Switching Beers? The Effects of Switching Costs on Prices, Market Shares, and Profits in the Beer Market*

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Abstract

We consider a dynamic oligopoly model on the beer market and simulate differential effects of varying switching costs. We consider market segments that are differentiated by customer income and beer quality. Our demand estimation results show that switching costs and price sensitivities are higher for low-income customers than for high-income customers. This implies asymmetric switching behavior of customers. Switching costs impose severe downward pressure on the low-quality brand price as the low-quality provider fights to prevent losing highly price sensitive low-income customers due to business stealing effects. Switching costs result in higher price and profit reductions for firms offering low-quality brands. Firms with high-quality brands are better shielded from price competition and profit losses due to their less price-sensitive customer base. In addition, we find that prices follow a U-shaped pattern as switching cost increase. When switching costs are low (high), firms reduce (increase) price to to maximize long-run profit.

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1 Introduction

In many consumer packaged goods markets (cereal, yogurt, juice, beer, etc.) consumers repeatedly purchase the same brand. Such inertia in consumers' brand choices is often explained by (psychological) switching cost for consumers (see Klemperer (1995) and Farrell and Klemperer (2007)).[1] Switching costs can have many causes, one of which is brand loyalty. Brand loyalty provides an extra surplus to loyal consumers such that switching to a different brand comes at a (non-monetary) cost. In the presence of switching costs, firms account for repeated brand purchases, which adds nontrivial dynamic implications to firms' pricing decisions having an effect on firms' market shares, and profits.

This study providers further insights into the effects of switching costs in oligopolistic markets. While many empirical studies explore the competitive effects of switching costs in a monopolistic environment (see Dubé et al. (2008)), less attention has been devoted to oligopolistic markets with differentiated products. The analysis of switching cost effects in oligopolistic markets can be distinct from monopolistic markets since oligopolistic firms account for additional forces, such as business stealing effects (see also Siebert (2015)). We consider oligopolistic firms offering brands that are differentiated in quality, and target different customer segments separated by customer income. Since customer segments are characterized by different switching costs and price sensitivities, firms' pricing strategies are dependent on product quality. We putting special attention to differential switching cost effects (across products with different quality) on prices, market shares, and firms' long-term profits.

A large strand of theoretical and empirical studies investigate the impact of switching cost on consumer choices and firms' pricing strategies (for theoretical approaches see, e.g., von Weizsaecker (1984) and Klemperer (1987); for empirical researches see, e.g., Knittel (1997), Miravete and Palacios-Huerta (2014), and Richards and Rickard (2021)).

[1] In general, switching costs can stem from a variety of monetary and nonmonetary sources, including brand loyalty, psychological aspects, product adoption costs, search costs, and learning. For further information on switching cost, see also von Weizsaecker (1984), Klemperer (1995), Erdem (1996), Keane (1997), Seetharaman, Ainslie, and Chintagunta (1999), Huang, Perloff, and Villas-Boas (2006), Dubé et al. (2009), and Miravete and Palacios-Huerta (2014), among others).

Klemperer (1987) highlights that firms consider two countervailing forces that determine their pricing decisions (see also Farrell and Klemperer (2007)). First, switching costs make consumers less likely to switch brands. 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 increases customer loyalty to a brand and, therefore, serves as an investment into future profits, also referred to as the investment motive (see Villas-Boas (2004)).

In addition to the downward pricing pressure from investment considerations, oligopolistic firms account for business-stealing effects; that is, firms prevent their own customers from switching to a competitor's brand, and they also consider stealing loyal customers from their competitors (see Arie and Grieco (2014) and Pavlidis and Ellickson (2017)). 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 reduce prices with the intention to steal loyal consumers from rival firms. Moreover, firms also need to protect themselves against other firms' attempts to steal customers, which results in price reductions. Overall, in a competitive market with switching costs, pricing becomes complicated. That is, firms not only account for investment and harvesting motives, but also have to consider business-stealing effects. Moreover, firms have to adopt intertemporal pricing strategies since switching costs imply that current pricing not only impacts the current customer base but also affects the future customer base.

