummies for a representative consumer, i.e. consumers' heterogeneity is ignored. Each dollar value is the percentage change in price that makes consumers remain indifferent before and after a certain change in a variable when other things are equal. Having newness solely induces 25.3 percent increase in price. A driver's price should fall by 4.9 percent in each month to compensate the aging effect when other things are kept equal. An increase of 10cc in head size corresponds to 1.6 percent increase in price. Among the product characteristics, the premium of newness stands out in its dollar value. The second part of Table 5 shows that having one of the major brand names induces price increase to a great extent. All of seven major brands reveal that more than 200 percent of increase in price compared to minor brands. It is largely because consumers do care the brand name when they choose a driver, i.e. consumers believe that brand name signals the quality.

5.2 Experiments

In this subsection we perform three experiments. Model I and II experiment with different consumers' behavioral assumptions, while model III adopts an approximation method where the assumptions on consumers' economic behavior remains same as the baseline model.

Model I: Myopic consumers

When consumers are assumed to behave myopically, we force $\beta = 0$ for all i and t. Then the model becomes equivalent to the static BLP model. Note that the influence of seasonality becomes dichotomous, i.e. $Z_t = m_t$. First set of parameter estimates in Table 7 displays the estimation results under the assumption of myopic consumers. Overall, parameters in mean utility are estimated with the expected signs. The impact of seasonality is obtained much smaller than the baseline model.

Model II: Quasi-hyperbolic discounting of seasonality with December shock

The dynamic movement of sales in Figure 1 (a) shows a consistent cyclical pattern: high demand in summer and small peak in December. To incorporate this pattern in the model, we make two behavioral assumptions: 1) consumers have time-inconsistent preferences, i.e. quasi-hyperbolic discounting of seasonality, and 2) consumers have high holiday demand at year-end. In other words, $m_t = 1$ when t is in December, where all other m_t values remain the same as above. The assumption of quasi-hyperbolic discounting is justified when consumers are in fact present-biased, i.e. consumers reveal strong tendency to care the current seasonality state. Let π be an additional discount factor that represents the dynamic inconsistency. The second assumption is by high holiday demand and/or companies' promotions at year-end. For example, Callaway has the "Preferred Retailer Program" that offers the year-end rebates and discounts for participating retailers, part of which in turn transfers to consumers. The present discounted value of all future m_t's in May is then obtained as

$$
\begin{aligned}
Z_t &= m_t + \pi \sum_{\tau=t+1}^{\infty} \beta^{\tau-t} m_\tau \\
&= (1 + \pi\beta + \pi\beta^2 + \pi\beta^3 + \pi\beta^4) + \pi\beta^7 + (\pi\beta^{12} + \pi\beta^{13} + \pi\beta^{14} + \pi\beta^{15} + \pi\beta^{16}) + \pi\beta^{19} \dots \\
&= (1 + \pi\beta + \pi\beta^2 + \pi\beta^3 + \pi\beta^4) + \frac{\pi\beta^{12}(1 + \beta + \beta^2 + \beta^3 + \beta^4)}{1 - \beta^{12}} + \frac{\pi\beta^7}{1 - \beta^{12}}
\end{aligned}
$$

$$= (1 + \pi\beta + \pi\beta^2 + \pi\beta^3 + \pi\beta^4) + \pi\beta^{12}B + \frac{\pi\beta^7}{1-\beta^{12}}, \tag{25}$$

where B is defined as in (19). Similarly, all other Z_t values are calculated in Table 6.

