Switching Beers? The Effects of Switching Costs on Prices and Profits in Competitive Markets*

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Abstract

We study differential effects of switching costs on prices, market shares, and profits in a dynamic oligopoly with differentiated products. We use a large dataset on the beer market, which includes detailed customer-level information on beer purchases. Our estimation results show large differences in brand loyalty and switching costs across customer segments and therefore across beer brands. Our results show that allowing for competition is an important aspect as switching costs can have strongly different effects across beer brands on beer prices, market shares, and profits. Price strategies vary across switching costs and across firms. As switching costs evolve, prices and profits of beer brands follow a U-shaped pattern. If switching costs are low (high), firms adopt an investment (harvesting) strategy, while they adopt differential pricing strategies if switching costs are in the intermediate range. For the most part, switching costs can severely toughen competition, impose downward pressure on prices, and reduce profits. Only if switching costs are high, the price and profit of the beer brand serving the high customer segment surpass the corresponding price and profit without switching costs.

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Keywords: Consumer Heterogeneity; Dynamic Oligopoly; Dynamic Pricing; Loyalty; State Dependence; Switching Costs.

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1 Introduction

Many consumer packaged goods (cereal, yogurt, juice, beer, etc.) are distinctly identified such that consumers often develop a loyalty to brands. Brand loyalty provides an extra surplus to loyal consumers, which increases the probability of consumers to repeatedly purchase the same brand and results in persistence of consumer choices (see Dubé et al. (2010)). A large strand of literature has focused on brand loyalty to explain consumers' repeated brand choices (see Erdem (1996), Keane (1997), Seetharaman, Ainslie, and Chintagunta (1999), Horsky, Misra, and Nelson (2006), and Dubé et al. (2008), among others).

Brand loyalty implies that consumers repeatedly purchase the same brands such that switching to a different brand comes at an opportunity cost, also referred to as a (psychological) switching cost for consumers (see Klemperer (1995) and Farrell and Klemperer (2007)). Switching costs have dynamic implications on firms pricing strategies, market shares, and profits. While several studies explored the competitive effects of switching costs in a monopolistic environment (see Dubé et al. (2008)), little attention has been devoted to oligopolistic markets with differentiated products. The goal of this paper is to explore differential competitive effects that switching costs have on firms prices, market shares, and profits in oligopoly. We are especially interested in examining whether switching cost effects vary across customer segments targeted by different brands.

Consumer switching costs can result in repeated brand purchases, which adds a dynamic aspect to firms' pricing behavior. That is, due to the existence of switching costs, firms prices not only influence contemporaneous demand, but also future demand, and this introduces a nontrivial source of dynamics into firms' pricing decisions. In the presence of switching costs, Klemperer (1987) highlights that firms consider two countervailing forces that determine their pricing decisions (see also Farrell and Klemperer (2007), Dubé et al. (2008), and the literature cited therein).

First, switching costs make consumers less likely to switching brands and less sensitive to price. This allows firms to charge higher prices, also referred to as the harvesting motive in the literature.

Second, firms adopt a dynamic pricing strategy in which they reduce prices to attract additional customers. The price reduction makes more customers loyal to the brand and, therefore, serves as an investment into future profits, also referred to as the investment motive (see Villas-Boas (2004) and Freimer and Horsky (2008)).

In addition to the downward pricing pressure from investment considerations, oligopolistic firms also account for business-stealing effects; that is, firms prevent own customers from switching to a competitor's brand, and they also consider stealing loyal customers from their competitors (see Arie and Grieco (2014)). In contrast, a monopolist would not consider business-stealing effects, as it is not competing with other firms.

More specifically, against the background of competitive markets, firms see more opportunities for customers to switch to nearby products, so firms lower their prices to prevent customers from switching and to protect themselves against other firms' attempts to steal customers. With regard to these two pricing motives, the pricing problem becomes complicated because current period pricing decisions influence the loyalty state and, thus, affect the future state.

Consumers hold heterogeneous preferences for product characteristics such as flavor, nutritional content, quality, brand recognition, etc. Firms account for consumers heterogeneous preferences by offering differentiated brands that can be sold for different equilibrium prices, which affects market shares and profits (see Gabszewics and Thisse (1979), Shaked and Sutton (1982), and Siebert (2015)). Firms can also target different customer segments, such as low- and high-income segments, that exhibit different switching costs, which have an influence on pricing strategies, market shares, and profits.

Our study focuses on an oligopoly where firms offer differentiated goods that target different customer segments while allowing for switching costs. As switching costs increase, we evaluate how optimal pricing strategies, market shares, and profits evolve for products that target different segments. Note that previous studies frequently focused on monopolies, while our study considers an oligopoly. The optimal pricing problem in oligopoly with differentiated products is nontrivial, as it adds complexity, originated by the increasing number of firms and products offered on the market that increase the dimension of the state space. Our study is most closely related to Dubé et al. (2008) and Dubé et al. (2009) (more details follow later), but neither of these consider firms' dynamic pricing in oligopolistic markets to explicitly evaluate the differential effects of switching costs across differentiated products that belong to different market segments.

We use a large dataset on the beer market that includes detailed customer-level information on beer purchases from 2016. We estimate a demand model that allows for flexible consumer-specific switching costs while accounting for observed and unobserved heterogeneous consumer preferences and price sensitivities. Switching costs are estimated across low- and high-income consumer segments.

The demand estimation results show strong evidence for switching costs having an effect on consumers beer choices even after controlling for (unobserved) consumer heterogeneity. Consumers obtain an extra surplus by making the same beer choice over time, which reduces the price elasticity of demand. The average switching cost amounts to 20% of the product price. We find that switching costs differ substantially across customer segments, and therefore, across beer brands, as they serve different shares of consumers from low- and high-income segments. Specifically, we find low-income customers are more price sensitive and exhibit higher switching costs.

On the supply side, we consider a dynamic oligopoly model in which forward-looking firms adopt pricing policies to maximize the discounted sum of future profits. Firms choose Markovian strategies in which prices are a function of every firms' market share across customer segments while accounting for consumers' switching costs.

Our estimation of the dynamic oligopoly model concentrates on two beer brands that represent differentiated products.[1] We identify Busch and Samuel Adams as brands serv-

[1] We limit our supply estimation algorithm to two beer brands to avoid computational intractabilities arising from large state spaces, as will be explained in the model section. We also apply robustness checks that include more beer brands.

ing the low and high market segments since the majority of their customers are associated with low- and high-income segments, respectively.[2]

We consider variation in switching costs and simulate the differential effects on brand prices, market shares, and profits. Our results show that allowing for an oligopolistic market is an important aspect as switching costs can have strongly different effects across beer brands on prices, market shares, and profits.

We find that, for the same switching costs, firms apply different pricing (harvesting and investment) strategies. Moreover, as switching costs increase, firms' prices and profits follow a U-shaped pattern. For all levels of switching costs, the beer brand in the low market segment (Busch) is sold mostly to low-income customers, while the brand in the high market segment (Samuel Adams) predominantly sells to high-income customers. This has implications on optimal prices, since low-income (high-income) customers are characterized by higher (lower) price sensitivity and higher (lower) switching costs.

If switching costs are low, firms adopt investment strategies and drastically reduce prices (compared to when switching cost are nonexistent) as they compete for loyal customers. The high-segment beer brand (Samuel Adams) is able to gain market shares across both customer segments while stealing customers from the low-segment beer brand (Busch). As price of the low-segment brand is reduced with the intention to diminish the loss of loyal customers, price competition becomes intense, and both brands generate lower profits.

If switching costs are in the intermediate range, firms' pricing strategies differ. The firm with the high-segment brand adopts a harvesting strategy and increases price.[3] In contrast, the firm with the low-segment brand continues following an investment strategy

[2]We also use further classifiers such as average price and the mean utility from the demand estimation.

[3]Note that this result is different than the one reported in Dubé et al. (2008). Their setting is described by a multiproduct monopolist, which can internalize externalities caused by business-stealing effects. They show that firms adopt an investment strategy for the high-quality product to steer consumers toward the more profitable product. The monopolistic firm is concerned about loyal consumers leaving high-quality products as this would diminish its profit. One reason we receive a different result is that they consider a monopolist is able to internalize business-stealing and cannibalization effects across its own products. We consider an oligopolistic framework, which implies that business-stealing and cannibalization effects are not internalized across firms.

and reduces price with the intention of diminishing further customer loss. If switching costs are high, firms have few incentives to invest in loyal customers. Instead, they adopt a harvesting strategy and increase prices, which results in profit gains.

Overall, for the most part, firms set lower prices and earn lower profits when switching costs are prevalent. If switching costs are high, the firm with the high-segment brand increases its price and earns higher profits compared to the case when switching costs are nonexistent. In sum, we find that switching costs mostly increase competition, as they impose downward pressure on prices and reduce profits.

The remainder of the paper is organized as follows: Section 2 discusses the related literature. Section 3 introduces the industry and the data sources and provides summary statistics. In Section 4, we introduce the empirical model, and Section 5 details the estimation procedure. We discuss the estimation results in Section 6, and we conclude in Section 7.

2 Literature Review

Brand loyalty implies that consumers repeatedly purchase the same brands such that switching to a different brand comes at an opportunity cost, also referred to as switching cost (see Klemperer (1995), Erdem (1996), Keane (1997), Seetharaman, Ainslie, and Chintagunta (1999), Horsky, Misra, and Nelson (2006), and Dubé et al. (2008), among others). Switching cost is a widespread phenomenon that is associated with a wide array of goods such as consumer packaged goods, financial and health services, etc. Switching costs can stem from a variety of monetary and nonmonetary sources, including brand loyalty, psychological aspects, product adoption costs, search costs, and learning (see Klemperer (1995) and Dubé, Hitsch, and Rossi (2009)).

The effects of switching costs on consumer behavior and households' brand choices have received much attention in the literature (see Seetharaman et al. (1999), Seetharaman (2004), Anand and Shachar (2004), and Horsky and Pavlidis (2011)). Several empirical studies have shown that switching costs imply state dependence in demand where consumers' current product choices determine their future product choices. Switching costs are usually not directly observed, and one empirical challenge is that they must be identified separately from heterogeneity in consumers' preferences for products (Dube et al. (2010)). Empirical studies on switching costs have shown that the associated structural state dependence in choices and persistent heterogeneity in household preferences can be confounded (see Heckman (1981), Horsky et al. (2006), and Dubé et al. (2010)).

To separate consumer-specific switching costs from heterogeneous preferences, data on frequent purchases and consumer switching between brands due to price variations are required. The intuition for identification is as follows: A brands temporary price reduction can induce consumers to switch and buy that brand. Once the price returns to its original level and the newly gained customers continue purchasing the same product, customers develop a brand loyalty and gain a utility extra surplus, which identifies brand loyalty and switching costs (see also Dubé et al. (2010)).

In the presence of switching costs, theoretical studies conjecture that the harvesting strategy is the dominant force and will increase prices and make markets less competitive (see Beggs and Klemperer (1992), Klemperer (1995), and Farrell and Klemperer (2007)).[4]

Most empirical studies evaluate the effects of switching costs on prices in the context of a monopoly. For example, Dubé et al. (2008) considers a monopoly that offers differentiated products on the market while accounting for consumer switching costs. The study shows that the single firm chooses lower prices if switching costs are considered. Contrary to findings of studies without switching costs, they show that the price of the high-quality product falls even below the low-quality product's price as a result of steering more loyal consumers to the high-quality product. Similar to most empirical studies on monopolies, they provide evidence for a dominating investment motive; that is, prices further decline as switching costs increase. This monopoly framework does not easily extend to oligopoly

[4]One explanation is that consumer switching costs are assumed to be infinite; this makes it difficult for customers to switch, which favors the harvesting motive.

markets where multiple firms compete for loyal customers.

