Trial and Adoption: Understanding Demand Drivers for New Products in a Mature, Non-Durable Category

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Abstract

The high failure rate of new product in consumer packaged goods (CPGs) makes understanding the driving factors behind new product adoption of great importance to both market researchers and product managers. Using the beer industry in the US as a representative category, we examine the factors that drive the two key consumer decisions pertaining to new product adoption, i.e., trial and repeat purchase. In particular, we examine and distinguish how consumers react to marketing mix variables of the product in each of two stages of new product adoption. We estimate a two-stage probit model using Nielsen scanner panel data for the beer category. We find that marketing mix variables are the most important determinant (relative to consumer characteristics) of consumer trial decisions, but their impact declines in the adoption stage. Consumers' past purchase behaviors are significant predictors in both stages. We further show how managers can utilize such information to design customized target pricing based on consumer past purchase behavior and demographics to increase the sales of the new product.

Key words: new product trial, adoption, consumer packaged goods, target pricing

Introduction

Competition is intense in mature product markets such as consumer packaged goods. In order to improve their competitive position and generate growth, a common strategy employed by firms is innovating their brands through line extensions. The room for technological innovations, however, is usually limited for mature products. For example, a survey shows that 86% of innovations in different product categories across various companies are classified as incremental (Kim et al. 2005). This is especially true for consumer packaged goods (CPGs), where more than 75% of new products are merely the recombination of the existing product attributes without significant technology innovation or new features and benefits (Times and Trends, 2004).

Notwithstanding their common use in many packaged goods firms, the strategy of line extension is risky and costly: R&D and marketing investments in new products are continuously increasing but the majority of new products fail (Gielens and Steenkamp 2007). For non-durable product categories such as CPGs, 85% of new products eventually fail (Wong 2016), most of them within two years of introduction (Wisner 2015). Since the purchase cycles of non-durable products are short and brand switching is prevalent, the ability to attract consumers to make frequent (not just one or two) repeat purchases for line extensions is a crucial factor in driving the success of a brand. Indeed, evidence shows that new product failures are usually due to not only insufficient trials but also insufficient repeat purchases. This suggests that it is of crucial importance to have a good research understanding of what drives trial and repeat purchasing behavior of consumers with regard to new products.

Using the beer industry in the US as a representative category, this paper focuses on a mature, non-durable category and provides a descriptive study of factors that drive the two key consumer decisions pertaining to new product adoption, i.e., trial and repeat purchase. In particular, we examine how consumers react to marketing mix variables of the product in each of two stages of new product adoption. During the sample period from 2006 to 2011, the beer market was characterized by the entry of several new products under established brands. These new products could be categorized as line extensions of low novelty that offered a recombination of existing product attributes without expanding the product attribute space. We first study the consumer decision to purchase a new product for the first time in the “trial stage,” and then focus on the consumer decision to repeat purchase the new product in the “adoption stage.” The adopters in our study are defined as consumers who not only repeat purchase the new product but also end up using the new product for most of their subsequent consumption within the same product category. In other words, these are consumers who embrace the new product as their favorite. We accommodate consumer heterogeneity in the trial and adoption stages by classifying households into different types. For this purpose, we specifically use households’ past purchase behaviors, including variables that measure purchase intensity, variety seeking propensity, and the most frequently purchased products prior to the new product introduction as predictors of new product trial. For the adoption decision, we additionally use how early a household purchased the new product for the first time as a predictor. We also investigate how the new product’s marketing mix variables, i.e., price, feature and display, affect the two stages of consumer adoption of the new product.

We estimate a two-stage probit model using Nielsen scanner panel data for the beer category. We find that marketing mix variables are the most important determinant (relative to consumer characteristics) of consumer trial decisions, but their impact declines in the adoption stage. Consumers’ past purchase behaviors are significant predictors in both stages. More specifically, we find that heavy users have a higher chance of trial but a lower chance of adoption, while consumers who actively seek variety are less likely to both try and adopt new products. We also find that individuals who are early triers are less likely to become adopters. These results may appear surprising considering our view of innovation as something that delivers unique and new benefits to consumers. However, it can be understood by the fact that new products in this category are of low novelty as they recombine existing attributes rather than break new ground by creating new attributes. In this respect, mature nondurable categories are very different from emerging or growing categories where new products tend to be true innovations. Therefore new product management strategies that have been advocated for innovations in the academic literature, mainly for durable goods and services (see Peres, Muller and Mahajan 2010), may not necessarily apply to new products in mature nondurable categories. In this sense, our study adds to the literature on new product adoption by drawing strategic implications specifically for new products in mature nondurable categories.

Understanding consumer purchasing behaviors across two separate adoption stages – trial and adoption -- can be very useful to firms in enabling the proper design of new product marketing strategies. As an illustration, we show that, in contrast to a constant price strategy, a penetration price strategy, that offers a deep price discount to induce consumer trials, can significantly increase both quantity sales and profit for a new product in a nondurable category such as beer. The key profit driver of this penetration strategy is the dynamic change in a consumer's price sensitivity from the trial to the adoption stage. If feasible, the firm must customize prices in the two stages, targeting consumers based on their past purchase behaviors. We show that both sales and profits will grow further under such price customization. In particular, targeting households based on their consumption intensity is the most profitable.

To summarize, *we contribute to the marketing literature by providing managerial insights for firms to predict and manage a consumer's new product* adoption *in a mature, non-durable category. To accomplish this, we use panel data to study the effects of various factors, such as observable consumer characteristics and past purchase behavior, on new product trial and adoption. Based on the results, we show how the optimal prices are different for consumers with unique characteristics at the trial and adoption stages.*

The rest of this paper is organized as follows. In the next section we review the pertinent literature and delineate how our study contributes to this literature. The data section describes the beer industry during the sample period, discusses the variables that we construct for this study, and provides some summary statistics. In the section of empirical analysis, we present the conceptual framework and the estimation results. We also present findings from a pricing exercise based on the estimation results. Section conclusion concludes.

Review of Pertinent Literature and Contribution of Our Study

Starting from Bass (1969), and over a period of five decades, has emerged a rich and influential marketing literature on new product diffusion models (see Peres, Muller and Mahajan 2010 for an excellent review of this literature). The central purpose of such diffusion models is to explain and forecast the market penetration of innovations in the population using two key influences: (1) external influences of firm communications such as advertising on potential adopters, and (2) internal social influences of existing adopters on potential adopters through word of mouth, network externalities, social signals etc. These models have been successfully used to explain the observed market penetration, as well as forecast future adoptions, of not only durable goods innovations such as personal computers, DVDs, satellite television, mobile phones, digital cameras etc. but also services such as online banking, online social networks etc. These diffusion models are designed to explain the adoption of (radical) technological innovations, and serve this purpose well (Sood and Tellis 2005, Aboulnasr et al. 2008). What they are not designed to do is to explain the adoption of incremental improvements or line extensions in mature nondurable categories, which is the focus of this study.