Table 6. The Present Discounted Value of Seasonality

month	Z_t
January	$\pi\beta^4 B + \frac{\pi\beta^{11}}{1-\beta^{12}}$
February	$\pi\beta^3 B + \frac{\pi\beta^{10}}{1-\beta^{12}}$
March	$\pi\beta^2 B + \frac{\pi\beta^{9}}{1-\beta^{12}}$
April	$\pi\beta B + \frac{\pi\beta^{8}}{1-\beta^{12}}$
May	$(1 + \pi\beta + \pi\beta^2 + \pi\beta^3 + \pi\beta^4) + \pi\beta^{12}B + \frac{\pi\beta^7}{1-\beta^{12}}$
June	$(1 + \pi\beta + \pi\beta^2 + \pi\beta^3) + \pi\beta^{11}B + \frac{\pi\beta^6}{1-\beta^{12}}$
July	$(1 + \pi\beta + \pi\beta^2) + \pi\beta^{10}B + \frac{\pi\beta^5}{1-\beta^{12}}$
August	$(1 + \pi\beta) + \pi\beta^{9}B + \frac{\pi\beta^4}{1-\beta^{12}}$
September	$1 + \pi\beta^{8}B + \frac{\pi\beta^3}{1-\beta^{12}}$
October	$\pi\beta^7 B + \frac{\pi\beta^{2}}{1-\beta^{12}}$
November	$\pi\beta^6 B + \frac{\pi\beta}{1-\beta^{12}}$
December	$\pi\beta^5 B + 1 + \frac{\pi\beta^{12}}{1-\beta^{12}}$

Note: Months in bold indicate the high demand: golf season and year-end. Z_t is the marketwise seasonality, β is the monthly discount factor is same across all consumers, and π is an additional discount factor which discounts future utility relative to current period utility. B is solely dependent to β.

Calibrating $\pi = 0.9$ along with $\beta = 0.992$, we have the time path of seasonality during the sample period as shown in Figure 8. Note that the level of Z_t is comparable to what we have in the baseline model shown in Figure 7 and the path also resembles the total sales in Figure 1 (a).

The second part of Table 7 shows the estimation results of Model II. As expected, they are much closer to the estimation results of the baseline model than Model I. Compared to the baseline model, almost all magnitudes of estimates are greater in Model II.

Model III: Approximation of continuation value a la Carranza (2007)

In this experiment, we adpot the approximation approach in obtaining the continuation value in (3) proposed by Carranza (2007). In order to facilitate the calculation, one can approximate the integral given by equation (17) in the following way: First, since we find the fact that $\mathbb{U}^0_{i,t+1}$ is solely

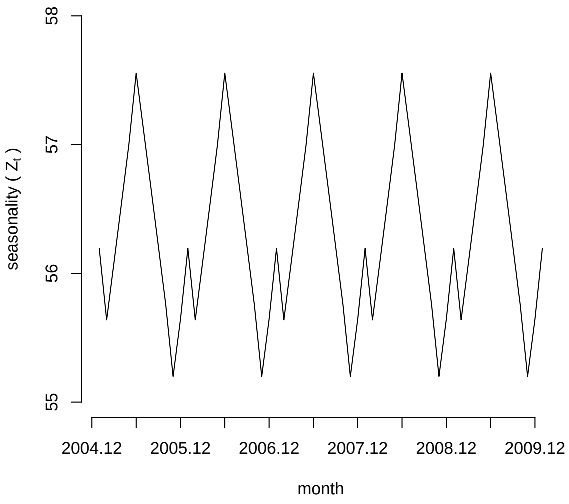


Figure 8. Time Path of Seasonality (Z_t)

Note: Z_t is the marketwise seasonality. The monthly discount factor β is set at 0.992 and an additional discount factor for dynamic inconsistency π is calibrated at 0.9.

dependent to r_{it}, we specify that

$$\beta \widetilde{\mathbb{U}}^0_{i,t+1}(r_{it}; \epsilon_{it}) = \eta_0 + \eta_1 \epsilon_{it} + \eta_2 r_{it} + \eta_3 r_{it} \epsilon_{it}, \tag{26}$$

where the unobservable component of state variables, $\epsilon_{it} \sim \mathcal{N}(0,1)$. We set $\eta_0 \equiv 0$ to identify the constant in the mean utility. Second, we replace $\mathbb{U}^0_{i,t+1}$ by $\widetilde{\mathbb{U}}^0_{i,t+1}$ in equation (17) and draw ϵ_l, $l = 1, \ldots, L$ from $\mathcal{N}(0,1)$. For each draw of ϵ_l, we draw $(\nu^1_n, \ldots, \nu^K_n, \nu_{\lambda n}, \nu_{\alpha n})$, $n = 1, \ldots, N$ from the standard multivariate normal distribution. The approximated market share is then given by