A few theoretical contributions consider switching costs in oligopolies, and they show that firms experience an additional downward pressure on prices to steal consumers who are loyal to competing firms (see Doganoglu (2010) and Arie and Grieco (2014)). Until now, however, limited empirical insights exist on the differential effects of switching costs on prices and profits in oligopolistic markets with market segmentation.

To the best of our knowledge there are very few empirical studies that explored the competitive effects of switching costs in oligopoly markets. Che et al. (2007) consider a finite horizon model that involves nonstationary pricing policies. In contrast to their study, we aim at a market that is characterized by an infinite horizon models, as this enables us to derive stationary long-term pricing strategies. Dubé et al. (2009) consider a multi-agent model with an infinite time horizon. They find that switching costs toughen price competition, where firms reduce prices by three to six percent and profits decline. In contrast to their work, our study explicitly examines the differential effects of switching costs on prices and profits of differentiated brands that target different market segments.

3 The Market and the Data

Our study builds on a large dataset on the beer market that was provided by AC Nielsen, among other sources that are introduced later. The data were collected by tracking households' beer purchases at retail stores (including grocery and drug stores) in the United States. The database consists of highly detailed Universal Product Code (UPC) scanner information at the store-level from 2016, as well as corresponding buyer-specific information.

The retail database contains consumer-specific beer purchase information at the (retail) store level. More than 35,000 retail stores belonging to 90+ chains are subject to this database. The data cover more than half the sales volume in the U.S.

We concentrate on beer purchases and are able to use information on the beer brands, the dates of purchases, the volumes purchased, the prices, and further product-related store information (e.g., promotions). The buyer-specific information includes buyer demographics such as income, family size, number of children, etc. We also added information on beer attributes at the brand level, including alcohol content, index of bitterness units (IBU), carbohydrates, calories, and sugar content.

We account for the fact that alcohol sales regulations can differ largely across states, so we concentrate on beer purchases in one state, Illinois. In comparing beer brand sales we can confirm that Illinois is representative of the entire United States. In our study, we include households that made beer purchases at least twice during our sample period, and we consider purchases on a monthly basis. This avoids potential rare event and missing data problems. It also ensures a focus on consumers' state-dependent (or repetitive) purchasing behavior.

After conditioning on these criteria, our database includes 63,147 households that made 9,354,956 shopping trips in Illinois in 2016, using monthly observations. On average, a household made 33 beer shopping trips throughout the year. In more than 90 percent of the shopping trips, consumers purchased less than 15 bottles of 12-oz beer. Therefore, any concerns that consumers engage in purchasing large quantities due to stockpiling reasons can be eliminated. If the customer does not purchase beer during the shopping trip, we treat it as purchasing an outside good.

Our study focuses on the top 20 beer brands (by sales volume) which account for 72 percent of total beer sales. Table 1 lists the top beer brands in alphabetical order. As shown in Column 2, 11 of the top 20 beer brands are headquartered in the U.S. Column 3 shows the beer prices in dollars per ounce, which vary from 0.05 to 0.12 dollars per ounce. Column 4 represents market shares, varying from 0.2 to 10 percent. The remaining Columns 5-9 show further beer attributes; we realize variation, especially in alcohol content, bitterness, and carbohydrates across beer brands.

Table 2, left panel, shows the different brands ordered by market shares in descending order (see Column 2). The top-selling beer brand is Budweiser, followed by several foreign beer brands such as Modelo, Corona, and Heineken. Other beer brands, such as Miller and Samuel Adams, are placed in the middle of this ranking. The market share ranking is not strongly correlated with the price per ounce, as shown in Column 3. This might be one indication that price differences are less explained by differential quantities and costs, but rather by tastes, reputation, and market segmentation. Table 2, right panel, shows the beer ranking ordered by prices (see Column 5). Stella Artois and Samuel Adams are among the more expensive brands, while Budweiser is in the intermediate price range followed by Coors, Miller, and Busch. Interestingly, Samuel Adams is significantly more expensive (about 250 percent) than Miller. Columns 8 and 9 display the minimum and maximum prices, respectively.

Next, we provide insights into beer purchases by customer segments and especially focus on large income variations across brands. Our dataset provides beer purchasers' income information, and we can associate this information with beer brand purchases. We categorize customers in low-income and high-income segments and calculate the corresponding market shares across income segments and beer brands.[5] Table 3 shows the prices and shares that brands hold in low-income and high-income segments. (Note that the low- and high-income shares relate to the corresponding shares of a beer brand, rather than market shares.) The beer brands are sorted (in descending order) by the share in the high-income customer segment, (in Column 5). A few aspects are worth mentioning. There is large variation in the market shares across brands. For example, Samuel Adams sells the most beer to high-income customers. Budweiser, Miller, and Coors serve more low-income customers, and Busch almost exclusively sells to low-income customers. It should be noted that beer brands selling to higher-income segments are priced higher than the beers that mostly sell to lower-income customers. Less (more) expensive beers hold a higher market share of customers in the lower- (higher-)income segment.

Table 4, Column 2 shows repeat purchases by customers across beer brands. On average, more than 60 percent of the time, purchasers choose the same brand as they

[5] We use the median income to separate low-income from high-income customers.

did in their previous shopping trip. This high number of repeat purchases indicates that consumers exhibit strong loyalty to beers, which implies switching costs. Repeat purchases range from 14 percent to 82 percent. Our main brands of interest—Samuel Adams, Budweiser, Coors, Miller, and Busch—all rank in the intermediate range. Interestingly, inexpensive beer brands experience high degrees of repeat purchases.

Finally, in following earlier studies, our analysis treats each county as a separate market. It should be noted that the long purchase histories of customers, the observed price variations, the observed switching patterns between brands, and the repeat purchases are especially useful in our case, as they help identify the unobserved switching costs. In many cases, the switching is initiated by a temporary price discount of the target beer. For example, observed price variations are motivations for consumers to switch away from their preferred products and even continue purchasing the new brands for loyalty and switching cost reasons even after prices return to their original levels. This observed switching between brands will helps us identify switching costs.

4 The Model

In this section, we introduce our empirical model consisting of the demand and the supply side.

4.1 The Demand Model

The demand for beer brands is modeled using a discrete choice random coefficient logit model. The availability of consumer-level scanner data enables us to consider individual-specific product choices.[6] We use an individual demand model in the spirit of Berry, Levinsohn, and Pakes (2004) and Dunn (2012) that is estimated by simulated maximum likelihood. This model is extended by allowing for structural state dependence (brand loyalty) and unobserved heterogeneous preferences. The heterogeneous preferences are

[6] Several studies have shown that the use of consumer-level data can drastically improve demand estimates (see Gaynor and Vogt (2003), Petrin (2002), and Goolsbee and Petrin (2004)).

captured using individual price and switching cost coefficients. This allows us to separate brand loyalty from heterogeneous consumer preferences.

We consider a beer market in which multiple firms sell beer brands that represent differentiated goods. Each individual consumer $i = 1, ..., N$ chooses a beer brand j from set of options $j \in \{1, ..., J\}$, or he/she does not buy any beer brand and chooses the outside good denoted by 0. In every period t, individual i makes a brand choice that maximizes her indirect utility u_{ijt}, individual i chooses beer brand j in period t, if $u_{ijt} > u_{ilt}, \forall l \neq j$. Individual $i's$ utility for brand j in period t is given by:

$$u_{ijt} = \alpha_i p_{jt} + \sum_{k=1}^{K} \beta_k x_{jk} + \lambda_i I \{s_{it} = j\} + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

where p_{jt} is the price of beer brand j at time t. The individual-specific coefficient (α_i) reflects a differential price sensitivity across individuals. The individual price coefficient allows for more reasonable substitution patterns across products (see also Berry et al. (1995)). Note that the random price coefficient captures consumers' heterogeneous preferences in prices. It helps disentangling preference heterogeneity from brand loyalty and prevents the estimate of the loyalty term from being confounded.

The vector x_{jk} denotes observed beer attributes $k = 1, ..., K$ of a brand j. The variable s_{it} refers to individual $i's$ beer purchase state (last purchase) in period t, and the indicator function $I \{s_{it} = j\}$ reflects that individual $i's$ state relates to product j (see also Erdem (1996), Seetharaman et al. (1999), and Dubé et al. (2008), among others).[7] Hence, if individual $i's$ last beer choice was brand j, the term controls for state dependence and reflects individual $i's$ loyalty specific to brand j. If the associated coefficient λ_i is larger than zero, individual i receives an extra utility or loyalty surplus from repeatedly purchasing the same beer brand. Therefore, the current indirect utility derived from the consumption of a brand increases if the same brand was purchased in the past. A larger coefficient reflects a higher utility that consumer i receives from the repeated purchase,

[7]Following earlier studies, we adopt the assumption that an individual's state remains unchanged if she chooses an outside product.

which results in higher loyalty. Consequently, a large λ_i coefficient reduces the probability of brand switching (such as choosing a different brand than in the previous purchase occasion), which can be interpreted as an individual-specific switching cost. Note that the individual switching cost can be calculated as $-\lambda_i/\alpha_i$. The term ξ_{jt} refers to a time-variant product characteristic that is unobserved by the econometricians but observed by the consumers and firms, and ϵ_{ijt} is an idiosyncratic error term that follows a Type I extreme value distribution. The indirect (mean) utility of the outside good is normalized to zero.

We decompose the random coefficients (α_i and λ_i) into several components. Regarding the individual-specific price coefficient, we write $\alpha_i = \widetilde{\alpha} + \sum_{h=1}^{H} \alpha_h z_{ih} + \alpha_{H+1}\gamma_i$, where $\widetilde{\alpha}$ is a component that is common across individuals. The remaining two components are consumer-specific. The first part ($\alpha_h z_{ih}$) depends on the consumer's observed demographics z_{ih}, where $h = 1, ..., H$ refer to the consumer attributes, such as income, age, family size, etc. The second part ($\alpha_{H+1}\gamma_i$) reflects an unobserved individual-specific consumer taste term (γ_i) that follows a standard normal distribution.

Regarding the individual-specific loyalty term, we write $\lambda_i = \widetilde{\lambda} + \sum_{h=1}^{H} \lambda_h z_{ih}$, where the common term $\widetilde{\lambda}$, and the remaining individual-specific parts follow the same rationale as the price coefficient.[8]

The indirect utility is written as

$$U_{ijt} = \delta_{jt} + \phi_{ijt}, \tag{2}$$

where the first part, $\delta_{jt} = \widetilde{\alpha} p_{jt} + \sum_{k=1}^{K} \beta_k x_{jk} + \xi_{jt}$, reflects the mean utility of product j at time t that is common to all consumers. The following part, $\phi_{ijt} = \sum_{h=1}^{H} \alpha_h z_{ih} p_{jt} + \alpha_{H+1}\gamma_i p_{jt} + (\widetilde{\lambda} + \sum_{h=1}^{H} \lambda_h z_{ih}) I\{s_{it} = j\}$, refers to individual-specific deviations from the mean utility that vary across brands and time periods.

[8]The flexible consumer heterogeneity provides confidence that we are capturing true state dependence (switching costs) and do not confound the empirical identification of switching costs with unobserved taste heterogeneity.