Given our focus on mature nondurable categories, it is necessary for us to understand how differences between the new product and incumbent products in terms of both fixed product attributes, as well as time-varying marketing mix variables, may explain trial and adoption of the new product. We explicitly address this in our research. This has been unnecessary for previous research on diffusion models since their focus has been on category-level, not product-level, adoption. Also, the attention of diffusion models is more on prediction and less on explication of the underlying drivers of new product adoption. Further, given our focus on mature nondurable categories, it is necessary for us to model repeat purchase, in addition to first purchase or trial, of the new product. Repeat purchases of durable goods are not explicitly observed in aggregate penetration data. However, appropriate parametric assumptions on repeat purchases have been used in diffusion models to better enable aggregate sales forecasting for new products (see, for example, Krishnan, Seetharaman and Vakratsas 2012). Besides the diffusion literature, there is also attempt to establish a set of model and measurement procedures using consumer survey data to predict the market share of the new product in CPG good category (Silk and Glen 1978), which also focus on the trial and repeat purchase rate rather than the impact of the marketing mix variables and consumer purchase history on the new product adoption. In our case, we use individual consumer-level data and, therefore, explicitly observe repeat purchases in the data. This allows us to distinguish repeat purchases that do not suggest eventual adoption of the new product (i.e., a few repeat purchases after which the consumer does not buy the new product) from repeat purchases that are reasonably interpreted as adoption of the new product (i.e., a sufficient number of repeat purchases that suggests that the consumer has effectively adopted the new product). This is an innovative aspect of our research and lets us explicitly understand the drivers of adoption, as distinct from the drivers of trial, of the new product. This is an important contribution of this research.

Previous research on diffusion models has also studied the implications of the estimated adoption pattern for an innovation for optimal new product pricing over time (see, for example, Dolan and Jeuland 1981, Horsky 1990, Krishnan, Bass and Jain 1999). In our case, since we distinguish between trial and adoption stages, we can study whether there are differences in pricing implications between the two stages. This is not unlike understanding the pricing implications of the presence of switching costs in consumer demand for durables, where one distinguishes between acquisition and retention pricing (Acquisiti and Varian 2006).

Separate from the diffusion literature referenced above, there is a rich and influential marketing literature on consumer demand for line extensions. Reddy, Holak and Bhat 1994, Calantone et al. 1996, Dekimpe et al. 2000 and Desiraju et al. 2004 use *aggregate* sales data to study what factors drive the success of line extensions (Reddy, Holak and Bhat 1994 and Desiraju et al. 2004 study nondurables, as in our case). However, we use *disaggregate* (i.e., household level) data in this paper. In doing this, we are able to study, unlike researchers who have used aggregate data, how consumers' past purchase behaviors, such as their purchase intensity, variety seeking propensity, and brand and product preferences influence their trial and adoption propensities for new products. This is a new contribution to the literature on line extensions.

Several researchers have used household level data, as we do in this study, to study consumer demand for line extensions. These papers include Chandrashekaran and Sinha 1995, Gauvin and Sinha 1997, Nijssen 1999, Steenkamp and Burgess 2002, Steenkamp and Gielens 2003 and Batra et al. 2010. However, these papers study trial only, and ignore adoption, which is a key focus of our research (in addition to trial). Some papers have additionally studied repeat purchases. These include Helsen and Schmittlein 1994, Kim & Sullivan 1998, Swaminathan et al. 2001, Swaminathan et al. 2003. However, these papers focus on just one or two purchases after trial. For non-durable goods, however, the eventual success of a new product relies on more than a few initial purchases. To the best of our knowledge, Gielens and Steenkamp (2007) is the only study that looks beyond a few initial purchases. The authors focus on the first year since consumer trial of a new product to study consumer acceptance of the new product. Our paper goes beyond even first year consumer acceptance of the new product. We define “adopters” as those who not only repeat purchase a new product but also make the new product their most frequently purchased product. In other words, adopters are customers who are converted to being “loyal customers” of the new product. Another major difference from Gielens and Steenkamp (2007) is that we explicitly investigate how a consumer’s past purchase behavior in the product category helps predict their trial and adoption decisions for the new product. We find that these factors play a significant role in driving demand in both stages, i.e., trial and adoption. While previous studies in the marketing literature (Ainslie and Rossi 1998, Kim et al. 1998, Seetharaman, Ainslie and Chintagunta 1999) have used past purchase behaviors of consumers, such as shopping intensity and purchase frequency, to identify heterogeneity in price sensitivities and brand preferences across households, ours is the first paper to use past purchase behaviors of consumers to study their impact on not only trial but also adoption of new products. Gielens and Steenkamp (2007) measure the “dispositional innovativeness” of individual households based on data collected from questionnaires. This measure is related to the variety-seeking measure that we construct in this study. We use readily observable data to represent individual characteristics, instead of using additional data from surveys or other sources. This is an important contribution to the literature on line extensions.

Data

We use Nielsen data from the Kilts Center for Marketing, specifically the Retail Scanner Dataset and the Scanner Panel Dataset, for this study. We focus on the beer category. The scanner panel dataset includes the purchase records of about 7,000 US households from 2006 to 2011. It also contains households' demographic characteristics -- income, age, race, education, and occupation -- as well as households' longitudinal purchase information in the beer category, i.e., time of purchase, store of purchase, purchased product, price paid, and quantity purchased. The retail scanner dataset contains store-level marketing information, specifically products' shelf prices, as well as product promotions such as displays and features.

To better understand and classify beer products in the data, we acquire information about how and where the beer was brewed from the 2016 Beer Style Guidelines by the Brewer Association. The Guidelines allow us to identify the major beer attributes and, therefore, classify our beer products based on brands, types and styles. There are three main beer types: Lager, Bock and Ale. There are also seasonal beer products whose flavors and tastes may change in different seasons. For each type, there are different beer styles that are determined by the origin and yeast.[1] Different combinations of types and styles contribute to different beer flavors. We also obtain the brand name of each product. This lets us operationalize the 74 beer products in our data as distinct brand-type-style combinations. For a product to be considered as a new product in a geographic market, which in our case is a Designated Market Area, or DMA, the product should not have been available for purchase in that DMA at the beginning of the sample period. There are a total of 201 DMAs in our dataset. In order for a product to be considered as a new product for further analysis in our study, it must not have been available in the first 50 weeks for at least 50 DMAs, or in the first 20 weeks for at least 100 DMAs. This prevents our labeling products that had already been introduced prior to our sample period for a vast majority of DMAs, but were introduced during our sample period to a few DMAs, as new products for our analysis. Further, among products that can be considered as new products in our study, we define a product as new to a specific market if it is not sold in any stores within that market for the first 50 weeks of data. That said, the introduction date of a new product can be different across markets. All of the new products in our data are line extensions, rather than true technological innovations, for existing brands. Table 1 lists the 14 new products that we have identified in our dataset.

[Insert Table 1 here]

We study households' trial and adoption decisions in the beer category by analyzing each household's purchase behavior toward a new product after the new product is introduced in the household's geographic market (Note: The new product could be any of the 14 new products discussed above). After the new product is introduced in a market, all households in the market are candidates in the trial stage, i.e., potential triers of the new product. After a household makes their first purchase of the new product, the household becomes a candidate in the adoption stage, i.e., potential adopter of the new product. In order to define specific households as adopters, we first calculate, for each household, the ratio of the number of purchases of the new product to the total number of beer purchases after the first purchase of the new product. Based on the 80-20 rule, we define adopters as households whose ratios are in the top 20% among all triers. Among all the adopters defined in this manner, the average purchase ratio is 61.46 %. In other words, for these adopter households the new product has become their most preferred product after its introduction. Table 2 shows that the total quantity sales and revenue, averaged across the 14 new products, are much higher for adopters than for triers. Overall, 51.24 % of quantity sales and 52.98 % of revenue come from adopters, although adopters only account for about 16 % of triers. This suggests that the success of line extensions in the beer category is driven by their ability to convert triers into adopters.