A major challenge of this type of analysis is that consumers hold observed and unobserved heterogeneous preferences for product characteristics such as flavor, nutritional content, quality, brand recognition, etc. Firms account target different customer segments—such as low- and high-income segments—that exhibit different switching costs and price sensitivity, which influences pricing strategies, market shares, and profits. Therefore, the empirical analysis needs to properly account for consumers' heterogeneous preferences to enable identification of switching costs from intertemporal purchasing behavior.

Our study focuses on an oligopoly where firms offer goods that are differentiated in quality and that target different customer segments while allowing for switching costs as well as observed and unobserved consumer heterogeneity. We investigate the effects of differential switching cost on prices, market shares, and profits for products that target different segments.

The optimal pricing problem in an oligopoly with differentiated products is nontrivial as strategic interactions between firms as well as business-stealing effects become important features. Consequently, the dimension of the state space increases, which adds complexity. We are not aware of studies that consider oligopolistic firms offering vertically differentiated products and explicitly evaluate the differential effects of switching costs on profits, prices, and market shares across products and customer segments.

We focus on the beer market since it provides a natural fit to study the implications of switching costs for the following reasons: First, the beer market is a concentrated market that characterizes the definition of an oligopolistic market. Beers are characterized by well-measured attributes including alcohol percentage, index of bitterness units (IBU), carbohydrates, calories, and sugar content. Beer can be categorized into vertically differentiated brands serving different market segments. Moreover, a high number of repeat purchases of beer brands provides supportive evidence that consumers exhibit strong loyalty to beers, which implies switching costs.

We use a large dataset on the beer market that includes detailed customer-level as well as store-level information on beer purchases in 2016.[2] The data confirm that beer brands can be differentiated and categorized into quality segments, where beer brands of low (high) quality often hold larger market shares of customers with low (high) incomes.[3] Our data also show that consumers repeatedly purchase the same beer brands.

We estimate a demand model that allows for consumer-specific switching costs where switching costs and price sensitivities are allowed to vary across consumer segments. The

[2]The dataset includes information from more than 63 thousand households and more than 9 million shopping trips. More details follow later.

[3]Beer brands are categorized into quality segments based on quality ratings, average prices, the customer segments they target, and the mean utility received from the demand estimation. Further details will be explained later.

estimation results return significant estimates on brand loyalty and switching costs. The estimated average switching costs amounts to 20% of the product price, which reduces the price elasticity of demand and explains persistent consumer purchasing behavior over time. The results also show that consumers belonging to low-income segments are more price sensitive than consumers with high-income. Since low-income (high-income) consumers primarily purchase low-quality (high-quality) beer brands, the differential price sensitivities determine differential consumer switching costs across segments. That is, switching costs are especially high for low-income customers (compared to high-income customers) who predominantly purchase low-quality brands.

We consider a dynamic oligopoly model to examine the differential effects of switching cost variation on firms' brand prices, market shares, and profits. Firms are forward-looking and maximize their own discounted profits. Firms choose Markovian strategies in which prices are a function of every firms' market share across customer segments while accounting for heterogeneous consumer switching costs and price sensitivities. The simulation of the dynamic oligopoly model concentrates on two firms that offer differentiated products, that is, low-quality and high-quality beer brands. It is important to note that we need to constrain our simulation to a few firms due to computational intractabilities arising from large state spaces in dynamic oligopoly. Therefore, the contribution of the simulation study should not be understood as an exact replication of outcomes in the beer market. It rather serves the purpose to provide conceptual insights into firms' dynamic behavior and competitive effects in markets characterized by differentiated products and heterogeneous switching costs.[4] We identify Busch as the firm that offers the low-quality brand and Sam Adams offers the high-quality brand.[5]

Our results show that brand prices and firms' profits follow U-shaped patterns as switching costs increase. Overall, we find that switching costs imply fiercer competition and have mostly adverse effects on prices and profits (with the exception of the high-

[4]We applied several robustness checks by including different brand combinations and including more than two beer brands in order to show that our findings are robust.

[5]We use multiple criteria to classify beer brands in quality segments as will be discussed later.

quality firm's brand price and profit when switching costs are very high).