Using the Type I extreme distribution of ϵ_{ijt}, we can write individual $i's$ probability, Pr_{ijt}, of choosing option j in period t in logit form:

$$Pr_{ijt} = \frac{\delta_{jt} + (\sum_{h=1}^{H} \alpha_h z_{ih} + \alpha_{H+1}\gamma_i)p_{jt} + (\widetilde{\lambda} + \sum_{h=1}^{H} \lambda_h z_{ih}) I\left\{s_{it} = j\right\}}{\sum_{\kappa=0}^{J} exp\{\delta_{\kappa t} + (\sum_{h=1}^{H} \alpha_h z_{ih} + \alpha_{H+1}\gamma_i)p_{\kappa t} + (\widetilde{\lambda} + \sum_{h=1}^{H} \lambda_h z_{ih}) I\left\{s_{it} = \kappa\right\}\}}. \tag{3}$$

After receiving consumers' choice probabilities, we turn to the derivation of market demand.

4.1.1 Market Demand

The market demand of a product is derived by aggregating over individuals' purchasing decisions. We separate consumers into $n = 1, ..., N$ segments where in the extreme case, each consumer could represent one segment. Each segment holds a specific market size denoted by μ_n. We aggregate individual beer demand within each segment and then across all segments to derive the market demand for each beer brand.

In aggregating over individuals' demands, we need to be aware that individual consumers are loyal to different brands. We denote ν_{kt}^n as the share of customers in segment n that is loyal to brand k at time t (those consumers have chosen brand k in their last purchase). We assume that each consumer within a segment is loyal to one product at a time such that $\sum_{k=1}^{J} \nu_{kt}^n = 1$. The segment-specific vector $\nu_t^n = [\nu_{1t}^n, ..., \nu_{Jt}^n]'$ shows the loyalty states of each customer segment n across all J products. Next, these segment-specific vectors ν_t^n enter the loyalty state in the market $S_t = [\nu_t^1, ..., \nu_t^N]$ that aggregates the shares of loyal customers across all segments and all products in period t. The loyalty state (S_t) evolves over time as customers make brand choices. Forward-looking firms account for the loyalty states when choosing their optimal pricing strategies.

Demand for product j in customer segment n at period t is given by:

$$D_{jt}^n = \mu_n [\sum_{k=1}^{J} \nu_{kt}^n Pr_{ijt}^n (s_{it}^n = k)], \tag{4}$$

where Pr^n_{ijt} relates to the choice probability Pr_{ijt} (see equation (3)) for customers belonging to segment n.

Aggregating D^n_{jt} across customer segments n yields the market demand for product j:

$$D_{jt} = \sum_{n=1}^{N} D^n_{jt}. \tag{5}$$

Next, we describe the evolution of the state variable, S_t.

4.1.2 Evolution of the State

We follow previous studies in describing the evolution of the state (see, for example, Dubé and Hitch (2009)). Remember, if a customer is loyal to product k, she will remain in state k as long as she purchases the same product or the outside good. Therefore, we must add the conditional probability of choosing the outside good to the diagonal elements of a Markov transition matrix in a consumer segment n, denoted as T^n_{jk}. More specifically, if $j = k$, then

$$T^n_{jkt} = Pr^n_{jt}(k, p) + Pr^n_{0t}(k, p) \tag{6}$$

where $Pr^n_{jt}(k, p)$ $(Pr^n_{0t}(k, p))$ denotes the probability that a customer in segment n purchases product j (the outside good) given she is loyal to product k and prices are represented in p.

If $j \neq k$, then

$$T^n_{jkt} = Pr^n_{kt}(k, p). \tag{7}$$

The state in segment n in the next period (S^n_{t+1}) depends on the state in the current period (S^n_t) and firms' prices as represented by the transition matrix, such that $S^n_{t+1} = T^n_{jkt} S^n_t$.

4.2 The Supply Model

We consider an oligopolistic market in which firms sell differentiated products. Firms are forward-looking, hence, they consider that current prices not only determine current demand but also have intertemporal effects on future demand and profits due to brand loyalty and switching costs.[9]

We consider a market with J competing firms, each of which produces a single beer brand. Each firm's per period profit (π_{jt}) depends on the share of loyal customers as captured by the state S_t, and the current prices entering the price vector p_t. In particular,

$$\pi_{jt}(S_t, p_t) = D_{jt}(p_{jt} - c_{jt}), \tag{8}$$

where D_{jt} is brand $j's$ demand in period t (see equation (5)) and c_{jt} is the marginal cost of producing brand j at time t.

Firms choose prices that maximize the flow of profits over an infinite horizon, where future payoffs are discounted using the discount factor $\beta \in [0, 1)$. The Bellman equation is written as:

$$V_j(S) = max\left\{\pi_j(S, p) + \beta V_j[f(S, p)]\right\}. \tag{9}$$

To solve the dynamic game, we use the concept of Markov Perfect Equilibrium and compute equilibrium prices in pure strategies. Firms choose Markovian strategies that depend on the current payoff-relevant information. Firms maximize their current and future profits conditional on the payoff-relevant information captured in the state vector. They choose prices that describe best responses to their competitors pricing strategies. Denoting the strategy profiles of competitors by σ_{-j}, the optimal strategy for firm j, σ_j^* satisfies

[9] Note that we follow previous studies (see Dubé et al. (2008) and other studies cited therein) and assume that firms are forward-looking while consumers are not. This is an appropriate assumption in our case since customers are unlikely to be consciously aware of the existence of psychological switching costs when making their beer purchases. Alternatively, one could relegate to consumers' bounded rationality to explain that consumers are not forward looking.

the following Bellman equation:

$$V_j(S) = max\left\{\pi_j[S, p, \sigma^*_{-j}(S)] + \beta V_j[f(S, p, \sigma^*_{-j}(S))]\right\}. \tag{10}$$

Doganoglu (2010) shows that a Markov Perfect Equilibrium exists in this setting (see also Dubé et al. (2009)). Next, we describe the estimation procedure.

5 The Estimation

We estimate the demand model, as introduced earlier, which returns estimates of elasticities, beer brand loyalty, and switching costs. We utilize this information to solve for firms' steady state prices, market shares, and profits. Finally, we simulate counterfactuals that demonstrate how changes in switching costs affect prices, market shares, and long-run profits.

5.1 The Demand Estimation

The estimation method uses micro-level or consumer-level data, so we follow the approach outlined in Berry, Levinsohn, and Pakes (2004), which is extended by incorporating state dependence (or brand loyalty) similar to Dubé et al. (2008 and 2009) and Dunn (2012).

Using individual i's probability of purchasing product j, given $s_t = k$ (purchased product k in the previous purchase occasion), the probability that product j is purchased in period t is:

$$Pr_{jt} = \int \frac{exp\{U_{ijt}(\theta)\}}{\sum_{\kappa=0}^{J} exp\{U_{i\kappa t}(\theta)\}} f(\theta)d\theta, \tag{11}$$

where $U_{ijt} = \delta_{jt} + \phi_{ijt}$ as mentioned above. The density function $f(\theta)$ contains parameters $\theta = [\theta_1, \theta_2]$, where $\theta_1 = [\widetilde{\alpha}, \beta_k]$ includes the parameters that are associated with the mean utility (δ_{jt}), and $\theta_2 = [\alpha_h, \alpha_{H+1}, \widetilde{\lambda}, \lambda_h]$ contains parameters that captures the individual-specific deviations (ϕ_{ijt}) from the mean utility.

One of the challenges we face in estimating equation (11) is the estimation of the mean utility δ_{jt} that enters U_{ijt}. Since the mean utility captures brand-, time-, and market-specific attributes, ideally, we would like to use the Cartesian product of all these attributes to capture the variation of δ_{jt}. This procedure, however, can quickly involve computational complexities that are caused by the large state space. To circumvent this issue, we follow previous studies and allow product prices to vary over time, while the average price is allowed to vary by markets. Therefore, we include the joint effect of brand and time with the market (m) to capture the variation of $\delta_{j(m)t}$, that is, $\delta'_{j(m)t} = aB_jT_t + bM_m$, where B_j is a brand-specific dummy variable, T_t denotes a time-specific dummy variable, and M_m is a market-specific dummy variable. Inserting this expression into the utility function, we have to estimate only parameters a and b together with the remaining parameters entering the utility function, instead of using a Cartesian product of all brand-, time-, and market-specific attributes.

Assuming that the coefficient of price (which includes a random component) follows a normal distribution with mean ω and covariance W, the market share for product j becomes

$$Pr_{jt} = \int \frac{exp\{U_{ijt}(\theta)\}}{\sum_{\kappa=0}^{J} exp\{U_{i\kappa t}(\theta)\}} f(\theta|\omega, W) d\theta. \tag{12}$$

Our demand estimation approach follows a two-step approach.

5.1.1 The First Step

In the first step, we estimate the mean utility (δ_{jt}), the associated parameters (a and b), and the individual-specific parameters ($\theta_2 = [\alpha_h, \alpha_{H+1}, \widetilde{\lambda}, \lambda_h]$). We estimate parameters using simulated maximum likelihood. In doing so, for each fixed value of b and W, we take R random draws from the distribution $f(\theta|\omega, W)$.[10] For every draw r, we write for

[10] We take R random draws from a normal distribution with mean zero. Note that the estimate of ω ($\widetilde{\alpha}$) is estimated in the second step.

the conditional probability (where the value of the r'th draw is denoted by ι^r)

$$Pr_{ijt}|\iota^r = \frac{exp\{U_{ijt}(\iota^r)\}}{\sum_{\kappa=0}^{J} exp\{U_{i\kappa t}(\iota^r)\}}. \tag{13}$$

Taking an average probability across all R draws, we get:

$$\overline{Pr_{jt}} = \frac{1}{R}\sum_{r=1}^{R} \frac{exp\{U_{ijt}(\iota^r)\}}{\sum_{\kappa=0}^{J} exp\{U_{i\kappa t}(\iota^r)\}}. \tag{14}$$

The simulated log-likelihood function can be written as:

$$SLL = \sum_{i=1}^{N}\sum_{j=1}^{J} I_{ij} ln(\overline{Pr_{ijt}}), \tag{15}$$

where $I_{ij} = 1$ if consumer i chooses product j. We maximize this simulated log-likelihood function by iterating over draws, and we receive parameter estimates for $[a, b]$, and θ_2.

5.1.2 The Second Step

In the second step, we estimate the remaining parameters of our interest—that is, $\theta_1 = [\widetilde{\alpha}, \boldsymbol{\beta}]$. We estimate the parameters based on the following equation:

$$\widehat{\delta_{jt}} = \widetilde{\alpha} p_{jt} + \sum_{k=1}^{K} \beta_k x_{jk} + \xi_{jt}. \tag{16}$$

When estimating this equation, we need to account for a potential correlation between brand-level demand shocks (ξ_{jt}, e.g., local advertisement campaigns) and prices (p_{jt}). It is assumed that profit-maximizing firms are aware of the brand-level demand shocks when they set prices. In order to obtain an unbiased estimate of the price coefficient α, we instrument for price. Valid instruments are variables that are highly correlated with the beer price in the same period, p_{jt}, but uncorrelated with the corresponding unobserved brand characteristic, ξ_{jt}. We follow previous studies and use Hausman-type instruments, such as prices from other markets, which serve as an appropriate instrument in our context since demand shocks and prices are determined at the local market level. More specifically, we use the average product prices from adjacent geographical markets in a specific period. This type of instrument is especially appropriate here since products in different markets share similar wholesale costs across markets and result in similar prices. Moreover, the instruments capture price variations across time periods and beer brands. Finally, the same brands sold in adjacent markets carry the same production costs, which ensures that price variations are closely related to demand shocks without any further complications arising from the supply side. We also include time dummy variables for time-varying demand shocks and market dummy variables for unobserved market-level differences. It should be noted that traditional marginal cost shifters (such as labor, materials, etc.) are not appropriate instruments in our study since factor costs for beer production do not fluctuate much across brands, that is, wages and prices for grain, hops, yeast, and water do not differ much across beer brands. We estimate equation (14) using a two-stage-least-squares (2SLS) method.