[Insert Table 2 here]

In order to study the drivers of demand for new products, we construct a set of potentially relevant explanatory variables at the household level. The first group of variables represents the marketing mix of the new product as faced by the household. For each household, we calculate the average values of display and feature of the new product in the household's most frequently visited store, separately for the trial and adoption stages. This measurement is dynamically adjusted over the two stages. In the trial stage, the average is calculated over a period starting from the week of introduction of the new product in the store until the week that the household purchases the product for the first time. In the adoption stage, the average is calculated over a period starting from the week after the first purchase until the last week of the sample period. If the household never purchases the new product in the sample period, the average is calculated over a period starting from the week of introduction in the store until the last week of the sample period.

The average *Display* and *Feature* are constructed in order to understand the effects of non-price promotional activities of the new product at the store on household demand for the new product. In order to study the impact of price of the new product, we construct an indicator variable, *Premium price*, which is equal to 1 if the average price of the new product at the household's most frequently visited store is higher than that of other beer products in the store. Using this variable allows us to investigate whether premium-priced new products show distinct trial and adoption patterns. Note that this variable may be correlated with the quality of the product, as well as marketing activities, such as advertising, of the new product, that we do not observe in the data. To that extent, therefore, its estimated impact on new product demand may represent the composite effect of multiple marketing factors and not just price of the new product. In order to address this concern, we construct another variable, *Relative store price,* which is the percentage difference between the price of the new product in the household's most frequently visited store and the price of the same product averaged across all other stores in the household's DMA. By construction, this variable cannot be correlated with the (unobserved) product quality or product advertising, neither of which is store-specific and, therefore, identical across all stores within the same market. Therefore, including this price variable allows us to understand the effect of the price of a new product on its trial and adoption patterns in the market. Understanding how marketing mix variables – price, display, feature -- influence new product demand in the two stages would be useful to derive prescriptions for how new products must be marketed at the time of launch versus at later stages of market penetration.

A second set containing one explanatory variable, *Competition*, is measured as the number of available beer products with the same type and style as the new product within the same geographic market. The more similar products are available, the higher is the competitive effect, which may hinder adoption of the new product; conversely, however, households in the market may be more familiar with the product attributes so there may be a higher acceptance of the new product.

A third, and perhaps most important, set of explanatory variables pertains to past purchase behaviors of households in the beer category. Including these variables allows us to understand the degree of heterogeneity within a market in households' trials and adoptions of the new product. We construct three categories of variables that are related to past purchase behaviors of households. First, we look at the beer product that was purchased most frequently by the household before a new product becomes available, which gives us a view of the household's favorite brand, type and style. We then construct three indicator variables, *Change brand*, *Change type*, and *Change style*, which are equal to 1 if the new product differs from the previously most purchased product in brand name, type, and style, respectively. We also construct an indicator variable, *Previous big brand*, which is equal to 1 if the previously most purchased product belongs to a big brand of beer that has top market share nation-wide.[2]

Second, we include variables pertaining to each household's variety-seeking propensity. We construct three indicator variables, *Brand variety seeking*, *Type variety seeking*, and *Style variety seeking*, that are equal to 1 if the household is among the top 20 % of consumers in our data who have tried the most brands, types, and styles of beer products, respectively, before the new product becomes available. Third, we include a household's purchase intensity as an explanatory variable. For this purpose, we first calculate the average amount of beer that each household purchases over a year prior to the new product introduction. We then construct an indicator variable, *Heavy drinker*, which is equal to 1 if the household is in the top 20 % of households in terms of beer consumption, and another indicator variable, *Occasional drinker*, which is equal to 1 if the household is in the bottom 20 %.

For the adoption decision, we additionally include an indicator variable, *Early trier*, which is equal to 1 if the household tries the new product in the first month after the product is introduced in the market.

As a fourth and final set of explanatory variables, we include household demographics, i.e., income, family size, age, education, race and occupation of the head of household, as well as the geographic region where the household resides. Finally, as control variables in the regression analysis, we also include four indicator variables for *German ale, German lager, American lager*, and *Seasonal*, which represent popular combinations of types and styles in our data, as well as an indicator variable for whether the new product belongs to a top selling brand (*Big brand*). Detailed descriptions and some summary statistics for all of the above variables are provided in Table 3.

[Insert Table 3 here]

Empirical Analyses

In this section, we first present a conceptual framework that explicates how different factors, as listed in the previous section, are expected to impact households' purchase decisions in the trial and adoption stages for new products in a nondurable category. We then describe a statistical model that we use to estimate the effects of these factors on households' trial and adoption decisions in the beer category. Third, we present the estimation results. Last, we derive managerial implications of our empirical findings by showing how a firm can price its new product over time in order to suitably target consumers with different behavioral profiles across the trial and adoption stages.

Conceptual Framework

Households' information sets regarding new products, as well as their perceived risk of purchasing new products, are expected to be different between the trial and adoption stages. As a consequence, we hypothesize that households' responsiveness to price and non-price promotions of the new product would be different across the two decision stages. For example, households may require a significantly low relative price or/and aggressive display and feature promotions for the new product in order to be induced to try it; however, once households have tried the new product and repeat purchase it a few times, their decision to adopt the new product may not rely as much on marketing mix variables of the new product. Further, households with strong preferences for product attributes which are not represented in the new product may have a lower propensity to adopt the new product even if they are likely to try it. Note that we focus on new products which are line extensions and lack substantial novelty of features and benefits; therefore consumers' reactions to these products will likely be different from those in categories where new offerings represent true innovations.

Marketing Mix. When a new product is launched in a market, households are initially uncertain about its efficacy. Price promotions and non-price promotions may, therefore, be necessary to convince risk-averse households to purchase the product for the first time. After the trial, households' uncertainty about the new product will reduce and, therefore, the impact of marketing mix on the adoption decision may diminish. This would suggest that households' responsiveness to marketing mix variables may be lower in the adoption stage than in the trial stage. In the beer category (or more generally, in a nondurable category), however, new products are a recombination of established brands with existing types and styles, and not true innovations. Therefore, households' perceived risk may be a less potent factor in the beer category.

In a mature nondurable product category such as beer, households typically have established preferences for existing products. Further, as an extensive literature in marketing (see, for example, Seetharaman and Chintagunta 1998, Cosguner et al. 2017) has documented, the effect of purchase inertia in such categories is very strong which generally prevents consumer household from switching to an untried product. In that case, price and non-price promotions may help break that barrier and initiate household trial for the new product. After the trial, the household's switching cost is reduced as the household has acquired first-hand experience with the new product. This, in turn, would suggest that the role of price and non-price promotions may be less important in terms of affecting consumers' adoption decisions.