$$\widetilde{s}_{jt}\big(x_{jt}, \xi_{jt}, Z_t, p_{jt}\big) = \frac{1}{L} \sum_{l=1}^{L} \left[\frac{1}{N} \sum_{n=1}^{N} \varphi_t^{(n,l)} \left(\frac{1}{1 + \exp\left(\beta \widetilde{\mathbb{U}}^{(n,l)}_{t+1} - r^{(n)}_t\right)} \right) \left(\frac{\exp\left(\delta_{jt} + \mu^{(n)}_{jt}\right)}{\exp\left(r^{(n)}_t\right)} \right) \right] \tag{27}$$

where

$$\mu^{(n)}_{jt} = \sum_{k=1}^{K} \sigma_k \nu^k_n x^k_{jt} + \sigma_\lambda \nu_{\lambda n} n_{jt} - \sigma_\alpha \nu_{\alpha n} \log p_{jt},$$
$$r^{(n)}_t = \log \sum_{j \in \mathcal{J}_t} \exp\left(\delta_{jt} + \mu^{(n)}_{jt}\right),$$

Table 7. Estimation Results: Experiments

Variable		Model I Estimate	Model I Std. Err.	Model II Estimate	Model II Std. Err.	Model III Estimate	Model III Std. Err.
Mean Utility (δ)							
(constant)	α_0	5.547	0.451	7.025	1.179	8.261	1.713
newness	λ	0.480	0.067	0.363	0.065	0.573	0.079
age	α_a	-1.101	0.157	-0.853	0.153	-1.283	0.186
head size	α_h	1.677	0.541	1.206	0.528	2.566	0.639
seasonality	α_s	0.254	0.047	1.461	0.034	0.503	0.055
Taylormade	$\alpha_b^{taylormade}$	3.484	0.168	3.187	0.164	3.743	0.198
Callaway	$\alpha_b^{callaway}$	2.444	0.116	2.287	0.113	2.591	0.137
Ping	α_b^{ping}	2.445	0.110	2.384	0.106	2.512	0.129
Cobra	α_b^{cobra}	1.644	0.100	1.683	0.096	1.629	0.118
Cleveland	$\alpha_b^{cleveland}$	1.570	0.102	1.621	0.098	1.519	0.120
Nike	α_b^{nike}	1.770	0.111	1.640	0.108	1.914	0.131
Titleist	$\alpha_b^{titleist}$	2.405	0.149	2.287	0.145	2.548	0.176
price	α_p	2.028	0.317	1.547	0.311	2.524	0.374
Consumer Heterogeneity (μ)							
newness	σ_λ	0.123	0.060	0.850	0.359	0.121	0.065
age	σ_a	0.104	0.033	0.031	0.012	0.109	0.086
head size	σ_h	0.102	0.115	1.780	0.632	0.307	0.112
seasonality	σ_s	0.135	0.127	0.524	0.236	0.132	0.148
price	σ_p	0.100	0.014	0.483	0.207	0.103	0.026
Continuation Value of Utility ($\mathbb{U}^0$)							
Idiosyncracy	η_1					0.359	0.061
Inclusive value	η_2					0.393	0.041
Interaction	η_3					0.060	0.025

Note: Model I assumes myopic consumers. Model II adopts two behavioral assumptions, consumers have dynamic inconsistency for seasonality and they have high demand in golf season and in December. Model III is the baseline model with approximated continuation value.

$$\beta\widetilde{\mathbb{U}}_{t+1}^{(n,l)} = \eta_0 + \eta_1\epsilon_l + \eta_2 r_t^{(n)} + \eta_3 r_t^{(n)}\epsilon_l,$$

and $\varphi_t^{(n,l)}$ is the "density" of consumer n at time t for the lth draw of ϵ. At $t = 1$, $\varphi_1^{(n,l)} = 1$ and for $t > 1$ each consumer leaves the market with probability $\left(\frac{1}{1+\exp(\beta\widetilde{\mathbb{U}}_{t+1}^{(n,l)} - r_t^{(n)})}\right)$ and thus $\varphi_t^{(n,l)} = \varphi_{t-1}^{(n,l)}\left(\frac{\exp(\beta\widetilde{\mathbb{U}}_{t+1}^{(n,l)} - r_t^{(n)})}{1+\exp(\widetilde{\mathbb{U}}_{t+1}^{(n,l)} - r_t^{(n)})}\right)$. The estimation strategy is same as what we have in Section 4. Under a certain regularity condition, the algorithm guarantees a unique solution by the contraction mapping theorem. Carranza (2007) shows $0 \leq \partial\beta\widetilde{\mathbb{U}}_{i,t+1}^{0}/\partial r_{it} < 1$ is a sufficient condition for the regularity conditions to guarantee the algorithm has a unique interior fixed point.