5.2 Supply-Simulation Algorithm

On the supply side, we consider a dynamic game between rational forward-looking firms. Every firm's optimal price depends on the firm's loyal customer share in all segments and those of all other firms.

The dynamic aspect in pricing and the strategic interactions between competitive firms require a solution of a dynamic programming problem (as shown in equation (9)) with a high-dimensional state space and high computational complexity. To circumvent these problems, we approximate the solution to the dynamic game by discretizing the state space in a multidimensional grid where each dimension refers to a brand j and the associated customer segments n. We consider each combination of a firm and a market segment as one axis in our state space such that the grid is formed by the Cartesian product of all states. Along each axis, we consider a finite number of G discrete grid points where each grid point along the axis for firm j and segment n is denoted as g^{nj}. For each firm and each customer segment, we consider 11 grid points (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, and 1).

To further facilitate computations, we adopt the assumption that within each segment n, the total share of loyal consumers equals 1 across brands—that is, $\sum_{j=1}^{J} g^{nj} = 1$. Therefore, we need to consider only the shares of consumers who are loyal to $J-1$ brands instead of J brands, which reduces the total number of grid points in the state space to $G^{N*(J-1)}$. At each point in the state space, we compute the optimal price policy and value function for each firm.

The solution to this dynamic problem is still complex due to the high dimensional state space and the value and policy functions that need to be solved for at every state. This requires the evaluation of $G^{N*(J-1)}$ value and policy functions, and this number increases exponentially as N and J increase. We need to further simplify our analysis and separate customers into two segments, a low- and a high-income segment. We also constrain our analysis to two representative beer brands that belong to the low- and high-market segments.[11]

We impose a further auxiliary condition stating that within each customer segment n, every customer shows loyalty to one product. Moreover, applying the condition that the total share of loyal consumers equals 1 across brands ($\sum_{j=1}^{J} g^{nj} = 1$), we need to consider only a subset of grid points. Consequently, we are able to further eliminate grid points, which helps to substantially reduce the dimension of the state space. As a result, we are able to reduce the number of grid points. Finally, we compute the value and policy function outside our grid space using polynomials based on interpolations.

Simulation Algorithm

We solve the dynamic game by adopting a two-stage approach that consists of value function and policy function iterations. The entire simulation process can be decomposed into inner loops and outer loops. The indexes for the rounds in the inner and outer loops

[11] Later, we provide robustness checks that consider three beer brands that are representative for the low-, intermediate-, and high-market segments.

are denoted by l and L, respectively. We use initially assigned guesses as starting points for the value and policy functions (V^0 and p^0) for each firm at each state.

In following earlier studies, we place several assumptions on our parameters. We assume that the discount rate β is 0.98. We normalize the market size to 1,000 and, in following earlier studies, we set the unit cost c_j at 60% of the lowest product retail price observed in the dataset.

First Stage: Value Function Iteration

At the beginning of each round of the game ($l = 1$), we use the policy function from the last outer loop (L-1) and keep it fixed through this process, $p^* = p^{L-1}$. During the first iteration ($L = 1$ and $l = 1$), we set $p^* = p^0$ at an arbitrary initial value, and we set $\epsilon^1 = 0$. We then adopt the following steps:

1.1) Given the current policy p^* and the value function from the last iteration V^{l-1}, we calculate the right-hand side of the Bellman equation (denoted here as TV^l) for each point in state space.

1.2) If the difference between TV^l and V^{l-1} is larger than the tolerance level (i.e. $|TV^l - V^{l-1}| > \epsilon^1$), we assign $\epsilon^1 = |TV^l - V^{l-1}|$ and V^l equal to TV^l and return to step (1.1) to conduct another round of iteration; otherwise, we go to the second stage.

Second Stage: Policy Function Iteration

In the second stage of the algorithm, we set $\eta_2 = 0$ and $\epsilon_2 = 0$.

2.1) After the value function converges in the first stage, we calculate the optimal price p^* that maximizes the Bellman equation at each grid point, and we obtain the optimal value of the Bellman equation, which we denote as TV^*.

2.2) We consider the difference between V and TV^*. If $|V - TV^*| > \epsilon_2$, we set $\epsilon_2 = |V - TV^*|$ and compare the difference between p^* and p^{L-1}. If $|p^* - p^{L-1}| > \eta_2$, we set $\eta_2 = |p^* - p^{L-1}|$ and $V = TV^*$. Moreover, we replace $p^L = \lambda \times p^* + (1-\lambda) \times p^L$ (where λ is assigned to be equal to 0.9).

If $\eta_2 > \overline{\eta}$, and $\epsilon_2 > \overline{\epsilon}$ (where $\overline{\eta}$ and $\overline{\epsilon}$ are the predetermined convergence thresholds), we restart from step (1.1). If the policy and value functions converge, we obtain the optimal price and value functions for each point in the state space.

After we obtained the steady states of prices, market shares and value functions for each grid point in the state space, we are able to simulate the counterfactuals that evaluate the differential effects of switching cost changes.

6 Results

In the following we discuss the demand and supply estimation results.

6.1 Demand

Table 5 shows the estimation results from the first step. We report the estimation results for three specifications.

Table 5, Column 1, shows the results for the first specification that concentrates on the estimation of state dependence (or brand loyalty) and switching costs and how they vary across consumer segments (low- and high-income segments). Remember that we control for heterogeneous consumer tastes and heterogeneous price sensitivities. The estimation results show a positive estimate on brand loyalty, which indicates that repeat purchases of the same product increase consumer's utility. The interaction effect of state dependence with income shows that low-income consumers have higher brand loyalty and higher switching costs than high-income consumers.[12] The interaction effect of price with income shows that low-income consumers are more price sensitive than high-income consumers. The estimated individual-specific taste effect is also significantly positive, which provides evidence that individual-specific tastes reduce price sensitivity.

Turning to the second specification, as shown in Column 2 of Table 5, we further interact family size with price. The results show that consumers with larger families are more

[12] Note that income takes on a value of one if the income is lower than the median level (which lies between $69,999 and $99,999 in Illinois).

price sensitive. It is noteworthy that brand loyalty are of the same signs and of similar magnitudes across both specifications. Given that we control for heterogeneous tastes, the results eliminate the concern that the estimated brand loyalty or state dependence effects are confounded by heterogeneous consumer tastes. The average switching cost amounts to 20 percent of the product price.

Table 5 shows the demand estimates from the second step estimated by two stage least squares (2SLS) using instruments for price. The first stage of the 2SLS estimation procedure returns a significant coefficient estimate for price that takes on a value of 0.815, which eliminates the concern of using only weak instruments. The second-stage estimation shows a negative and significant price coefficient. The coefficient estimates of the other product attributes are all positive and significant, except for carbohydrate, which is consistent with many dietary restrictions.

Overall, our demand estimates provide strong evidence for brand loyalty and switching costs. We find that switching costs vary across income segments, they are higher for low-income consumers and, therefore, for brands that hold higher market shares of low-income customers. In addition, we find that consumers belonging to low-income segments are more price sensitive than high-income consumers. Note that several beer brands hold larger shares of low- (high-)income customers; this implies a higher (lower) switching cost and a higher (lower) price sensitivity.

6.2 Supply

We consider the dynamic game outlined above and use the computational algorithm to simulate steady state prices, market shares, and profits for varying switching costs. Due to the large state space and the computationally complex algorithm, we limit the number of beer brands to two. This helps to avoid dimensionality and convergence problems. The beer brands were chosen based on the following criteria: We select domestic beer brands that hold large market shares to ensure that the beer brands are known by customers and offered by most stores in our dataset. We choose beer brands that target different customer segments so we can provide insights into how pricing strategies vary across beer brands. We categorize beer in a low- and a high-market beer brand as characterized by the fraction of customers in income segments, average price, and estimated mean utility.

The selection criteria return Samuel Adams and Busch. Samuel Adams is a premium beer that is usually associated with a high-market segment brand, as: (1) it is the only beer that is brewed according to purity law; (2) it is among beers with the highest average prices (see Table 2); (3) it is sold to a large fraction of high-income consumers (see Table 3); and (4) it received one of the highest mean utilities in the demand estimation (see Table 2).[13]

Busch is a popular beer that is commonly considered a low-segment beer brand. As shown in Table 2 (right panel) the share of low-income customers (as shown in Table 3) is among the highest, the average price is about the lowest, and the estimated mean utility for consumers is low.

It should be noted that the repeat purchase ratios of both selected beers are relatively high, taking on values of 36 to 51 percent (see Table 4). Moreover, the demand estimation returns brand loyalty fixed effects for these brands that are above average, which confirms that switching cost is a relevant attribute for these beer brands.

Based on the computational algorithm, we calculate steady state prices, market shares, and profits at each grid point in the defined state spaces.[14] We then simulate each firms' prices, market shares, and long-run profits for different switching costs. Since our demand estimations returned switching costs that are different across income segments, we account for differential switching costs across both income segments. The switching cost in the low-income segment is provided by the coefficient estimate on state dependence (see Table 5). The corresponding switching cost in the high-income segment is retrieved by using the coefficient estimate on brand loyalty and the interaction effect of brand loyalty and

[13]The term "purity law" indicates that beer is produced using only barley, hops, yeast, and water as ingredients. The purity law prohibits the use of any other ingredients. Therefore, brands brewed according to the purity law are considered premium beers.

[14]Note, for simplicity, profits are used interchangeably for present discounted values.

income weighed by the price coefficient. Next, we establish the relative switching costs between the low- and high-income segments by using the proportion of those switching costs that returns a ratio of 1.7. That is, the switching cost in the low-income segment is 1.7 times the switching cost in the high-income segment. We keep this ratio of 1.7 as fixed and vary the switching cost of the low-income segment in the interval [0, 1.5] (while adjusting the switching cost of the high-income segment).

6.2.1 Estimation Results

We now discuss the switching cost effects on prices, market shares, and profits. Figure 1 displays the evolution of each brand's equilibrium price as switching costs increase from 0 to 1.5. In the absence of switching costs (switching costs are zero), the premium beer brand (Samuel Adams) is sold for 9.1 cents per ounce, while the low-segment beer brand (Busch) is sold for about half the price (4.4 cents per ounce). As switching costs increase, prices of beer brands follow a U-shaped pattern (more details will be provided below).[15]

Figure 2 shows the evolution of market shares for both beer brands across both customer segments as switching costs increase. It should be recognized that the premium beer brand Samuel Adams serves more customers in the high-income segment than in the low-income segment throughout all switching cost levels. The opposite applies to the low-segment beer brand Busch. Moreover, the evolution of market shares across switching costs is different across both beer brands. The market shares for Samuel Adams follows a concave shape as switching costs increase, while they take on a convex shape for Busch.

Figure 3 demonstrates that firms' profits follow a U-shaped pattern as switching costs evolve. In the following, we discuss the results in further detail categorized by levels of switching costs.

Low Switching Costs

An increase in switching costs in the low area (from 0 to 0.5) causes beer prices for Samuel

[15]Note that the simulated prices replicate the data well, as they lie within the range of observations (see the right panel of Table 2.