Past Purchase Behaviors. It is well known in the marketing literature that households' preferences for product attributes are excellent predictors of their revealed product choices (see, for example, Chan 2006, Che, Sudhir and Seetharaman 2007). For that reason, we expect preferences for brand, type and style to be important determinants of households' purchase decisions in the beer category. If the new product has attributes different from those contained in the household's past favorite product, we expect the household to be less likely to try and adopt the new product. The existence of inertia may further lower the household's trial and adoption probabilities. We believe that households focus more on brand or type, and less on style, while making product choices in the beer category. For that reason, we expect style to have a less significant impact, if any, on households' trial and adoption decisions toward new products.

To the extent that variety-seeking consumers are known to seek novelty in their product choices, they may be more likely to try new products. However, as discussed earlier, line extensions are not true innovations in the sense of offering novel product attributes. Instead, line extensions represent recombinations of existing attributes in the category. Therefore, in our case, it is not clear that variety seekers will be more likely to engage in new product trial. Given the lack of novelty associated with the new product, we hypothesize that variety seekers may even be less likely to try and adopt the new product.

The effect of consumption intensity on new product adoption has been documented by Taylor and James (1977) and Morgan and Fred (1979). They find that consumers with higher consumption intensity are more likely to try new products. We believe that this result will hold in our case for line extensions as well. This is because the cost of sampling the new product must be smaller for households that consume more in the category. However, since these households are likely to have more knowledge and experience with the product category, they may be less likely to be satisfied with the new product (which simply recombines existing attributes) after trial, which, in turn, would imply that their adoption probability may be lower.

Statistical Model

We model a household's trial and adoption decisions using a two-stage probit model. In the trial stage, household i makes the decision of whether or not to purchase the new product j for the first time. We denote the two possible values of the trial stage outcome by $trial_{ij} = 1$ and $trial_{ij} = 0$, respectively. Once the household has tried the product, the household moves to the adoption stage, where the household decides whether or not to adopt the product. We denote the two possible values of the adoption stage outcome by $adopt_{ij} = 1$ and $adopt_{ij} = 0$, respectively. Let X_{ij}^1 be a row-vector representing the relevant explanatory variables for the trial stage, and X_{ij}^2 represent the explanatory variables for the adoption stage (see Section 3.1

for a detailed discussion of these variables, also see Table 3). The two-stage probit model is represented using latent variables y_{ij}^1 and y_{ij}^2 as follows:

Stage 1: Trial

$$y_{ij}^1 = X_{ij}^1\beta^1 + u_{ij}^1, \text{ and}$$

$$trial_{ij} = 1 \; if \; y_{ij}^1 \geq 0; 0 \; otherwise. \qquad (1)$$

Stage 2: Adoption

$$\text{If } trial_{ij} = 1,$$

$$y_{ij}^2 = X_{ij}^2\beta^2 + u_{ij}^2, \text{ and}$$

$$adopt_{ij} = 1 \; if \; y_{ij}^2 \geq 0; 0 \; otherwise. \qquad (2)$$

Explanatory variables are household-specific and constructed dynamically: for the trial stage, the variables are constructed using data from the period before the new product is available in the city in which the household lives; for the adoption stage, some of these variables, such as the new product's marketing mix, are updated to reflect their changed values (as explained earlier in the last section).

In order to accommodate correlation between trial and adoption outcomes, we assume that the stochastic components u_{ij}^1 and u_{ij}^2 follow a bivariate normal distribution, as shown below.

$$\begin{pmatrix} u_{ij}^1 \\ u_{ij}^2 \end{pmatrix} \sim N(0, \Sigma), \qquad \Sigma = \begin{pmatrix} 1 & \sigma^2 \\ \sigma^2 & 1 \end{pmatrix} \qquad (3)$$

where σ represents the correlation. We use simulated maximum likelihood to estimate model parameters.

Estimation results

Table 4 presents the estimation results for both stages – trial and adoption -- of the two-stage probit model in separate columns. In order to better reflect the economic meaning of the estimates, we also report the marginal effect of each statistically significant estimate on the trial and adoption probabilities. In order to calculate the marginal effect, we first assume all variables (including indicator variables) are at the average level in the data, and calculate the trial and adoption probability. Then we change the value of the focal variable by 1 percent, while fixing the values of other variables at the average level, and calculate the change of the probabilities. We discuss the estimation results separately for three categories of explanatory variables below.

[Insert Table 4 here]

Past purchase behaviors. Both in the trial and adoption stages, consistent with our expectations, the coefficients of *Change brand* and *Change type* are negative and significant, i.e., a household is less likely to both try and adopt the new product if its brand name or type differs from the brand name or type of its past favorite product. This suggests that a household's choice inertia toward its favorite brand and type represent effective barriers against new product trial and adoption. In fact, the marginal effect of *Change brand* is found to be larger than that of any other variable in the trial and adoption stages, which emphasizes the importance of brand loyalty as an important barrier to be overcome to induce new product trial and adoption, especially for new products launched by brands with a low installed base of loyal customers. The coefficients of *Change style*, on the other hand, are positive and significant, i.e., a household is more likely to try and adopt the new product if its style is different from the style of its favorite past product. In other words, households seem to prefer novelty in style in order to be induced to try and adopt a new product. This is an interesting, empirical finding for beer manufacturers. More generally, it suggests that not all attributes of a household's favorite past product in a nondurable category play a similar role in terms of whether a household would try a new product on account of its underlying attributes. This is similar to the finding in Che, Sudhir and Seetharaman (2006) that households seek temporal variety in some product attributes but are inertial in others while choosing products over time.

The coefficient of *Previous big brand* is negative and significant in the trial stage, and insignificant in the adoption stage. This suggests that households that are loyal to big brands are less likely to try the new product, but conditional on trial no different than other households in terms of their likelihood of adoption. This may be because a household's actual consumption of the new product, which happens after trial, may be sufficient to overcome the potential adoption hurdle posed by the household's prior loyalty to big brands.

In terms of the variables pertaining to variety seeking, we find that the coefficient of *Type variety seeking* is negative and significant in the trial stage and insignificant in the adoption stage. This means that a household that seeks a lot of variety in terms of product type is less likely to try a new product. This could be because such a household does not find the novelty value of the new product to be sufficient to induce trial. We also find that the coefficient of *Brand variety seeking* is negative and significant in the adoption stage and insignificant in the trial stage. This means that a household that seeks a lot of variety among existing brands is less likely to adopt a new product. This could be because the new product represents a brand name that is already familiar to the household. We find that *Style variety seeking* does not significantly influence either trial or adoption of a new product.

We find that the coefficient of *Heavy drinker* is positive and significant in the trial stage, i.e., heavy drinkers are more likely to try new products. This finding is consistent with the findings in Taylor and James (1977) and Morgan and Fred (1979). However, in an interesting reversal, the coefficient of *Heavy drinker* is negative and significant in the adoption stage, i.e., heavy drinkers are less likely to adopt new products conditional on trial. One explanation for this is that heavy drinkers face a relatively low cost / risk of trying the new product (since they already spend a lot on beer), but on account of their extensive experience / knowledge in the category are less likely to abandon their well-established consumption pattern and adopt the new product after trial.