The last two columns of Table 7 show the estimation results of Model III. Though this ap-

Table 8. Dollar Values of Characteristics: Experiments

Variable		% Changes in Price		
		Model I	Model II	Model III
Product Characteristics				
newness	λ	0.2670	0.2645	0.2549
age	α_a	-0.0442	-0.0449	-0.0415
head size	α_h	0.0181	0.0171	0.0223
Brand Dummies				
Taylormade	$\alpha_b^{taylormade}$	4.5731	6.8469	3.4060
Callaway	$\alpha_b^{callaway}$	2.3372	3.3857	1.7914
Ping	α_b^{ping}	2.3388	3.6695	1.7054
Cobra	α_b^{cobra}	1.2494	1.9681	0.9068
Cleveland	$\alpha_b^{cleveland}$	1.1688	1.8515	0.8254
Nike	α_b^{nike}	1.3936	1.8867	1.1347
Titleist	$\alpha_b^{titleist}$	2.2736	3.3857	1.7443

Note: The numbers are percent changes in price induced by the change in corresponding variables. Brand values are compared to minor brands with zero values of all brand dummies. In calculating the dollar values, a representative consumer is considered by ignoring consumers' heterogeneity.

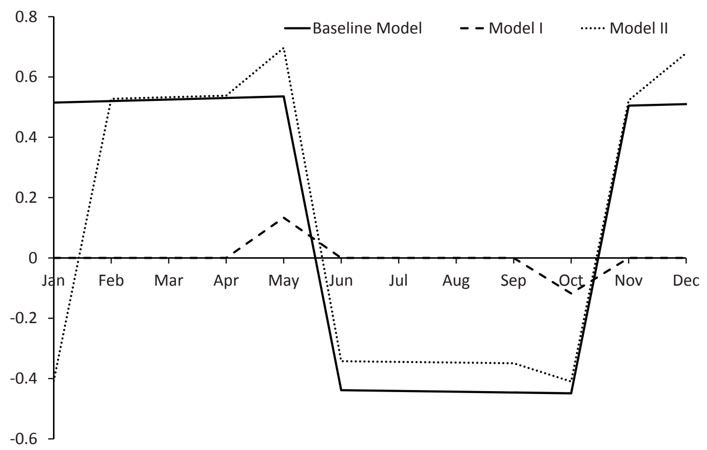


Figure 9. Dollar Values of Seasonality

Note: Dollar value represents the adjusted percent price to make a representative consumer equally satisfied as the previous month when other things are held equal. Positive value means that a representative consumer is willing to pay more in the corresponding month compared, *ceteris paribus*, to the previous month, and vice versa.

proximation approach is less structural than our model, the relative values of estimates are obtained similarly to the baseline model and Model II. Noticeably, the condition $0 \leq \partial\beta\widetilde{\mathbb{U}}^0_{i,t+1}/\partial r_{it} < 1$ is satisfied on average with $\widehat{\eta}_2 = 0.393$ and $\widehat{\eta}_3 = 0.06$.

Table 8 shows the dollar values calculated in the same way as in Table 5. In Model I that assumes myopic consumers, the effect of newness is the highest with 26.7 percent increase in price, while all other dynamic models result in less than 26.5 percent increases in price. Model II resembles the baseline model but less brand effect is obtained. Model III suggests even lesser brand effect.