Most importantly, we find that switching costs affect firms' prices, market shares, and profits differently depending on brand quality. The differential effects are stemming from brands with different qualities targeting differential customer segments with different price sensitivities. For example, the low-quality brand targets low-income customers that are highly price sensitive, while the high-quality provider targets high-income customers that are less price sensitive. Consequently, the high-quality provider is more successful in stealing customers from the low-quality provider (business stealing). As a response, the low-quality provider has to strongly reduce its product price to prevent its price-sensitive customers from switching to the high-quality-brand. This effect is especially strong when switching effects are low. The high-quality firm experiences less downward price pressure as it mainly serves customers with low price sensitivity.

The differential price sensitivity results in asymmetric switching behavior of customers, which puts much downward pressure on the low-quality providers' product price and results in lower profit. The high-quality firm realizes less competitive pressure on its brand price and is able to gain customers and profit if switching costs are high.

Our study provides novel insights into the effects of switching costs in competitive markets. We find that switching costs can have differential effects on firms' pricing strategies and profits. We also find that even low switching costs already can cause drastic price effects as firms try to avoid business stealing effects. It should be noted that the business steeling effect is stemming from the oligopolistic market assumption. What distinguishes oligopoly from monopoly is that price changes of oligopolistic firms have to be evaluated relative to the competitors' prices. Therefore, a price reduction by an oligopolist many not necessarily increase demand while in monopoly, a firm's price reduction usually increases demand.

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

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. 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)). 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 brand's temporary price reduction can steal customers that purchased other brands. Those newly attracted customers develop a loyalty to the new brand which adds an extra surplus to their utility. Once the price returns to its original level, the newly gained customers continue purchasing the same product due to the gained surplus caused by brand loyalty. Hence, price changes and consumers' alternated purchase decisions can identify brand loyalty and switching costs.

Theoretical studies show that consumer switching costs can increase prices and make markets less competitive (see, for example, von Weizsaecker (1984), Beggs and Klemperer (1992), Klemperer (1995), and Farrell and Klemperer (2007)). Studies also show that firms operating in oligopolistic markets with consumer switching costs experience large downward pressure on prices as firms attempt to steal loyal consumers from competing firms. Arie and Grieco (2014) and Doganoglu (2010) show that downward pressure on prices is dependent on switching costs.

Empirical studies estimate demand models while addressing state dependence and switching costs.[6] The studies provide evidence that switching costs imply state depen-

[6]Studies focus on different markets such as Huang, Perloff, and Villas-Boas (2006) on the orange juice market; Shum (2004) on the breakfast-cereals market; Stango (2002) and Barone, Felici, Pagnini (2011)

dence in demand where consumers' current product choices determine their future product choices. Studies emphasize that the ignorance of state dependency can drastically change demand estimation results and the evaluation of consumers' rational choices (see, for example, Miravete and Palacios-Huerta (2014)). Cosguner et al. (2018) concentrate on the effects of switching costs on pricing strategies adopted by manufacturers and retailers.

There are several empirical studies that focus on the estimation of switching costs in the beer market[7]

Studies that are possibly most closely related to ours include the following: Dubé et al. (2008) considers a monopoly that offers differentiated products on the market while accounting for consumer switching costs. Their study provides evidence for a dominating harvesting motive; that is, prices increase as switching costs increase. Note that their monopoly framework does not easily extend to oligopoly markets where firms strategically interact in prices and business-stealing effects become a relevant force as they compete for loyal customers.

Dubé et al. (2009) consider a multi-agent model with an infinite time horizon. They find that switching costs toughen price competition, where prices and profits decline as switching costs increase. 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.

Pavlidis and Ellickson (2017) address state dependence to parent brands and evaluate the effects on prices. Using numerical simulations, they show that loyalty (inertia) to the parent brand can decrease prices and reduce profits.

Richards and Rickard (2021) adopt the two-step estimation algorithm by Bajari et al. (2007) and estimate the demand for beer and evaluate the impact of beer firm buyout

on the credit market, Honka (2014) on the auto insurance market, Knittel (1997) for long-distance phone calls; Elzinga and Mills (2002) on the cigarette market; Borenstein (1991) and MacKay and Remer (2021) on the gasoline market; see also Shy (2002) for further information.