Adams and Busch to monotonically decline by 2 and 4.4 percent, respectively. Both firms adopt an investment strategy where price reductions aim toward increasing their loyal customer base while stealing consumers from competitors.

The impact of this investment strategy on market shares is illustrated in Figure 2. The figure shows that Samuel Adams' market shares increase by 3.2 and 3.5 percent in the low and the high consumer segment, respectively. Samuel Adams' gains in market shares imply that Busch loses a large portion of customers in both segments, that is, 5.1 percent and 6.7 percent in the low- and high consumer segments, respectively. In the context of a monopolistic market, where a price reduction usually implies an increase in the customer base, Busch's loss in market share while adopting an investment strategy appears unreasonable. However, in an oligopolistic market environment, demand is not only dependent on own price but also on the competitors' pricing strategies. Hence, price changes have to be evaluated relative to the competitors' prices. Here, both firms engage in intense price competition while Samuel Adams is able to steal customers from Busch. Samuel Adams price reduction is especially attractive to its customers as switching costs are low. Despite the fact that Busch responds by reducing its price, it is only able to limit the number of customers that switch to Samuel Adams. Even though both firms adopt investment strategies and reduce prices, Samuel Adams is able to expand its customer bases across both consumer segments while Busch loses market shares in both segments. The finding that Busch is not able to attract more customers while adopting an investment strategy confirms the highly competitive environment when switching costs are low.

Figure 3 shows that both brands profits monotonically decline as switching costs increase from 0 to 0.5. Samuel Adams' profit declines by 2.4 percent while Busch experiences a more drastic profit reduction of 14.8 percent, which is explained by the loss of customers to its competitor.

In sum, our simulation results show that when switching costs are low, firms intensively compete on prices. The premium brand Samuel Adams is able to attract more customers across both customer segments while the price of the low-segment brand, Busch, is reduced in an attempt to diminish the loss of customers in the low-income segment. The market becomes highly competitive and reduces both firms' profits, with a more negative impact on the profits of the firm offering the low-segment beer brand.

Intermediate Switching Costs

If switching costs rise in the intermediate area (from 0.5 to 1), firms apply different pricing strategies, as depicted in Figure 1. Samuel Adams adopts a harvesting strategy and moderately increases the price. Note that, while the price increased, it still remains below the price without switching costs. Despite the fact that the price of Samuel Adams increased, the brand is able to attract further high-income customers (see Figure 2), which is explained by the fact that high-income customers have lower switching costs and are less price sensitive. The market share of low-income customers remains about the same.

In contrast, Busch continues reducing the price by 4.3 percent with the intention of diminishing customer migration to Samuel Adams. As a result, the loss of high-income customers diminished from formerly 6.7 percent (for low switching costs) to 3 percent.

Busch's abated customer loss is even more pronounced in the low-income segment, where migration diminished from 5.1 percent (for low switching costs) to 0.6 percent. Fewer low-income customers leave Busch (compared to high-income customers) as those customers are more price sensitive and more responsive to a price reduction.

Regarding the impact on profits, Figure 3 shows that Samuel Adams' harvesting strategy returns a 1.7 percent gain in profits, but profits still remain below the ones without switching costs. Busch's investment strategy diminishes the profit loss, from formerly 14.8 percent for low switching costs to 3.6 percent.

Overall, if switching costs are in the intermediate area, firms adopt differential price strategies. While Samuel Adams switches to the harvesting strategy, Busch continues adopting an investment strategy. Busch's ongoing investment strategy serves to diminish further losses, especially of price sensitive customers in the lower income segment. In the high-income segment, Busch still loses market shares since those customers have a lower price sensitivity.

High Switching Costs

Figure 1 shows that an increase in switching costs in the high area (from 1 to 1.5) implies price rises for Samuel Adams and Busch by 2.5 and 3.2 percent, respectively. Both firms exploit the fact that switching costs are high and customers show a high loyalty to their former brand choices. It is noteworthy that Samuel Adams' price surpasses the price without switching costs while Busch's price remains below that price. Hence, switching costs raise prices only for the high-segment beer brand (Samuel Adams) and only if switching costs are large; otherwise, switching costs result in lower prices.

Regarding the effects on market shares, Figure 2 shows that Samuel Adams' price increase has little impact on high-income customers, but it provides incentives for low-income customers to switch to Busch.

Figure 3 shows that Samuel Adams's profits increase by 5.4 percent when switching costs increase from 1 to 1.5. Its profits eventually exceed profits that were earned without switching costs. Busch's profits increase by 10 percent but still remain below the profits when switching costs are non-existent.

We applied several robustness checks. First, we applied a different ratio between the low-income and high-income segments; that is, we replaced the current ratio of 1.7 with 1.2. The results remain quantitatively and qualitatively unchanged.

Second, we replaced the existing low-segment beer brand Busch with Miller Light, which is characterized by a similar average price per ounce as Busch, see the right panel of Table 2. Therefore, the use of Miller Light serves as a robustness check whether our effects are representative to beer brands in the lower market segment rather than being specific to beer brands. As shown in Figures 4-6, the results remain unchanged.

Third, we extend our estimation exercise to three beer brands—Miller Lite, Budweiser, and Samuel Adams—that represent brands in the low-segment, intermediate-segment, and high-segment, respectively. Details on the selection criteria, the setting, and the results are relegated to Appendix A. The results are illustrated in Figures 7-9. The results confirm close similarities to our results presented above.

Most importantly, switching costs can have large and differential effects on beer prices, market shares, and profits that are dependent on customer segments and, therefore, on beer brands. As switching costs evolve, firms change pricing (harvesting and investment) strategies and, for the same switching costs, firms' pricing strategies differ. If switching costs are low, all firms adopt investment strategies and drastically reduce prices as they compete for loyal customers. However, only the high-segment beer brand (Samuel Adams) gains market shares as it steals loyal customers from its competitors; all firms' profits decline. For high switching costs, the firms with the low- and high-segment brands have little incentives to invest in loyal customers. Instead, they adopt harvesting strategies and increase prices. In contrast, the firm with the intermediate-segment brand adopts an investment strategy to steal customers from its competitors, particularly from the low-segment brand.

In general, as switching costs increase, the firm's profit with the high-segment (low-segment) brand increases (decline), while the profit of the firm with intermediate-segment brand follows a U-shaped pattern. The competitive pressure imposed on the low-segment brand is immense and causes large losses for the low-segment firm.

7 Conclusion

Most products embody a brand image and establish brand loyalty in customers' purchasing behavior. Brand loyalty can exhibit (psychological) switching costs for consumers when they change brands. Switching costs imply that firms' pricing decisions include a dynamic aspect since firms account for the fact that current brand purchases increase the loyal customer base and the probability of repeated purchase of the same brand in the future. These dynamic pricing decisions can become computationally highly complex, especially when firms operate in competitive environments such as oligopolistic markets. The goal of this study was to provide insights into the differential effects of switching costs on prices, market shares, and profits in an oligopoly where firms offer differentiated goods that target different market segments.

We use a comprehensive database on the beer market that contains detailed beer purchase information. The data confirm that customers repeatedly purchase the same brands. The data also show that customer segments are different across beer brands, where less (more) expensive beer brands hold larger market shares of customers with lower (higher) incomes.

Our demand estimations return substantially different switching costs and price sensitivities across customer segments, and therefore, across beer brands. On the supply side, we consider variations of switching costs and simulate prices, market shares, and profits of beer brands targeting different customer segments. Our main results show that prices and profits evolve in a U-shaped pattern as switching costs increase. Switching costs mostly result in more competitive market outcomes. Price competition becomes especially severe when switching costs are low. In this case, firms intensely compete for loyal customers and adopt investment strategies that help especially the high-segment beer brand to steal customers from the low-segment brand. The prices exceed the price level without switching costs only for the high-segment brand and only if switching costs are high. Firms' profits are mostly below those without switching costs and are only higher for the high-segment firm if switching costs are sufficiently high.

Our results provide novel insights into the competitive effects of switching costs. We show that switching costs (for the most part) increase competition, resulting in lower prices and lower profits. However, if switching costs are large, they can increase price and profits for the high-segment firm. Therefore, this study can serve to bridge potentially conflicting conjectures on competitive effects of switching costs in the theoretical and empirical literature.

This study faces its limits when computing price strategies and value functions for a large set of firms. It would be interesting to examine how the competitive effects change as the product space becomes less differentiated and more products are offered on the market. This applies especially to the high-market segment as the high-segment firm was able to adopt more profitable pricing strategies. This extension, however, would likely require the adoption of a different dynamic methodology and we leave this topic for future research.

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Appendix A

We extend our estimation exercise to three beer brands—Miller Lite, Budweiser, and Samuel Adams—that represent brands in the low-segment, intermediate-segment, and high-segment, respectively. In the following, we report the simulation results for prices, market shares, and profits as switching costs change.

A.1 Estimation Results for Prices

We first present the simulated equilibrium prices of each brand as switching costs increase from 0 to 1.5. Figure 7, upper panel, shows that the price for Samuel Adams follows a U-shaped pattern as switching costs increase. More specifically, if switching costs are low (for values between 0 and 0.5), the price monotonically declines. This indicates that the firm offering the premium brand adopts an investment strategy where the price reduction helps it compete against other firms with the intention of gaining loyal customers. For intermediate switching costs (values between 0.5 and 1), the firm switches to a harvesting strategy as represented by the moderate price increase. If switching costs are high (values larger than 1), Samuel Adams more drastically increases price. The firm exploits the fact that switching costs are high and their largest customer base (high-income customers) shows little price sensitivity, which allows the firm to increase price.

The middle panel of Figure 7 shows Budweiser's price evolution. For low and intermediate switching costs, the firm follows a similar pricing strategy as the premium beer, Samuel Adams, and adopts an investment and harvesting strategy, respectively. If switching costs are high, however, the price of Budweiser starts decreasing. The price decline indicates Budweiser's attempt to impose higher price pressure and to steal consumers from competitors. The lower panel of Figure 7 indicates that the price of Miller follows a similar pattern as the price for Samuel Adams, but price increases more drastically for larger switching costs.

The price patterns show several features across beer brands. First, for low switching costs, all three beer brands adopt an investment strategy imposing downward pressure on prices. Hence, for low switching costs, firms intensely compete on prices, so as to increase their future loyal customer base while stealing customers from competitors. It is noteworthy that the price reduction is largest for the intermediate brand (Budweiser). Second, for intermediate switching costs, all three firms adopt the harvesting strategy and increase prices by about the same magnitude. Third, for high switching costs, firms adopt different pricing strategies. While the firms offering low- and high-segment brands adopt a harvesting strategy and increase prices, the firm with the intermediate-segment brand engages in an investment strategy and reduces price.

A.2 Estimation Results for Market Shares

Figure 8 shows the evolution of market shares in the low- and high-income segments as switching costs increase. The upper panel shows that Samuel Adams is purchased mostly by high-income customers (relative to low-income customers) throughout all switching cost levels. More than half the high-income consumers purchase the high-segment beer brand. If switching costs are low, Samuel Adams attracts customers from both competitors across both income segments. Customer stealing occurs since the firm with the premium brand adopts an investment strategy that is more effective than the investment strategies of the firms that focus on the lower customer segment. If switching costs are in the intermediate area, Samuel Adams' price surge results in fewer low-income customers for both firms, while it gains customers from both competing firms in the high-income segment. For high switching costs, the market share of the low-income segment increases despite the fact that Samuel Adams is raising its price. The gain in consumers is explained by the price increase of the competing firm Miller, which loses a drastic number of low-income customers.