Figure 9 is the dollar values of seasonality for the baseline model, Model I, and Model II. Dollar value represents the adjusted percent price to make a representative consumer equally satisfied as the previous month when other things are held equal. Positive value hence means that a representative consumer is willing to pay more in the corresponding month compared, *ceteris paribus*, to the previous month, and vice versa. Baseline model shows a dichotomous behavior such that a representative consumer consistently is willing to pay around 50 percent more in the off season, i.e. from November to May, and 44 percent less in the peak season, i.e. from June to October, as time is increased by a month. In other words, during the off season, consumers are willing to pay more as the golf season comes closer. It agrees with what companies reveal in regard to seasonality, e.g. Callaway Golf Company Annual Report 2010 states that "*[t]he Company's business is subject to seasonal fluctuations (16p.) [B]ecause of this seasonality, a majority of the Company's sales and most, if not all, of its profitability generally occurs during the first half of the year (33p.)*" Model II exhibits similar pattern to the baseline model but higher peaks are observed in May and December and lowest dollar values are obtained in January and October. Deviations in May and October are due to the assumption of hyperbolic discounting while those in December and January are as a result of additional seasonality shock given in December. The myopic model, Model I, suggests much smaller dollar value of seasonality. Due to the assumption of myopic consumers, the influence of shifting one month forward is only effective in May and October, the beginning of golf season and off season, respectively.

From the results found in Table 7 and Figure 9, the misspecification of the static model results in the effects of newness and seasonality are smoothed out. It is because the denominator in equations (17) and (22) do not account for the heterogenous continuation value of utility, i.e. $\exp(r_{it}) + \exp(\beta \mathbb{U}^0_{i,t+1})$ becomes $\exp(r_{it}) + 1$.

5.3 A simple counterfactual analysis: merger of Callaway and Ping

To see the impact of consumers' preferences for newness, we perform a counterfactual analysis with two firms ranked second and third in total sales shown in Figure 1 (b), namely Callaway and Ping. Consider they are merged before the sample period and do business under the brand of Callaway.

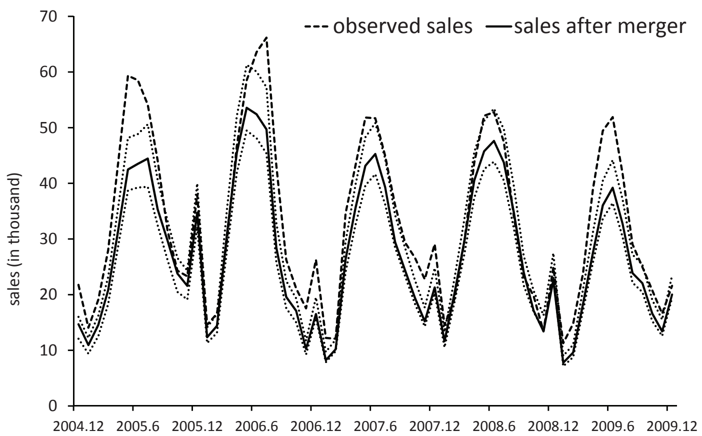


Figure 10. Sales of Callaway and Ping: Observed and Counterfactual

Note: Dashed line is the observed total sales of Callaway and Ping and solid line is the counterfactual total sales when they are merged. Dotted lines denote the 95% confidence interval of the counterfactual total sales.

The impact of merger is higher frequency of model changes. In our model, it yields the modification of newness values. In other words, consumers observe more frequent introductions of new Callaway models after merger and the existing models lose newness faster than before. We assume the pricing decisions of two firms remain same as observed. Figure 10 plots the observed total sales of Callaway and Ping, and the counterfactual total sales when they are assumed to be merged. Overall, the sales are reduced when they are merged. In particular, the loss in sales is more conspicuous when they have relatively high frequency of introductions, in the summer of 2005, 2006 and 2009. It suggests that the cannibalization effect in sales plays more significant role when the model changes are made faster than observed, i.e. optimal pace of model changes.

6 Concluding Remarks

In this study, we identified consumers' preferences for newness of products and measured the amount of prestige effect that the newness of a product brings. With strong preferences for newness of products, forward-looking heterogenous consumers are modeled to behave time optimally in their purchasing decision. The deterministic transition of seasonality is also modeled. Estimation results show the evidence of strong preference for newness, depreciation with respect to age, and brand premium. Experiments with behavioral assumptions and approximation confirm the robustness of the results.

A simple counterfactual analysis shows the negative effect on two firms' total sales when they are assumed to be merged. It is due to the faster loss of newness in some products after merger. While emphasizing on consumers' preferences for newness of products, this study omits modeling firms' pricing, introduction, and endogenous choice of product characteristics.