[7]Examples include Slade (1998 and 2004), Manuszak (2002), Pinkse and Slade (2004), Barnes et al. (2004), Calagione (2005), Rojas (2008), Rojas and Peterson (2008), Rossiter and Bellman (2012), Ashenfelter et al. (2015), Hamilton and Empen (2015), Miller and Weinberg (2017), Grieco et al. (2018), and Heimeshoff and Klein (2021).

transactions on retail beer prices and firm profitability. It should be noted that we are not able to adopt the two-stage estimation technique by Bajari et al. (2007) since we are interested in conducting counterfactuals that require us to vary the magnitudes of switching costs. Their estimator is not applicable here since switching cost is a structural parameter (or primitive) and changes in structural parameters would imply changes in agents behavior such that the first stage policy functions that had to be re-estimated, see Ryan (2012). However, changes in consumer behavior originate by changes in switching costs are unobserved in our context and we do not observe an external policy that would have an effect on switching costs. We therefore have to adopt a fully dynamic model To evaluate the effects of switching cost changes on prices, market shares, and profits. We solve for policy and value functions in Markov Perfect Equilibrium, which becomes computationally complex as will be detailed later.

3 The Market and the Data

Our study builds on a large data set on the beer market that was provided by AC Nielsen, among other sources that are introduced later. We combine the Nielsen retail scanner data with the household panel data. The household panel data were collected by tracking households' beer purchases at retail stores (including grocery and drug stores) in the United States. The database contains consumer-specific beer purchase information as well as consumer-specific demographic information including income, family size, number of children, etc. The retail scanner database consists of highly detailed Universal Product Code (UPC) scanner information at the store-level from 2016.[8] More than 35,000 retail stores belonging to 90+ chains are included in this database. The data cover more than half the total sales volume in the U.S.

We concentrate on beer purchases and are able to use information on the beer brands,

[8] We consider one year to increase the likelihood that we observe the same households in our panel, which is important for estimating switching costs in our demand model. Moreover, it enables us to limit computational complexities.

the dates of purchases, the volumes purchased, the prices, and further product-related store information (e.g., display promotions).

In addition to information available in Nielsen, we also added information on beer attributes at the brand level, including alcohol percentage, 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. Furthermore, we concentrate on one state to avoid confounded effects stemming from different regions. The computational complexity of our algorithm also requires us to impose this constraint. In comparing beer brand sales we can confirm that Illinois is representative of the entire United States. We define each county as a market and there are 34 markets in Illinois in total. This market definition is consistent with consumer beer purchase behavior considering average driving distance (around 4 miles) and providing opportunities for consumers to shop in different grocery stores (i.e., shop beer in different stores within a geographic region). 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 events and missing data problems. It also ensures a focus on consumers' repeat 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 outside goods.

Our study focuses on the top 20 beer brands (by sales volume) which account for 72 percent of total beer sales.[9] Table 1 lists the top beer brands in alphabetical order.

[9]Considering the dimensional issue in the choice model, we're not able to include all beer brands within the choice set of each individual.

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 cents per ounce, which vary from 4.7 to 12.3 cents per ounce. Column 4 represents market shares, varying from 0.2 to 10 percent. The remaining Columns 5-9 show further beer attributes; we observe 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 brands are Budweiser, Modelo, and Miller Lite. Other domestic beer brands, such as Busch 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 average prices in descending order (see Column 5). Stella Artois and Samuel Adams are among the more expensive and highest quality-rated brands (see Column 8).[10] Budweiser is in the intermediate price and quality range followed by Coors, Miller Lite, and Busch. Noteworthy, Samuel Adams is significantly more expensive (about 250 percent) than Miller Lite and Busch, and its quality rating is more than twice as high. Columns 6 and 7 show that there is large price variation in the dataset which helps identify brand loyalty and switching costs.

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.[11] Table 3 shows the prices and shares that brands hold in low-income and high-income segments. (Note that the reported low- and high-income shares relate to the division of customers of one brand

[10]The quality information is taken from ratebeer.com.
[11]We use the median income to separate low-income from high-income customers.

into low- and high-income segments. It does not refer to overall brand market shares in low- and high-income segments.) 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 market shares, income segments and beer brands. For example, Samuel Adams sells more beer to high-income customers than low-income customers. Budweiser, Miller Lite, 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. Lower- (higher-)quality 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 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 Lite, and Busch—all rank in the intermediate range. In general, inexpensive beer brands appear to benefit more from repeat beer purchases than more expensive beers. For example, Busch exhibits 51% of repeat customers while Samuel Adams has only 36%.