Turning to Budweiser and Miller (see middle and lower panels of Figure 8), each firm attracts more low-income than high-income customers. If switching costs are low, both brands lose customers despite the fact that they adopt an investment strategy. In the context of a monopolistic market, this result appears unreasonable. However, in a competitive market environment, demand is not only dependent on own price but also on the competitor's pricing strategies. Even though Budweiser and Miller both reduced prices, customers switched to the premium brand, whose price reduction became more attractive to customers. The fact that Budweiser and Miller were not able to catch more customers while adopting an investment strategy emphasizes the high competitive pressure if switching costs are low. Therefore, if switching costs are low, an investment strategy is most beneficial for the firm offering a premium brand, and it is the only firm that is able to steal customers from competitors. These results show that competition is a relevant aspect to consider.

If switching costs are in the intermediate area, both firms (Budweiser and Miller) continue losing high-income customers to the firm with the high-segment brand. In contrast, both firms gain low-income customers at the expense of the high-segment brand. Hence, for intermediate switching costs, a price increase by all firms results in a loss (gain) of high- (low-) income consumers for Budweiser and Miller.

If switching costs are high, Miller and Samuel Adams follow a harvesting strategy, while Budweiser adopts an investment strategy and intensely competes for loyal consumers. In fact, Budweiser successfully increases market shares across both segments. Miller loses customers in both market segments (at the expense of the other firms) with the loss being more pronounced for the low-income segment. Samuel Adams loses market shares in the high-income segment. It is noteworthy that Samuel Adams' harvesting strategy is able to attract customers from the low-income segment, while Miller's harvesting strategy reduces its share of low-income customers. Miller's loss of low-income customers could be explained by its more drastic price increase in conjunction with Budweiser's competitive investment strategy.

Our results show that firms apply different pricing strategies as switching costs change. Moreover, firms' pricing strategies differ even for the same switching costs. In general, however, firms tend to adopt investment (harvesting) strategies if switching costs are low (high). Moreover, the impact on firms' market shares depends on the customer segments they serve. For example, for low switching costs, an investment strategy by the firms with the high-segment brand increases market shares, while the same pricing strategy exerts a negative impact on the market shares of other brands. If switching costs are high, the high-segment brand's price increase results in market share gains that are explained by low-income customers that were loyal to the low-segment brand and switch to the high-segment brand. The switching is explained by low-income consumers facing lower switching costs. The loss of the low-segment brand's consumers is further explained by the investment strategy of the intermediate-segment firm, Budweiser. Budweiser itself adopts a more competitive strategy when switching costs are high, which results in higher market share gains across both segments, market share losses for both firms in the high-income segment, and losses in the low-income segment for the low-segment brand.

It is noteworthy that as switching costs increase, the high-segment brand's high-income market share increases (except those with very large switching costs). Moreover, as switching costs increase, the low-segment brand's high-income market share almost monotonically declines, which shows that high-income customers do not show much loyalty to this brand.

A.3 Estimation Results for Firms' Profits

Figure 9 displays the evolution of firms' profits as switching costs increase. The upper panel shows that Samuel Adams' profits are monotonically increasing with the level of the switching costs. The strong profit increase is explained to a large extent by the increase of the high-income segment. It is noteworthy that Samuel Adams has a more drastic increase in profits for large switching costs, which is explained by the harvesting strategy.

The profits of Budweiser and Miller (see middle and lower panels in the figure) decline as switching costs are low, which is explained by the customer losses. For intermediate switching costs, Budweiser's and Miller's profits slightly increase due to the increase in the market share of low-income customers. Most noteworthy is that Budweiser's profits increase for large switching costs due to its investment strategy and the increasing market shares in both income segments. In contrast, Miller's profits decline for large switching costs, as explained by the harvesting strategy that results in customer losses.

We also applied further robustness checks related to the two-brand case in the main text. First, we applied a different ratio between the low-income and high-income segments; that is, we replaced the current ratio of 1.7 with 1.2. The results remain quantitatively and qualitatively unchanged. Second, we replaced the existing low-segment beer brand Miller with Coors since the latter is characterized by an even lower average beer price. The main results continue to hold.

Table 1: Beer Prices, Market Shares, and Attributes

Brand Name	Headquarter	Price (cents/oz)	Market Share (%)	Alcohol	IBU	Carbohydrates	Calories	Sugar
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Beck's	Bremen, GER	8.2	1.2	4.8	20.0	8.6	144	0
Budweiser	St. Louis, USA	6.9	9.9	5.0	10.0	10.6	145	0
Busch	St. Louis, USA	4.8	3.6	4.3	12.0	6.9	114	0
Coors	Chicago, USA	6.5	2.6	5.0	6.0	11.7	147	0
Corona	Leuven, BEL	10.8	6.4	4.6	19.3	13.0	148	0.7
Dos Equis	Amsterdam, NL	10.1	1.6	4.2	10.0	11.0	131	0
Heineken	Amsterdam, NL	10.4	4.9	5.0	23.0	11.0	142	0
Icehouse	Chicago, USA	4.7	3.8	5.0	8.0	8.7	132	0
Labatt Blue P	Toronto, CAN	5.9	1.0	4.7	9.0	9.1	132	0
Miller G	Chicago, USA	6.2	6.0	4.6	7.0	12.2	140	0
Miller Lite	Chicago, USA	4.9	6.7	4.6	7.0	12.2	141	0
Milwaukee's	Milwaukee, USA	5.1	0.8	4.8	10.0	11.4	128	0
Modelo	Leuven, BEL	10.2	7.4	4.6	18.0	4.0	150	0
Natural Ice	St. Louis, USA	4.7	1.5	5.9	5.0	8.9	130	0
Negra Modelo	Mexico City, MEX	10.8	0.9	5.4	19.0	16.0	180	0
Pabst Blue Ribbon	Los Angeles, USA	5.1	4.0	4.7	12.0	12.8	144	0
Rolling Rock	St. Louis, USA	4.9	2.3	4.5	9.0	10.0	135	0
Samuel Adams	Boston, USA	11.6	2.7	4.9	30.0	18.0	176	0
Steel Reserve	Milwaukee, USA	9.8	0.2	8.1	11.0	16.0	222	0
Stella Artois	Breda, NL	12.3	2.9	5.2	30.0	11.9	156	0
Tecate	Monterrey, MEX	6.2	2.7	4.5	22.0	13.5	141	0

This table shows the beer brands sorted in alphabetical order. Sources: AC Nielsen Data and firms' websites.

Table 2: Beer Prices, Market Shares, and Mean Utility

Brand Name	Market Share (%)	Price (cents/oz)	Brand Name	Price (cents/oz)	Market Share (%)	MU	Price Min	Price Max
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Budweiser	9.9	6.9	Stella Artois	12.3	2.9	12.5	4.5	15.1
Modelo	7.4	10.2	Samuel Adams	11.6	2.9	12.1	9.1	14.9
Miller Lite	6.7	4.9	Negra Modelo	10.8	0.9	10.7	9.0	13.6
Corona	6.4	10.8	Corona	10.8	6.4	12.9	9.2	13.4
Miller G	6.0	6.2	Heineken	10.4	4.9	10.7	8.0	15.1
Heineken	4.9	10.4	Modelo	10.2	7.4	11.1	8.8	14.6
Pabst Blue R	4.0	5.1	Dos Equis	10.1	1.6	7.3	3.7	11.9
Icehouse	3.8	4.7	Steel Reserve	9.8	0.2	12.1	4.2	21.8
Busch	3.6	4.8	Beck's	8.2	1.2	10.5	7.9	13.6
Stella Artois	2.9	12.3	Budweiser	6.9	9.9	8.3	5.6	9.0
Samuel Adams	2.7	11.6	Coors	6.5	2.6	7.4	5.2	9.8
Tecate	2.7	6.2	Tecate	6.2	2.7	9.7	5.4	9.7
Coors	2.6	6.5	Miller G	6.2	6.0	7.0	5.6	10.1
Rolling Rock	2.3	4.9	Labatt Blue P	5.9	1.0	7.7	5.5	7.9
Dos Equis	1.6	10.1	Milwaukee's	5.1	0.8	7.3	3.5	9.7
Natural Ice	1.5	4.7	Pabst Blue R	5.1	4.0	8.1	3.9	8.6
Beck's	1.2	8.2	Rolling Rock	4.9	2.3	7.6	4.2	6.4
Labatt Blue P	1.0	5.9	Miller Lite	4.9	6.7	7.0	4.2	9.7
Negra Modelo	0.9	10.8	Busch	4.8	3.6	7.8	4.1	7.9
Milwaukee's	0.8	5.1	Icehouse	4.7	3.8	7.8	4.0	7.4
Steel Reserve	0.2	9.8	Natural Ice	4.7	1.5	7.4	3.5	10.4

This table shows market shares and prices in descending order. Sources: AC Nielsen Data. MU indicates the mean utility retrieved from the demand estimation.

Table 3: Beer Prices, Market Shares, and Income

Brand Name (1)	Price (cents/oz) (2)	Market Share (%) (3)	Low-income (%) (4)	High-income (%) (5)
Dos Equis	10.1	1.6	26.1	73.9
Tecate	6.2	2.9	27.8	72.2
Beck's	8.2	1.2	27.9	72.1
Corona	10.8	6.4	31.6	68.4
Pabst Blue R	5.1	4.0	33.1	66.9
Samuel Adams	11.6	2.7	33.6	66.4
Stella Artois	12.3	2.9	44.8	55.2
Labatt Blue P	5.9	1.0	45.8	54.2
Coors	6.5	2.6	46.2	53.9
Miller Lite	4.9	6.7	51.8	48.2
Heineken	10.4	4.9	55.7	44.4
Miller G	6.2	6.0	56.7	43.3
Modelo	10.2	7.4	60.0	40.0
Budweiser	6.9	9.9	69.6	30.4
Rolling Rock	4.9	2.3	70.3	29.7
Negra Modelo	10.8	0.9	74.2	25.8
Icehouse	4.7	3.8	80.5	19.5
Steel Reserve	9.8	0.2	95.0	5.0
Busch	4.8	3.6	97.7	2.4
Milwaukee's	5.1	0.8	99.1	0.9
Natural Ice	4.7	1.5	100.0	0.0

This table concentrates on the share of low-income segments by brands sorted in descending order. Note that the Low- and High-income shares relate to the corresponding shares of a beer brand, rather than market shares. Source: AC Nielsen Data.

Table 4: Repeat Purchases, Market Shares, and Income Groups

Brand Name (1)	Repeat Purchases (%) (2)	Share of Trips (3)	Price (cents/oz) (4)	Market Share (%) (5)	Low-income (%) (6)	High-income (%) (7)
Heineken	81.5	6.8	10.4	4.9	55.7	44.3
Steel Reserve	78.8	6.3	9.8	0.2	95.0	5.0
Natural Ice	75.8	0.7	4.7	1.5	100.0	0.0
Rolling Rock	71.9	2.5	4.9	2.3	70.3	29.7
Icehouse	71.7	3.5	4.7	3.8	80.5	19.5
Milwaukee's	71.2	1.2	5.1	0.8	99.1	0.9
Pabst Blue R	68.2	6.0	5.1	4.0	33.1	66.9
Negra Modelo	64.5	3.4	10.8	0.9	74.2	25.8
Miller Lite	63.3	5.6	4.9	6.7	51.8	48.2
Miller G	62.2	2.0	6.2	6.0	56.7	43.3
Budweiser	61.5	10.1	6.9	10.0	69.6	30.4
Busch	50.6	3.2	4.8	3.6	97.6	2.4
Corona	40.4	1.5	10.8	6.4	31.6	68.4
Samuel Adams	36.4	6.4	11.6	2.7	33.6	66.4
Coors	35.9	12.1	6.5	2.6	46.2	53.8
Modelo	32.0	0.9	10.2	7.4	60.0	40.0
Dos Equis	30.4	18.3	10.1	1.6	26.1	73.9
Labatt Blue P	29.2	2.5	5.9	1.0	45.8	54.2
Tecate	27.8	4.4	6.2	2.7	27.8	72.2
Stella Artois	23.0	1.7	12.3	2.9	44.8	55.2
Beck's	14.0	1.0	8.2	1.2	27.9	72.1

This table concentrates on the repeat purchases by customers in percentage. Note that the Low- and High-income shares relate to the corresponding shares of a beer brand, rather than market shares. Source: AC Nielsen Data.