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Appendix: Head Size as a Quality Measure in 2005-2009

In this appendix, we discuss why almost all observable product characteristics are taste characteristics: consumers perceive many product characteristics in a Hotelling sense, as modeled in Section 3. Also we see why the size of a driver's head can serve as a quality measure in the time frame of dataset analyzed in this study: 2005-2009.

As introduced in Section 1 a specific feature of the golf driver is almost all observable product characteristics depend on consumers' taste while having a quality difference over products at least over time. This feature poses both a challenge and an opportunity to the researcher. A challenge to an econometrician is requesting to find an appropriate observable and discernable quality measure in a vertical sense. On the other hand, an opportunity of examining consumers' behavioral characteristics opens up once the quality is controlled for. A carefully chosen quality measure successfully explains true quality of products and lets consumers' behavioral characteristics identified if there is any.

The characteristics of a driver that depend on consumers' taste are decomposed into two parts: (1) bona fide taste characteristics and (2) characteristics having trade-offs between them. This decomposition is worth to compare to the distinction between search and experience characteristics as described in Stigler (1961). Before they purchase consumers can observe and verify search characteristics, e.g. the shape and loft of head. Contrastingly, experience characteristics are not typically known to consumers before testing the product, e.g. feel of grip or ball flight. Consumers however may have information on experience characteristics via magazine reviews, announced test results, or golf buddies' opinion. Characteristics in our first category is a comparable mix of search and experience characteristics whereas the second category mainly consists of experience characteristics.

First, the bona fide taste characteristics include all characteristics subject to each consumer's own taste purely. Hence no consensus can be obtained due to the nature of them. Some consumers like the hitting sound of a driver, which is an important factor that golfers care when they test a new driver, but some think its sound is detestable. Letting alone the unobservable taste characteristics, many of observable characteristics of a driver fall into this category including the shape and loft of head, length and stiffness of shaft, and feel of grip among others. The bona fide taste characteristics are completely free from consideration in a vertical sense.

The second category of characteristics needs more careful attention. Many characteristics of a driver, observable at least indirectly through a good many available test results, are conceptualized in a vertical sense individually, e.g. hitting distance, forgiveness, accuracy, and controllability (or playability[9]) In other words, consumers unanimously agree that a certain behavior of a driver is superior to the opposite behavior on a specific characteristic *ceteris paribus*, e.g. consumers prefers longer distance and higher accuracy holding others equal. Due to the technological trade-off among the characteristics in this category, however, a combination of this type of features is not well-ordered. A driver loses forgiveness in exchange of improved distance, one of the well-known trade-offs. Consumers' choices regarding these two characteristics are made in a horizontal sense depending on their taste or more precisely own order of importance between the characteristics. Moreover, even on a specific characteristic each consumer assesses differently: one feels driver A hits longer than B but another may think in the opposite direction.

Both Table 9 and Table 10 show the professional test results of selected golf drivers: notice both categories of taste characteristics are tested. To evaluate the characteristics of drivers, 60 golfers of varying skill levels hit a group of 5 to 7 driver models each year. They are told not to compare one driver to another but only to rate how they performed with each driver. The ratings are highly concentrated within a range far less than 1 in all criteria on a scale of 1 to 10 in each year as a result of averaging over testers with varying skill levels therefore wide range of taste.

A question worth to investigate is then whether the quality is enhanced over time or not in a vertical sense. As the ratings in Tables 9 and 10 are normalized over time, the test results suggest

Table 9. Driver Test Results on a Scale of 1 to 10 (2006)