Finally, we find that the coefficient of *Early trier* is negative and significant in the adoption stage, i.e., households that try the new product in the first month of launch are less likely to eventually adopt the new product than households that try the new product in later months. On one hand, if a household buys a new product right after its launch, it may signal high preference for the new product and hence higher eventual adoption probability for the new product. On the other hand, early trial may indicate that the household is quickly sampling the new product to see whether it is sufficiently novel when compared to existing products. In that case, the household will not adopt the new product if it does not deliver on novelty, which is likely the case for mature, non-durable categories. Our result supports the second argument. Another explanation for our finding could be that late triers are more likely to be influenced by positive word of mouth from past adopters (when compared to early triers who are more likely trying the new product for intrinsic reasons) and, therefore, may be more likely to eventually adopt the new product.

Marketing mix variables. The coefficients of display in the trial and adoption stages are both positive and significant, i.e., display activities on the new product at the store increase households' trial and adoption probabilities for the new product. The coefficient of feature is positive and significant in the trial stage and insignificant in the adoption stage. The insignificant impact of feature, which is an out-of-store marketing variable and, therefore, more likely to influence the household prior to visiting the store, in the adoption stage is consistent with our *a priori* expectations that household adoption should rely less on marketing mix variables and more on direct consumption experience. In both stages, the coefficients of *Premium price* are positive and significant, i.e., households are more likely to try and adopt products that are premium priced. As discussed in the previous section, the *Premium price* variable may be correlated with the new product's unobserved product quality and marketing activities. Therefore, the estimated positive coefficients of *Premium price* could reflect households' higher willingness to try and adopt premium products when they are introduced. In contrast, in both stages, the coefficients of *Relative store price* are negative and significant, which reflects the more traditional price effect, i.e., the lower the price of a new product in a store relative to other stores, the higher the trial and probabilities for the new product at that store. We interpret these coefficients as representing the price sensitivities of households in new product trial and adoption. In fact, the marginal effect of *Relative store price* is found to be the third largest (after *Change brand* and *American lager*) among all variables in the trial stage, which emphasizes the importance of price in inducing new product trial. The coefficients of *Competition* are not significant in both trial and adoption stages.

Household demographics. We find that household income, size, age, and education do not have significant effects on either trial or adoption. We find that Asians are less likely to try new products than Whites, but more likely to adopt new products than Whites conditional on trial. This suggests that Asians are more "conservative" than Whites in terms of trying new products, but given trial (for reasons such as word-of-mouth from friends or personal research, which are not observed in the data) are more likely to adopt the tried new product. African Americans, on the other hand, are found to be less likely to adopt new products than Whites. This could be because African Americans' product preferences in mature categories are more established and less amenable to change.

In terms of geography, we find that households in the Mid Atlantic, South Atlantic, and Pacific regions are more likely to try new products than households in New England (excluded region). However, in another interesting asymmetry, households in these regions are found to be less likely to adopt new products conditional on trial. Again, this may signal the fact that households in these regions are more "adventuresome" in terms of trying new things, but have more established product preferences that are less amenable to change in the long run. Further, we find that households in the West North Central, East South Central, West South Central, and Mountain regions are less likely to adopt new products than those in New England. Overall, geography is observed to play a more important role in the adoption stage than the trial stage. Our estimated heterogeneity in new product adoption rates across geographic regions creates an opportunity for beer manufacturers to set different prices for the same new product across different regions in order to increase their profits. We find that occupations 7 and 10 are associated with higher trial probabilities, while occupations 4, 7 and 8 are associated with higher adoption probabilities, and occupation 6 is associated with lower adoption probabilities, when compared to other occupations.

As far as product attributes are concerned, the coefficient of *Big brand* is negative and significant in the trial stage. The coefficient of *American Lager* is negative and significant in both the trial and adoption stages. Since *American Lager* is the most common type of beer in the US market, a new product under this umbrella is less likely to be noticed as "really new" and, therefore, is less likely to attract either consumer trial or adoption. We find that a new product of *German Lager* is also less likely to be adopted. In contrast, however, we find that a new product of *German Ale*, is more likely to be adopted.

Finally, the correlation between the error terms in the two stage probit model is estimated to be positive and significant, which suggests that after controlling for all observables, we find that households that have a higher propensity for new product trial (for idiosyncratic reasons) also have a higher propensity for new product adoption.

We investigate the robustness of our empirical findings by excluding various subsets of explanatory variables and observing whether any changes occur in the signs of the estimated coefficients of the included variables. We are happy to report that our main findings, discussed above, remain robust to these checks. Among the different categories of explanatory variables used in our model, we find that past purchase behaviors and the marketing mix contribute the most to the model fit.[3]

Importance weights of variables. Looking at the estimated marginal effects of all variables across the two stages, we find that *Change brand* and *American lager* have the two largest marginal effects in both stages. In the trial stage, *Relative store price* has the third largest marginal effect. Its effect is relatively muted in the adoption stage. Household demographics have large marginal in the adoption stage.

We assess the relative importance of the different variables as follows: for each variable whose estimated coefficient is statistically significant, we calculate the difference between the maximum value and the minimum value of the variable in the data, and then multiply this difference by the variable's estimated coefficient.[4] We then take the absolute value of this difference, and divide this absolute value by the sum of the absolute values of all variables we use in the regression. This procedure gives us the importance weight of each variable. Results are reported in the upper panel of Table 5.

[Insert Table 5 here]

Consistent with the marginal effects discussed above, we see that *Change brand*, *Relative store price*, and *American Lager* are the three most influential factors in the trial stage, whose relative importance weights range from 19% to 22%. All other variables have much lower relative importance weights. Interestingly, we find that these three variables are the most influential factors in the adoption stage as well, although their relative importance weights are smaller, ranging from 14% to 18%.

We group the explanatory variables into four categories: marketing mix, past purchase behaviors, demographics, and product attributes. We report the sum of the relative importance weights of all variables within each category in the lower panel of Table 5. Results show that marketing mix variables are the most important category of factors in terms of explaining households' trial decisions (with 34% weight), which highlights the importance to firms of using price and non-price promotions to induce new product trial. Past purchase behaviors are found to have a large impact on both trial and adoption stages (weights of 32.8% and 31.6%). This suggests that firms must account for households' past purchase behaviors, as revealed in their customer databases (collected using loyalty programs, for example) while targeting them for marketing activities. Demographics have a large impact on households' adoption decisions (27.2% weight) but only a modest impact on their trial decisions (9.4% weight).

Managerial Implications

To illustrate the managerial implications of our empirical findings, we perform a numerical exercise to show how price discounts on new products would impact households' trial and adoption decisions. First, we fix the price of each new product at its average level in each geographic market, and simulate the trial and adoption probabilities of each household using our estimated two-stage binary probit model. We then assume that the prices of the new products are discounted by 20%, and re-simulate the trial and adoption probabilities of households. We present the results of this numerical exercise in the form of the probability distribution of households' purchases in Figure 1, with the left figure representing trials and the right figure representing adoptions. Each figure reports two probability distributions, one for average prices, and another for discounted prices. The dark area in each bar is the region where the two probability distributions overlap. The grey area denotes the region of higher frequency under average prices, and the lighter area denotes the region of higher frequency under discounted prices.