Table 5: Stage One Estimation Result (θ_2 parameters)

	(1)	(2)
Brand Loyalty (BL)	2.36***	2.36***
	(0.21)	(0.21)
BL x Income	1.68***	1.68***
	(0.30)	(0.30)
Price x Income	-5.55***	-5.59***
	(1.68)	(1.68)
Price x Family Size		-4.71***
		(1.34)
Price x ι	9.92***	9.73***
	(3.73)	(3.43)
BL x Brands		
Y***		

This table shows the estimation results of the first step of the demand estimation. BL stands for brand loyalty and ι is defined in equation (13). Note, prices are measured in \$/oz. Standard errors are shown in parentheses; *** (*) indicates a significance level of 1% (10%).

Table 6: Stage Two Estimation Result (θ_1 parameters)

	First Stage Results (1)	Second Stage Results (2)
IV	0.82***	
	(0.01)	
Price		-72.47***
		(4.00)
Alcohol	0.03e-02	0.44***
	(0.04e-02)	(0.11)
Calorie	0.01e-02***	0.04***
	(0.002e-02)	(0.01)
Carbohydrates	-0.03e-02***	-0.19***
	(0.01e-02)	(0.02)
Sugar	0.47e-02***	4.67***
	(0.11e-02)	(0.32)
IBU	0.03e-02***	0.19***
	(0.00e-02)	(0.01)
Constant	-0.95e-02***	-6.99***
	(0.10e-02)	(0.32)
Time Fixed Effect	Y***	Y***

This table shows the estimation results of the second step of the demand estimation, using 2SLS. Note, prices are measured in \$/oz. Standard errors are shown in parentheses; *** indicates a significance level of 1%.

Figure 1: Equilibrium Price (cents/oz)

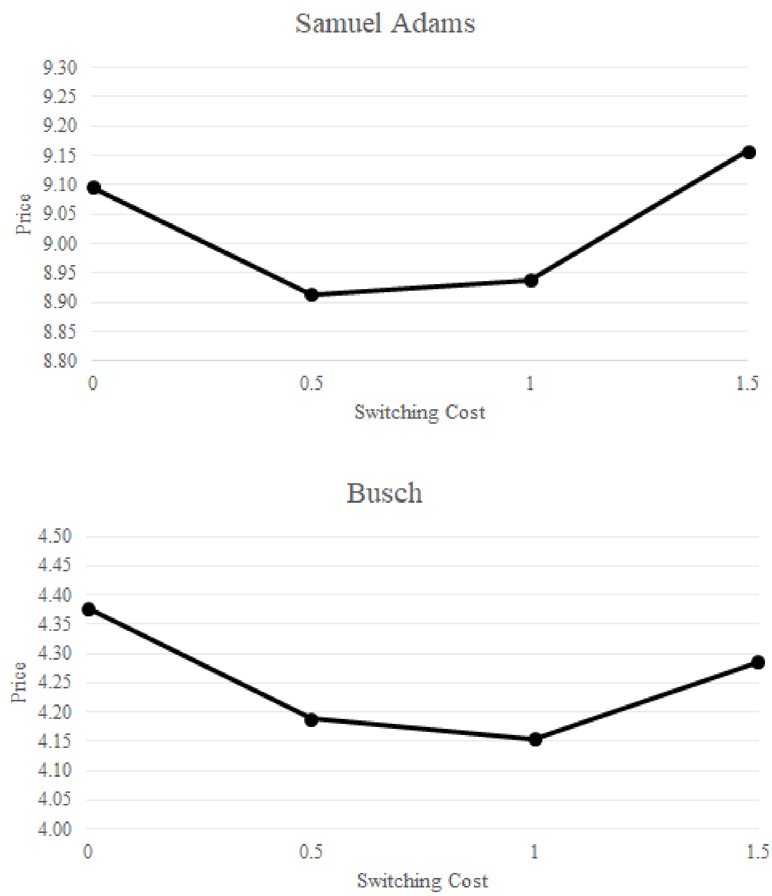

Figure 2: Market Share (%)

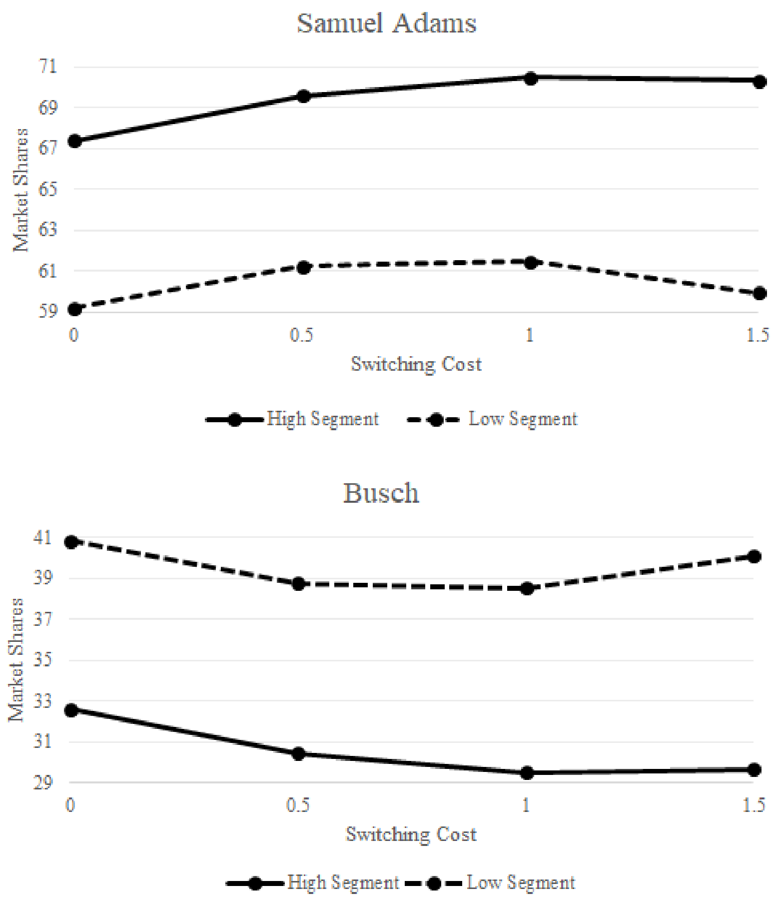

Figure 3: Value Function

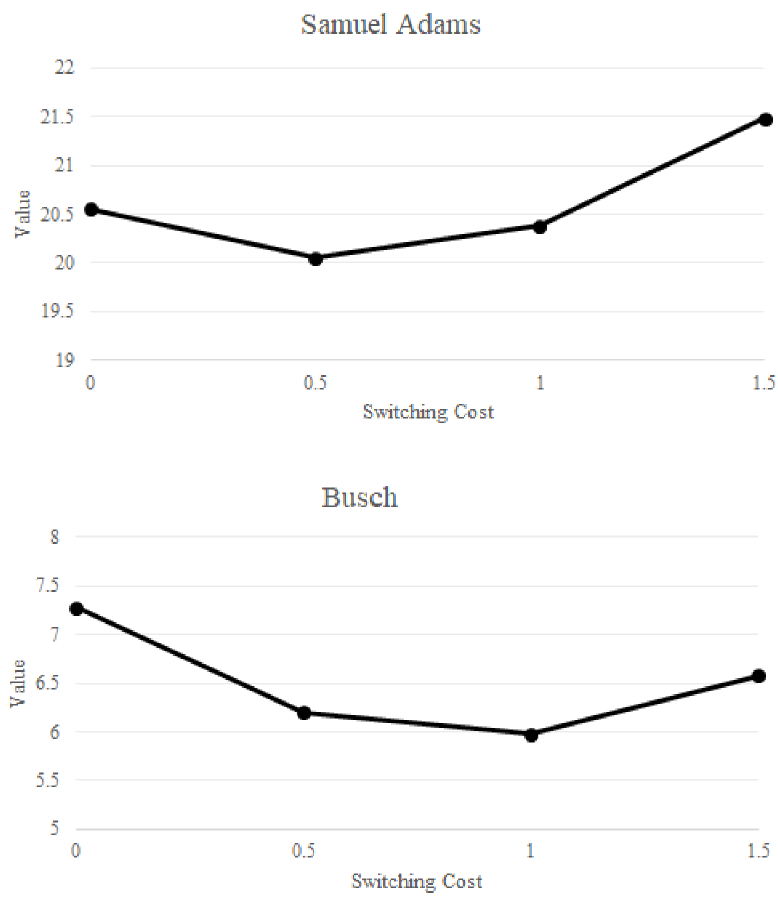

Figure 4: Equilibrium Price (cents/oz)

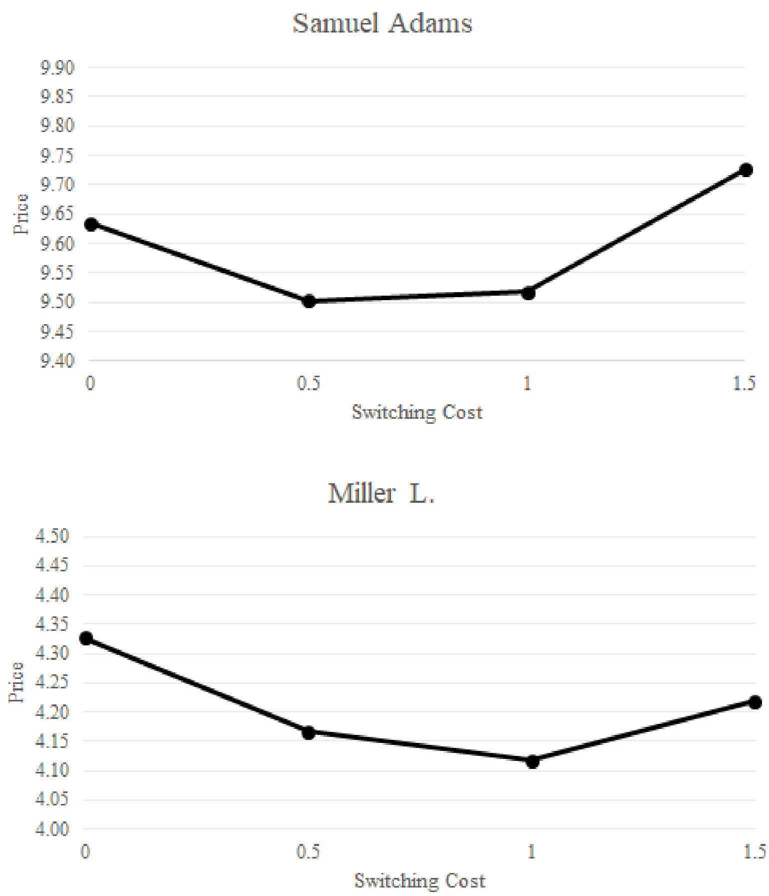

Figure 5: Market Share (%)