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. 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 after prices return to their original levels. This price variation and observed switching between brands will help 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. Several studies have shown that the use of consumer-level data can drastically improve demand estimates (see Petrin (2002), Gaynor and Vogt (2003), and Goolsbee and Petrin (2004)).

We use the random-coefficient logit model, more details are provided later.[12] This model allows for brand loyalty and unobserved heterogeneous preferences. The heterogeneous preferences are 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 a set of options $j \in \{1, ..., J\}$, or does not buy any beer brand and chooses the outside goods 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 $u_{ijt} > u_{ilt}, \forall l \neq j$.[13] Individual $i's$ indirect utility for brand j in period t is given by:

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

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.

[12] See also Berry (1994), Chintagunta et al. (2005), and Dunn (2012).

[13] For notational simplicity, we drop market subscripts.

(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. (2009), among others).[14] 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, 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 econometrician but observed by the consumers and firms. This term is supposed to capture brand-specific quality that is allowed to vary over time. The time-varying component is especially useful in our context since commercials and promotions can temporarily influence consumers' purchase decisions. Finally, ϵ_{ijt} is an idiosyncratic error term that follows a Type I extreme value distribution. The indirect (mean) utility of the outside goods 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

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

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 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.[15]

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.

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:

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

where $\kappa \in \{1, ..., J\}$ refers to the beer brands. After receiving consumers' choice probabilities, we turn to the derivation of market demand.

[15]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.

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 $\nu_{\kappa t}^n$ as the share of customers in segment n that is loyal to brand κ at time t (those consumers have chosen brand κ in their last purchase). We assume that each consumer within a segment is loyal to one product at a time such that $\sum_{\kappa=1}^{J} \nu_{\kappa t}^n = 1$. 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:

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

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

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

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

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

4.1.2 Evolution of the State

We describe the evolution of the state. Remember, if a customer is loyal to product κ, she will remain in state κ as long as she purchases the same product or the outside goods. Therefore, we must add the conditional probability of choosing the outside goods to the diagonal elements of a Markov transition matrix in a consumer segment n, denoted as $T^n_{j\kappa}$. More specifically,
if $j = \kappa$, then

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

where $Pr^n_{jt}(\kappa, p)$ [16] and $Pr^n_{0t}(\kappa, p)$ denote the probability that a customer in segment n purchases product j and the outside goods, respectively, given she is loyal to product $j = \kappa$ and prices are represented in p.

If $j \neq \kappa$, then

$$T^n_{j\kappa t} = Pr^n_{\kappa t}(\kappa, p). \tag{7}$$

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 $S^n_{t+1} = T^n_{j\kappa t} S^n_t$.

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. Note that we follow previous studies and assume that firms are forward-looking while consumers are not. This is an appropriate assumption in our

[16] $Pr^n_{jt}(\kappa, p) = \frac{exp(U^n_{jt}(\kappa,p)}{\sum_l^N exp(U^n_{lt}(\kappa,p))}$, which is in conditional logit form. The utility function is segment specific, depending on switching cost and price sensitivity of consumer from each segment.

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 consumers' bounded rationality to explain that consumers are not forward looking.

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:

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

where f denotes the transition function describing the evolution of states. 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 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. Next, we describe the estimation procedure.

5 The Estimation

We estimate the demand model, as introduced earlier, which returns estimates of price 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

We use individual consumer choice data to estimate an individual demand model while adopting a two-stage procedure.[17] In the first step, we estimate product-time fixed effects using simulated maximum likelihood. In the second step, we adopt an instrumental variable regression.