Driver	Dist.	Ctrl	Accuracy	Forgiveness	Ball Flight	Sound	Feel	Overall
Cleveland Launcher Ti460	8.3	7.9	7.8	7.8	8.3	8.1	8.5	8.2
Mizuno MX500 460	8.4	8.2	8.2	7.9	8	8.1	8.4	8.2
Yonex Cyberstar Nanospeed 460	8.4	8	8.1	8	8.2	8	8.4	8.2
Nickent Genex 3DX T-spec 460	8.2	8.1	8	8	8.3	8.1	8.4	8.1
Nike SasQuatch 460	8.4	8.1	8.2	7.9	8.3	7.9	7.9	8.1
Callaway Fusion FT 3 460	8.4	8.1	8	7.6	8.2	7.7	8.1	8
MacGregor MACTEC NVG 445	8	8	8.1	7.8	8	7.5	8.1	8
Ping G5 460	7.9	7.8	7.9	7.7	7.9	7.9	8.3	7.9
Feel TI-Carbon 460	7.9	8	7.8	7.8	8	8	8.1	7.9
TechPower Speed Offset 460	7.8	8	8	7.8	7.7	7.8	7.9	7.9
Adams Redline RPM 460D	8.1	8.1	8	7.7	8.2	7.7	7.9	7.8
KZG Gemini 460	8	7.8	7.8	7.7	7.9	7.7	8	7.8
Bridgestone J33R 460	8.1	7.7	7.7	7.6	8	7.5	7.9	7.8
Infiniti ProPlusion Ti Comp 460	8	7.7	7.8	7.7	7.8	7.6	7.9	7.8
Natural Golf ST Hammer 420	7.9	7.8	7.7	7.9	7.8	8	7.8	7.8
Black Shark S.E.T. 455	7.8	7.7	7.8	7.9	7.7	7.8	7.6	7.8

Note: Source: http://www.golftestusa.com/drivers.html. Refer to the webpage for complete listing of test results. The test scores are normalized across years.

[9]The term "playability" is defined as the degree of how easy or difficult the clubs are to play for golfers of different skill levels. For example, a cavity back iron with significant perimeter weighting is clearly easier for most golfers to handle than a muscleback blade. We say the former shows higher playability. To golfers with advanced skills who care accuracy or distance a lot, however, higher playability of a golf club does not necessarily mean better quality since there is a trade-off between accuracy or distance and in ease of control.

Table 10. Driver Test Results on a Scale of 1 to 10 (2009)

Driver	Dist.	Ctrl	Accuracy	Forgiveness	Ball Flight	Sound	Feel	Overall
Titleist 909 D2	8.7	8.6	8.5	8.5	8.6	8.5	8.7	8.7
Cleveland Launcher	8.6	8.5	8.5	8.6	8.5	8.5	8.5	8.6
Titleist 909 D3	8.5	8.5	8.5	8.4	8.5	8.4	8.6	8.6
Ping G10	8.6	8.6	8.5	8.6	8.6	8.5	8.5	8.6
Mizuno MX 700	8.5	8.4	8.5	8.6	8.5	8.4	8.5	8.5
Pat Simmons Liberator 460	8.6	8.4	8.5	8.4	8.5	8.3	8.4	8.5
Cleveland HiBore Monster XLS	8.4	8.4	8.5	8.5	8.4	8.2	8.5	8.5
Bobby Jones Workshop Edition	8.4	8.3	8.5	8.7	8.4	8.5	8.5	8.4
Nike SQ DYMO	8.5	8.4	8.5	8.5	8.5	8.5	8.5	8.4
Infiniti xMOI Propulsion	8.3	8.3	8.4	8.3	8.4	8.2	8.2	8.3
Natural Golf Hammer	8.3	8.3	8.4	8.4	8.2	8.2	8.2	8.3
Nickent 4DX EVOLVER	8.3	8.4	8.3	8.3	8.2	8.3	8.3	8.3
Pat Simmons Liberator 420	8.3	8.2	8.3	8.2	8.2	8.3	8.3	8.3
Pinemeadow Doublewall	8.3	8.3	8.2	8.4	8.3	8.2	8.3	8.3
Srixon Z-RW	8.2	8.2	8.3	8.2	8.3	8.3	8.3	8.3
Wilson Staff Spine	8.3	8.2	8.4	8.3	8.3	8.3	8.2	8.3

Note: Source: http://www.golftestusa.com/drivers.html. Refer to the webpage for complete listing of test results. The test scores are normalized across years.

overall quality has been improved from 2006 to 2009: average of overall rating has risen from 7.9 to 8.43. Even though the difference is not huge the newer model of each brand receives generally higher ratings throughout all test categories (see Cleveland Launcher Ti460 (2006) versus Cleveland Launcher (2009) and Mizuno MX500 460 (2006) versus Mizuno MX 700 (2009) for instance.) It arouses the need of quality measure that captures evolution of products, as firms advertise more often than not that their new model is longer, faster, and stronger than its predecessors. Enhanced quality is achieved in two ways: (1) a Pareto improvement, e.g. showing longer hitting distance with better forgiveness or at least without weakening forgiveness, and (2) not a Pareto improvement but the gain in a characteristic dominates the loss in another, e.g. achieving much longer distance with a slight loss in forgiveness.[10]