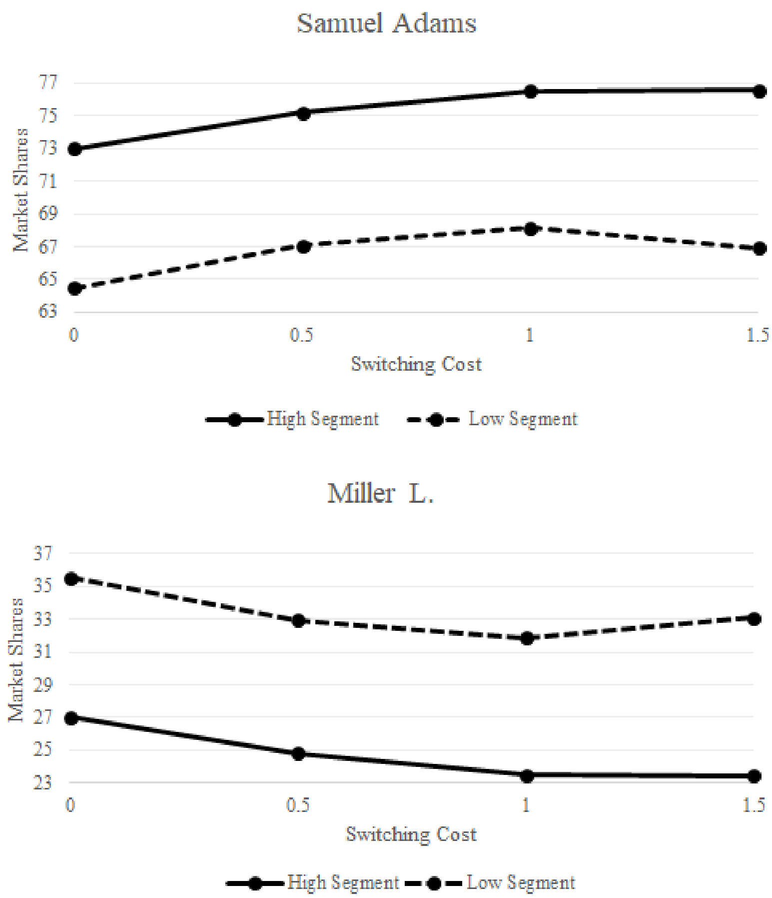

Figure 6: Value Function

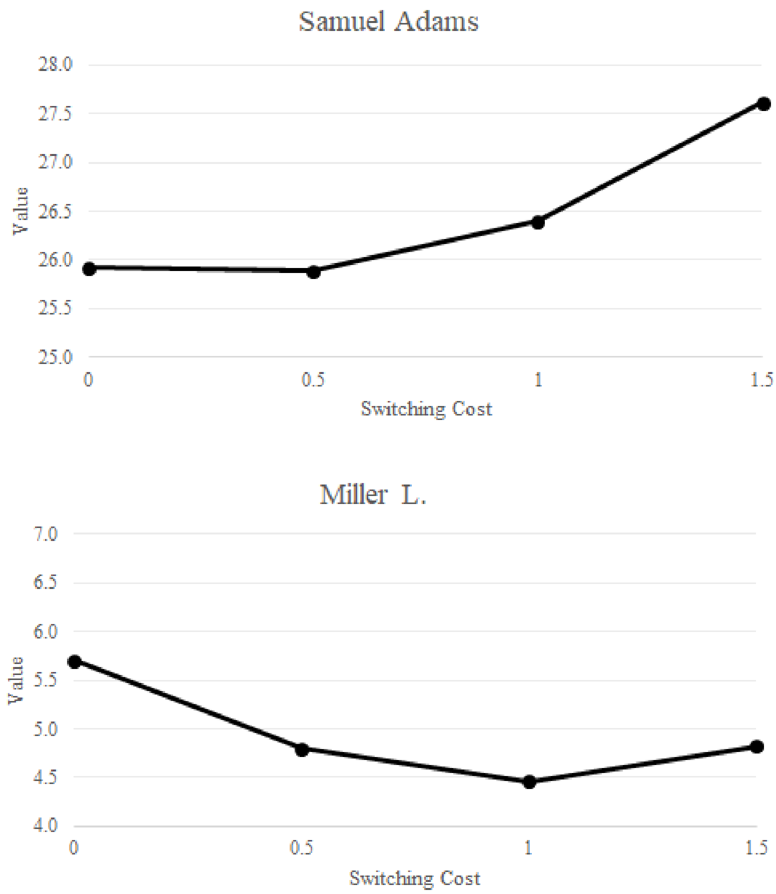

Figure 7: Equilibrium Price (cents/oz)

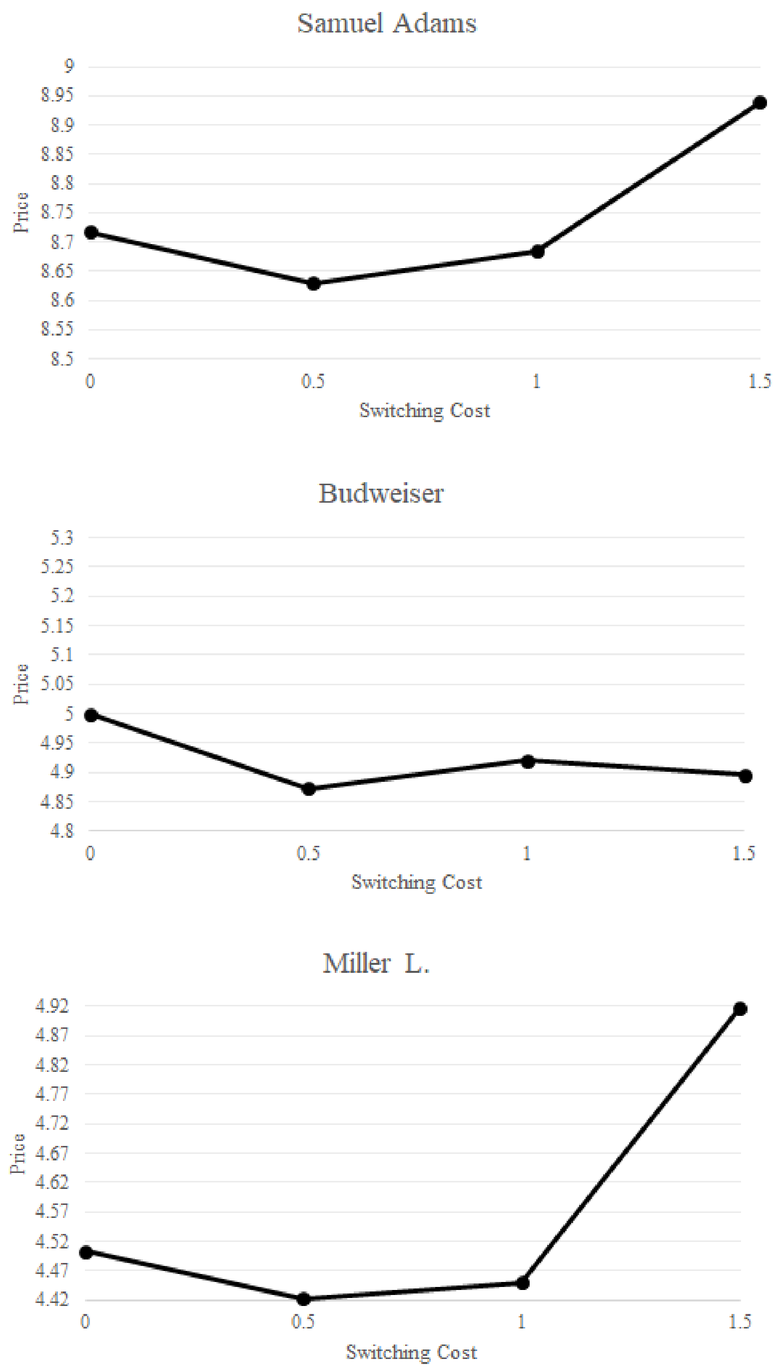

Figure 8: Market Share

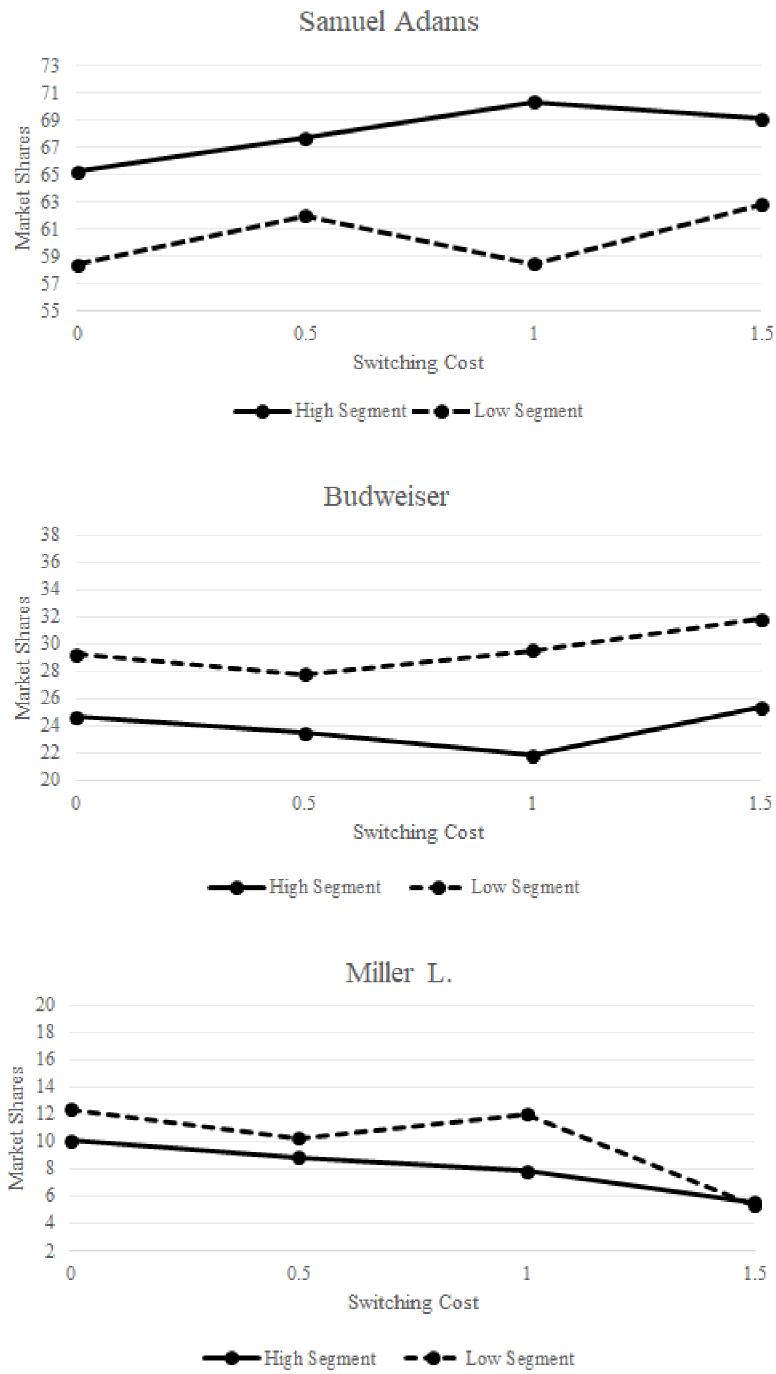

Figure 9: Value Function