Using individual i's decision of purchasing product j, given $s_t = \kappa$ (purchased product κ 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 $U_{ijt} = \delta_{jt} + \phi_{ijt}$ is 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, which capture 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-specific, time-specific,

[17]See also Chintagunta, Dubé, and Goh (2005) and Dunn (2012).

and market-specific (m) attributes, ideally, we would like to use the Cartesian product of all these attributes to capture the variation of $\delta_{j(m)t}$. This procedure, however, can quickly involve computational complexities that are caused by the large state space. To circumvent this issue, we capture the brand, time, and market variation using $\delta^{'}_{j(m)t} = aB_jT_t + bM_m$, 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 indirect 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 and a mean 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 ($\theta_2 = [\alpha_h, \alpha_{H+1}, \widetilde{\lambda}, \lambda_h]$). (Note that the estimate of ω ($\widetilde{\alpha}$) is estimated in the second step.) We estimate parameters using simulated maximum likelihood. In doing so, we take R random draws from a normal distribution with mean zero.

For every draw r, we write for 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:

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

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., 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 $\widetilde{\alpha}$, we instrument for price. Valid instruments are variables that are highly correlated with 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 such as advertisement and promotion are determined at the local market level. This enables us to 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 and production costs such that no further complications would arise from the supply side. Moreover, the instrument captures price variations across time periods and beer brands. We also include time dummy variables for time-varying demand shocks and market dummy variables for unobserved market-level differences.

We estimate equation (16) 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.[18] 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 v^{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, $\sum_{j=1}^{J} v^{nj} = 1$. 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 $N*(J-1)$. At each point in the state space, we compute the optimal price policy and value function for each firm.

[18] See also Dubé et al. (2009).

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 introduce a dummy variable for income that takes a value of one if income income is lower than the median level (which lies between $69; 999 and 99; 999$ in Illinois). We also constrain our analysis to two representative beer brands that belong to the low- and high-market segments.[19]

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 within each segment and across brands equals 1 ($\sum_{j=1}^{J} v^{nj} = 1$), 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. Finally, we compute the value and policy function outside our grid space using polynomials based on interpolations.

In sum, we solve the dynamic game by adopting a two-stage approach that consists of value function and policy function iterations.It should be noted that the algorithm is still complex and the program runs for several days. After we obtained the steady states of prices, market shares, and value functions for each grid point in the state space, we simulate the counterfactuals that evaluate the differential effects of switching cost changes. A detailed description of the simulation algorithm can be found in Appendix A.

6 Results

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

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

6.1 Demand

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

Table 5, Column 1, shows the results for the first specification that concentrates on the estimation of 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 of brand loyalty and income shows that low-income consumers have higher brand loyalty and higher switching costs than high-income consumers. Remember that income is a dummy variable that takes a value of one if income is lower than the median level. The interaction effect of price with income shows that low-income consumers are more price sensitive than high-income consumers. The estimated individual-specific effect (ι) is also significantly positive, which provides evidence for individual-specific differences of price sensitivity. Given that we control for heterogeneous preferences (as reflected by the random coefficients α_i and γ_i), the results eliminate the concern that the estimated brand loyalty and switching cost effects are confounded by heterogeneous customer preferences. The average switching cost amounts to 20 percent of the product price.

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 price sensitive. It is noteworthy that brand loyalty are of the same signs and of similar magnitudes across both specifications.

Table 6 shows the estimation results of step two of the demand estimation procedure. We adopt a two stage least squares technique (2SLS) using instruments for price. The first stage of the 2SLS estimation procedure (Column 1) returns a significant coefficient estimate for price that takes on a value of 0.82, which eliminates the concern of using weak instruments. The second-stage estimation (Column 2) returns a negative and significant price coefficient. The coefficient estimates of the other product attributes are all positive and significant, except for carbohydrates, 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 low-(high-)quality beer brands hold larger shares of low- (high-)income customers, which implies a higher (lower) switching cost and a higher (lower) price sensitivity. The fact that the low-quality beer brand exhibits higher switching costs is also supported by Table 4, which shows that they benefit from higher repeat purchases.