Figure 1 makes it clear that the masses for both trial and adoption probabilities shift to the right (i.e., both trial and adoption become more likely) under a price discount. For example, the left figure shows that a large number of households with trial probabilities below 2 % at regular prices have trial probabilities that have increased to 3 % or higher at discounted prices. The right figure shows that a significant number of households with adoption probabilities below 10 % at regular prices have adoption probabilities that have increased to 25 % or higher at discounted prices.[5]

[Insert Figure 1]

We noted earlier that the estimated effect of *Relative store price* is stronger (i.e., more negative) in the trial stage than in the adoption stage. This raises an interesting question about the strategic implication of this asymmetric price impact on new product pricing. Would it be profitable for a manufacturer to adopt a dynamic pricing scheme in which they systematically change the price of the new product from the trial to the adoption stage? In other words, should the firm charge different prices to a household depending on whether the household is in the trial stage (i.e., has not purchased the new product) or the adoption stage (i.e., has made its first purchase of the new product)? In reality, firms may not be able to differentiate between these two groups of households (unless they have a customer database where previous purchases of households are observed). In that case, firms could implement the dynamic pricing policy as follows: when a new product is first introduced, the majority of households are in the trial stage and therefore trial pricing can be used; after a few (i.e., 4-5) months, by which time most trials would have happened, the firm could move to adoption pricing. We answer this question using a numerical exercise. In order to calculate the firm's combined profit over two periods (trial and adoption), we assume that the marginal cost of the new product is constant over time. Let $E(q_1)$ and $E(q_2)$ be the expected sales quantity in the trial and adoption stage, respectively. The expected profit of the firm can be written as

$$\Pi\,(p_1, p_2) = (p_1 - c) \cdot E(q_1) + (p_2 - c) \cdot E(q_2) \qquad (4)$$

where p_1 and p_2 are the prices in the two stages and c is the marginal cost. We normalize the market size to 1, and assume that each consumer will buy at most 1 unit in the trial period. The expected sales in the trial stage would, therefore, be equal to the average trial probability, $T(p_1)$. In the adoption stage, the expected sales would be equal to the product of $T(p_1)$ and the average conditional adoption probability, $A(p_2)$, further multiplied by the average purchase quantity per period (Q) and the total number of periods that the household continues to be an adopter of the new product (N). The expected profit, therefore, can be rewritten as

$$\Pi\,(p_1, p_2) = (p_1 - c) \cdot T(p_1) + (p_2 - c) \cdot T(p_1) \cdot A(p_2) \cdot Q \cdot N. \qquad (5)$$

We do not observe products' marginal costs in the data. Therefore, we estimate the marginal cost c of the new product, that is needed in the above equation, by assuming that the average price of a new product, p (across all geographic markets and all periods), is the optimal price that the firm would charge (i.e., $p_1 = p_2 = p$) in order to maximize the expected profit. We assume that $N = 1$. We calculate the average annual purchase quantity of new products (among 12 oz. beer) for each adopter in the data and take its average value, 54.28 units, as the value of Q. We find that the estimated marginal cost (c) is about 73.8% of the average price (p), which appears quite realistic given that the average gross margin of Anheuser Busch beer was in the range of 28-38% range in 2007 and 2008.[6] Under average prices, the predicted trial probability (1.6 %) and the predicted (conditional) adoption probability (15.7 %) are reported in the first row of Table 6.

Next, we numerically search for the optimum prices that maximize $\Pi\,(p_1, p_2)$ in equation (5). Results are reported in the second row of Table 6. The optimal strategy is to offer a deep price discount (32 % lower than current average price) in order to induce trials and then to raise the price (53 % higher than current average price) to households that have already tried the new product. As an example, the average price of one unit of *Budweiser Chelada* is currently \$1.25. Under the proposed dynamic pricing scheme, the optimal prices are \$0.85 in the trial stage and \$1.92 in the adoption stage. With the marginal cost being \$0.92, the firm will incur a loss of 7 cents on each trial purchase, but will make a profit of \$1 on each purchase unit from an adopter. Since households have been estimated to be very price sensitive in the trial stage, the steep price discount is necessary to significantly boost households' trial probabilities (from 1.61 % to 3.87 %). While a household's adoption probability conditional on trials decreases (from 15.71 % to 10.43 %) on account of the higher second-stage price, the household's unconditional adoption probability still increases because of the increase in the household's trial probability. As a result, total sales quantity sales and profit of the new product over the two stages both increase.[7] The marketing literature on new product diffusion models has found that *skimming* (i.e., initial high price followed by decreasing price) is generally optimal for the pricing of durable goods over time because early adopters tend to be less price sensitive and late adopters tend to be more price sensitive (Bass and Bultez 1982, Kalish 1983, Kalish and Lilien 1983, Dockner and Jorgensen 1988, Bass, Krishnan and Jain 1994). In our case, however, we find that *penetration pricing* (i.e., initial low price followed by higher price) strategy is optimal for the pricing of non-durable goods but not on account of heterogeneity in the type of buyers adopting early versus late, but because of the dynamic change in the price sensitivity of households from the trial to the adoption stage. *This is a new and interesting pricing implication for the new products literature.*

[Insert Table 6]

Our estimation results show that the trial and adoption decisions are systematically different across different types of households depending on their past purchase behaviors. Therefore, if firms can target different households, based on their past purchase behaviors, with different prices across the two stages, firms may be able to further increase their profits. To illustrate this result, we perform additional numerical exercises where we allow firms to charge different p_1 and p_2 to different household segments. Results are also reported in Table 6.

Consumption intensity. We first identify heavy drinkers, medium drinkers and occasional drinkers based on their purchasing behavior in the sample, and then separate them in to three household segments. For a heavy drinker, the average annual purchase quantity is 178 units. For medium and occasional drinkers, the average purchase annual purchase quantities are 24.8 and 21.1 units, respectively. From rows 3-5 of Table 6, we see that firms should offer a heavy price discount (62 % lower than the average price) to heavy drinkers, and a moderate price discount (11-12 %) to medium and occasional drinkers, in the trial stage. The higher price in the adoption stage, however, is roughly similar across all three consumption segments. The reason for this is that heavy drinkers are much more profitable in the long run; therefore, firms must be much more aggressive in lowering price to induce trials from such households. We find that trials and adoptions among heavy drinkers increase by 244 % and 24 %, respectively, in response to our optimal pricing policy. Total sales and profit increase by 200 % and 120 %, respectively, which are substantively huge increases.

Previous favorite product. Next we separate households in to two segments based on whether the new product type is different from the type of the household's favorite product (i.e., *Change type* = 1) or not (i.e., *Change type* = 0). From rows 6-7, we see that in the trial stage, firms should give a more aggressive price discount to the *Change type* = 0 segment (42 %) than to the *Change type* = 1 segment (32 %), but charge both segments roughly similar prices in the adoption stage. When we divide households in to *Change brand* = 0 and *Change brand* = 1 segments, however, we find that the trial stage price is roughly similar across both segments, but the adoption stage price is much higher for the *Change brand = 0* segment (65 % higher than average price) than for the *Change brand* = 1 segment (53 %). In contrast to the case of targeted pricing based on *Change type*, when we divide households in to *Change style*, = 0 and *Change style* = 1 segments, we find that the trial stage price is much lower for the *Change style* = 1 segment (33 % lower than average price) than for the *Change style* = 0 segment (15 %). This is consistent with our result in Table 4 that *Change style* = 1 has a positive effect (in contrast to *Change type* = 1 having a negative effect) on trial and adoption probabilities of households.