It is not appropriate to take the ratings in Tables 9 and 10 as a measure of quality since they are on the taste characteristics as described above and rating values are tightly close to each other subsequently.[11] In short of remained observable characteristics, a candidate for a quality indicator must explain the technological difference within the time frame of the study by representing the main stream innovation issue successfully in a specific period with sufficient variability.

The time period of 2005-2009 was the era of maturing the head size. Figure 11 shows the time paths of average head size in the market: simple and weighted (by sales) averages from December 2004 to December 2009. Both simple and weighted averages show a gradual increase in average head

[10]Think of putting two balls in different size, red and white, into a box. You want the total volume of balls as big as possible in your own preference. If you prefer red balls much to white balls, you put a big red ball into the box by sacrificing the size of white ball, and vice versa. What really matters is then the size of the box, not each ball's relative size. Each person has different preference on relative size of balls but can always obtain bigger sum of ball sizes as she would like when the box got larger. Quality of a driver corresponds to the box size in this example.

[11]Another challenge in practice is not all models in the data are tested and rated due to various reasons. Some major brands decline to participate in the test and many minor models are not included lacking in mass interest.

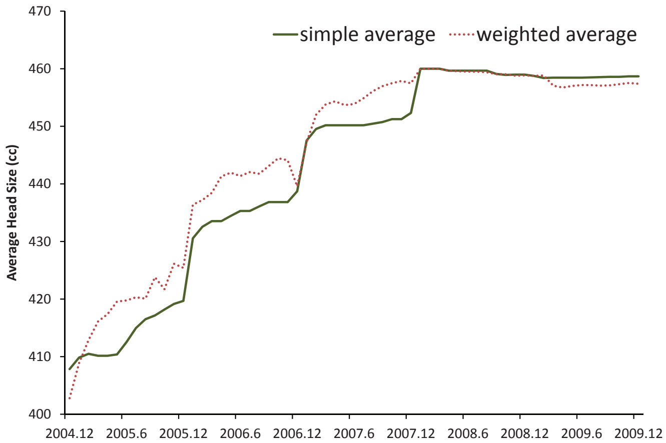

Figure 11. Monthly Average Head Size of Drivers

Note: Head size is in cubic centimeters. The US Golf Association institutes a size rule which states that no clubhead can measure greater than 460cc. The weighted average is weighted by the volume of sales.

size. They hit the maximum volume level of 460cc at the start of 2008 then stay close to it.

The heads of almost all drivers are made of titanium and the Coefficient of Restitution (COR) of all drivers has reached its permitted limit.[12] It is generally accepted that a driver with a bigger head outperforms the significantly smaller-headed ones. First and foremost, it definitely yields better forgiveness with a larger face. Even though a golfer mis-hits a ball more or less, it may carry the ball in the desired direction. As a result of the rapidly-increasing size of driver heads in the late 1990s and the advantage of a bigger head size, the US Golf Association (USGA) curbed the volumetric growth of drivers by instituting a size rule which states that no clubhead can measure greater than 460 cubic centimeters. Manufacturers maintain a light enough weight of a big-headed driver with the use of lighter, stronger, and more expensive material, titanium. Firm's cost of developing/manufacturing a bigger head would be higher than smaller ones. It calls for the use of expensive material and requires more subtle technology to balance the center of gravity and so on. In sum, a bigger head size typically represents a better performance and a higher manufacturing cost.

[12]The material of head has been meliorated from wood to stainless steel in late 1980's and to titanium in mid-1990's. The COR has been grown. The COR is a measure of the energy loss or retention when two objects collide. The higher the value of COR a driver has, the harder a ball is bounced resulting a longer hitting distance. A time of competition to improve the COR has passed since all drivers reached the limit permitted by the US Golf Association (USGA) as of early 2000s. Once a technological improvement has been matured in an aspect then R&D efforts and accordingly advertising is focused on new innovation.