Variety seeking. When we separate households in to variety seeking segments based on type and brand, we find that targeted pricing based on variety seeking type makes no difference to firm profit, while targeted pricing based on variety seeking brand involves charging a much lower trial stage price for a non-variety seeker on brand (37 % lower than average price) than for a brand variety seeker (11 %).

Conclusion

In this paper, we focus on a mature, non-durable goods category and examine what factors drive household-level trial and adoption of new products; in particular we explore how households react to the marketing mix across the two stages. The new products in our study are line extensions that represent incremental innovations within existing brands. We show that households' past purchase behaviors (such as the brand name or type of the previously most purchased product, variety seeking behavior toward product types or styles, consumption intensity etc.) are the most important predictors of households' trial and adoption decisions. Demographic variables are relatively unimportant in terms of predicting new product trial, but hugely important in terms of predicting new product adoption after trial. As for the marketing efforts, while display is found to impact both trial and adoption, feature is effectual only in the trial stage. Price is the dominant marketing variable in terms of influencing new product trial and adoption. Using a numerical exercise based on our model parameters, we illustrate how a price penetration strategy, where the new product is initially priced low (perhaps even below cost) to stimulate trial and then priced high after adoption, would yield substantively huge dividends, in terms of increased sales and profit, for firms introducing new products.

The key differences between our study and the previous marketing literature on new product adoption are as follows: (1) We study a mature, non-durable category, where new products represent incremental innovations, unlike a majority of previous studies that have focused on durable good categories, where new products represent technological innovations with novel attributes and benefits; (2) We study household-level adoption, unlike previous studies that have largely focused on aggregate adoptions at the market level; (3) Our primary interest is in explicating the effects of marketing mix variables, as well as household-level demographics and past purchase behaviors (such as consumption intensity, variety seeking etc.), on new product trial and adoption, unlike previous studies that have been focused on forecasting the adoptions of new products; (4) We separately study the trial and adoption stages, unlike previous studies that have typically lumped the stages in to one observable outcome (transaction); in doing this, we are able to study the impact of early trial on adoption.

We note some caveats here. First, we study the beer category because of the large number of new product introductions that were observed in this category during our study period. In order to test the generalizability of our findings across other mature, non-durable categories, it is incumbent on future research to locate and then analyze data from other categories with a large number of product introductions. Second, our empirical analysis is descriptive in nature. In order to better understand the behavioral process that underlies households' trial and adoption decisions a structural model could be proposed and estimated on our data. We view our paper as a useful first step that spurs more research on new product trial and adoption in mature, non-durable categories.

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Endnote

1. For example, Budweiser and Heineken both produce the same type of Lager beer, but Budweiser's beer is classified as American-Style Pilsner while Heineken is classified as Münchner (Munich)-Style Helles in the Beer Guideline.

2. We define four big brands, Corona, Budweiser, Miller, and Heineken. They account for 68-72 % total quantity sales in the beer market in our data from 2006 to 2011.

3. In order to save space, we do not report the full set of estimation results. They are available from the authors upon request.

4. The exception is for indicator variables representing geographical regions, races and occupations. We calculate the difference between the indicator that has the largest coefficient and the indicator with the smallest coefficient to represent the importance of these variables.

5. We undertake similar exercises for display and feature, assuming that firms increase display or feature by 20% from the sample average. Changes in trial and adoption probabilities following these non-price promotions are much smaller than the changes associated with price discounts. These results are available from the authors upon request.

6. https://csimarket.com/stocks/singleProfitabilityRatios.php?code=BUD&gro

7. In order to check the robustness of this result, we vary the length of time that consumers continue to adopt the product from 1 period to 3 periods, and vary the profit margin from 5 % to 30 %. Our result remains insensitive to these changes.

8. In Table 4 "*"means p <0.1, "**"for p<0.05 and "***"for p <0.01

Tables

Table 1: Description of New Products

Product	*Brand*	*Type*	*Style*	*Quantity Sales (12 oz.)*	*Revenue ($)*	*Market Share (%)*
DESCHUTES BREWERY SEASONAL	DESCHUTES BREWERY	Ale	American	1924	4541.90	0.20
ALASKAN AMBER ALT	ALASKAN Brewing Company	Ale	German	5069	3239.68	0.13
BUDWEISER & CLAMATO CHELADA	BUDWEISER	Lager	American	294	263.04	0.01
YUENGLING AMBER LAGER	YUENGLING	Lager	American	358	1206.58	0.05
MILWAUKEE'S BEST ICE	MILWAUKEE 'S BEST	Lager	American	2174	10286.20	0.42
CORONA FAMILIAR	CORONA	Lager	American	2218	5534.13	0.24
HENRY WEINHARD'S PVT RSV	HENRY WEINHARD'S	Lager	American	10480	36722.92	1.51
OLD STYLE	OLD STYLE	Lager	American	1684	3243.20	0.14
SOL	SOL	Lager	American	2828	9522.28	0.42
HEINEKEN	HEINEKEN	Lager	German	3388	8687.60	0.36
STELLA ARTOIS	STELLA ARTOIS	Lager	German	420	1322.60	0.06
VICTORIA	VICTORIA	Lager	Vienna	4080	14946.06	0.62
NEW BELGIUM BREWING CO SSNL	NEW BELGIUM	Seasonal		372	1514.07	0.06
SIERRA NEVADA SEASONAL	SIERRA NEVADA	Seasonal		10364	25782.90	1.10

Table 2: Purchases of Triers and Adopters

	Triers			Adopters		
	Min	Mean	Max	Min	Mean	Max
Percentage of households	0.16%	0.89%	1.90%	0.03%	0.18%	0.60%
Sales (12 oz.)	97.84	1604.79	4058.82	101.6	1854.5	6549.4
Revenue (dollar)	87.54	4580.48	14088.74	175.5	5147.6	22634.2

Table 3: Variables used in the Analyses

Category	Variables	Description	Mean	Min	Max
Dependent Variables	*Trier*	1 if the household purchases the focal new product at least once	0.02	0	1
	Adoption	1 if the purchase intensity of the household toward the focal new product is in top 20%	0	0	1
Past Purchase Behavior	*Change brand*	1 if new product differs on brand from the previous favorite product, 0 otherwise	0.89	0	1
	Change type	1 if new product differs on type from the previous favorite product, 0 otherwise	0.68	0	1
	Change style	1 if new product differs on style from the previous favorite product, 0 otherwise	0.89	0	1
	Previous big brand	Brand of the beer purchased most frequently (Corona, Budweiser, Miller, or Heineken)	0.35	0	1
	Brand variety seeking	1 if in top 20% of those who have tried the most brands of beer products	0.2	0	1
	Type variety seeking	1 if in top 20% of those who have tried the most types of beer products	0.2	0	1
	Style variety seeking	1 if in top 20% of those who have tried the most styles of beer products	0.2	0	1
	Heavy drinker	1 if in top 20% by consumption	0.2	0	1
	Occasional drinker	1 if in bottom 20% by consumption	0.2	0	1
	Early trier	Tries the new product within a month since it becomes available in the local market	1.56E -03	0	1
Marketing Mix	*Display*	Average number of times that a new product has special display arrangement at a household's most visited store	0.01	0	1
	Feature	Average number of times that a new product is marked as featured item at a household's most visited store	0.01	0	1
	Premium price	1 if the price of a new product in the favorite store exceeds the weighted average price of all beer products	0.35	0	1
	Relative store price	Percentage difference between the price of new product in the favorite store and its average price across all stores	0.03	-0.53	1.25
	Competitio n	Number of available beer products with at least one identical attribute in the same local market.	25	2	50
Demographic s	*Household income*	Income in US $	21	3	30
	Family size	Number of people in household	2.35	1	9

	Household head age	Average of male and female household heads	7	1	9
	Household education	Average of male and female household heads	4	1	6
	Race	Caucasian, African, Asian and others*			
	Region	9 Regions defined by Nielsen*			
	Occupation	12 Categories defined by Nielsen*			
Product Attributes	*German ale*	German style ale	0.12	0	1
	German lager	German style lager (including Vienna style Lager and Munich style Helles)	0.12	0	1
	American lager	American style Lager (including Amber Lager, Ice Lager, Light Lager and Pilsner)	0.49	0	1
	Seasonal	Seasonal	0.19	0	1
	Big brand	1 if the focal new product is a big brand	0.16	0	1

Table 4: Estimation results[8]

Category	Variable	Trial Estimate	Trial Marginal Effect	Adoption Estimate	Adoption Marginal Effect
Past Purchase Behaviors	*Change brand*	-2.1861***	-5.88E-04	-0.8999***	-2.90E-04
	Change type	-0.1459*	-2.70E-05	-0.1021***	-2.30E-05
	Change style	0.3731***	9.10E-05	0.3426***	9.90E-05
	Previous big brand	-0.1912***	-1.90E-05	-0.031	
	Brand variety seeking	-0.0911		-0.2402***	-1.10E-05
	Type variety seeking	-0.4293***	-6.90E-05	0.0182	
	Style variety seeking	0.1302		0.0336	
	Heavy drinker	0.4230***	2.30E-05	-0.2848***	-1.90E-05
	Occasional drinker	-0.0842		-0.0023	
	Early trier			-0.1030**	0.00E+00
Marketing Mix	*Display*	0.6299***	1.00E-06	0.1386*	0.00E+00
	Feature	0.4979***	1.00E-06	0.014	
	Premium price	0.4303***	7.00E-06	0.3398**	4.00E-06
	Relative store price	-1.2886**	2.15E-04	-0.5306***	3.90E-06
	Competition	0.057		0.0361	
Demographics	*Household income*	0.0122		-0.0376	
	Household size	0.006		0.0702	
	Household head age	-0.0311		-0.0117	
	Household education	0.0277		-0.0478	
	African American	-0.2617		-0.3232**	-9.00E-06
	Asian	-0.2433***	-2.00E-06	0.5012***	4.00E-06
	Other race	-0.1094*	-2.00E-06	-0.0516	
	Middle Atlantic	0.2771***	3.00E-06	-0.5609***	-7.00E-06
	East North Central	0.0915		-0.4679	-2.90E-05
	West North Central	-0.0112		-0.5877***	-8.00E-06
	South Atlantic	0.2300**	1.10E-05	-0.5194***	-3.00E-05
	East South Central	0.0763		-0.4216***	-8.00E-06
	West South Central	-0.0286		-0.7318***	-2.10E-05
	Mountain	0.2721		-0.6122***	-2.60E-05
	Pacific	0.3394***	2.40E-05	-0.6003***	-4.90E-05
	Occupation 2	-0.022		-0.3045	
	Occupation 3	-0.0516		-0.0048	
	Occupation 4	0.0907		0.0931***	2.00E-06
	Occupation 5	-0.0564		-0.1597	
	Occupation 6	-0.0028		-0.4653***	-1.00E-05

	Occupation 7	0.2702***	0.00E+00	0.1251*	0.00E+00
	Occupation 8	-0.1156		0.2478***	3.00E-06
	Occupation 9	0.3341*	0.00E+00	0.0728	
	Occupation 10	0.4869***	0.00E+00	0.1383	
	Occupation 11	0.1332			
	Occupation 12	-0.0408		-0.2217	
Product Attributes	*Big brand*	-0.2281**	-1.00E-05	-0.1467	
	German ale	0.0709		0.2354***	1.00E-05
	German lager	-0.0946		-0.1796*	-7.00E-06
	American lager	-2.4988***	-3.31E-04	-1.1538***	-1.82E-04
	Seasonal	0.0621		-0.1025	
Covariance of errors		0.4998***			
#. Of Observations		60252		1178	

Table 5 Relative importance weights for explanatory variables in the trial and adoption stages

Parameter weight			
Trial stage		Adoption stage	
Display	5.51%	Display	2.22%
Feature	4.36%		
Premium price	3.76%	Premium price	5.44%
Relative store price	20.37%	Relative store price	15.12%
Change brand	19.12%	Change brand	14.40%
Change type	1.28%	Change type	1.63%
Change style	3.26%	Change style	5.48%
Previous Big brand	1.67%		
		Brand variety seeking	3.84%
Heavy drinker	3.70%		
Big brand	2.00%		
		Early trier	1.65%
Race	2.13%	Race	8.02%
Geographical regions	2.97%	Geographical regions	11.71%
Occupation	4.26%	Occupation	7.45%
American Lager	21.86%	American Lager	18.47%
Aggregate weight:			
Past purchase behaviors	32.79%	Past purchase behaviors	31.57%
Marketing mix	34.00%	Marketing mix	22.78%
Demographics	9.36%	Demographics	27.18%
Product attributes	23.85%	Product attributes	18.47%

Table 6: Dynamic pricing schemes and market outcomes

Variable	Value	Price change in trial stage (%)	Price change in adoption stage (%)	Trial prob. (%)	Conditional adoption prob. (%)	Change in total sales (%)	Change in total profit (%)
Original		-	-	1.61	15.71	-	-
Dynamic pricing		-32.00	53.00	3.87	10.43	167.87	72.11
Targeted Dynamic Pricing:							
Consumption intensity	Heavy	-62.00	49.00	9.21	6.72	205.48	122.16
	Medium	-12.00	54.00	2.02	11.20		
	Occasional	-11.00	54.00	2.40	11.75		
Change type	1	-27.00	52.00	3.70	9.09	165.47	75.57
	0	-42.00	55.00	3.99	13.28		
Change brand	1	-32.00	53.00	3.78	10.42	170.13	72.24
	0	-34.00	65.00	5.51	17.42		
Change style	1	-33.00	54.00	4.21	10.45	168.37	72.94
	0	-15.00	50.00	1.47	9.97		
Previous big brand	1	-30.00	53.00	1.93	9.28	174.05	72.25
	0	-33.00	53.00	4.99	11.06		
Variety seeking type	1	-30.00	53.00	2.50	9.71	174.61	72.39
	0	-34.00	53.00	5.88	11.46		
Variety seeking brand	1	-11.00	47.00	1.50	6.61	193.28	84.24
	0	-37.00	54.00	4.61	11.06		

Figures

Figure 1: Probability distributions under average and discount prices