6.2 Supply

We consider the dynamic game outlined above and use the computational algorithm to simulate steady state prices, market shares, and long-run profits for varying switching costs. (Note, for simplicity, (long-run) profits are used interchangeably for net present discounted values.) Due to the large state space and the computationally complex algorithm, we limit the number of beer brands to two (later, we conduct robustness checks that involve three brands). 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 income customer segments so we can provide insights into how pricing strategies vary across beer brands while accounting for different brand loyalty, switching costs, and price sensitivities. We categorize beer brands into low- and high-market segment brands (or low- and high-quality beer brands) depending on the market shares of customers they serve in the low- and high-income segments, their average price, and their 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 the highest quality-rated beer (see Table 2); (3) it is among beers with the highest average prices (see Table 2); (4) it holds a large market share of high-income consumers (66.4%, see Table 3); and (5) the demand estimates returned one of the highest mean utilities in the demand estimation (see Table 2).[20]

Busch is a popular domestic beer that is commonly associated with lower quality, as: (1) it received the second-lowest quality rating (see Table 2); (2) the average price is about the lowest (see Table 2); (3) the share of low-income customers (see Table 3) is among the highest; and (4) the estimated mean utility for consumers is among the lowest (see Table 2).

It should be noted that the repeat purchase ratios for Samuel Adams and Busch are relatively high, taking on values of 36% and 51%, respectively (see Table 4). Moreover, the estimated brand-specific fixed effects in the demand are above average, which further confirms that brand loyalty and switching costs are relevant attributes for these two chosen beer brands. In Table 4, we show the repeat purchase rate at the brand level and the interlink between repeat purchase and consumer income for beer brands with different quality.

Based on the computational algorithm, we calculate steady state prices, market shares, and profits at each grid point in the defined state spaces. We then simulate each firms' prices, market shares, and long-run profits for different switching costs. Since our demand estimations return 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

[20]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. Brands brewed according to the purity law are considered premium beers.

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 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 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-quality 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).[21]

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 lower-quality beer brand Busch. Moreover, the evolution of market shares along switching costs is different across both beer brands. The market shares in both Samuel Adams' customer segments follow concave shapes as switching costs increase, while they take on convex shapes for Busch. Moreover, throughout all switching cost levels, the premium (lower-quality) brand holds a higher (lower) market share in both segments.

Figure 3 demonstrates that firms' profits follow a U-shaped pattern as switching costs evolve. It should be noted that the firm with the premium beer earns higher profits

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

(relative to zero switching costs) if switching costs are large. In contrast, the firm with the low-quality beer brand earns lower profits if switching costs are present (compared to non-existent switching costs).

In the following, we discuss the results in further detail categorized by different levels of switching costs.

Low Switching Costs

Figure 1 shows that an increase in switching costs in the low area (from 0 to 0.5) causes beer prices for Samuel Adams and Busch to monotonically decline by 2 and 4.4 percent, respectively. Both firms adopt an investment strategy where price reductions follow the intention to keep loyal customers or even steal consumers from competitors. The impact of this investment strategy on market shares is illustrated in Figure 2. The figure shows that Samuel Adams' price reduction implies a market share increase of 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 shares across both customer segments (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. 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 engage in intense price competition and reduce prices, only the premium brand, Samuel Adams, is able to expand its customer base while stealing customers from Busch across both customer income segments (the business stealing is facilitated by the fact that overall switching costs are low). The finding that Busch is not able to attract more customers even though it reduced its price confirms the highly competitive environment when switching costs are low. Busch loses more customers from the high-income segment, as those customers have relatively lower switching costs (compared to customers in the low-income segment). It is noteworthy that customers rather switch from the low-quality firm's to the high-quality firm's product if switching costs are low. The asymmetry in consumer switching behavior puts high downward pressure on the low-quality firm's price, resulting in larger profit losses.

Figure 3 shows that both firms' 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 large loss of customers in conjunction with the higher downward pressure on price.

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 (while still remaining below the price without switching costs). Despite the price increase, Samuel Adams is able to attract more customers, especially from the high-income segment (see Figure 2). Similar to the earlier finding, customers (especially high-income consumers) more easily switch from the low-quality product to the high-quality product. This is explained by the fact that high-income customers have lower switching costs and lower price sensitivity.

Busch, in contrast, continues adopting an investment strategy and reduces its price by 4.3 percent with the intention of attenuating the loss of customers to Samuel Adams. As a result, the loss of high-segment customers diminished from what was 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 the loss is diminished from 5.1 percent (for low switching costs) to 0.6 percent. Busch's price reduction helps it better retain low-income customers, as those customers are more price sensitive; switching to Samuel Adams becomes a less attractive option.

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

Overall, if switching costs are in the intermediate area, firms adopt differential pricing strategies. While Samuel Adams switches to the harvesting strategy, Busch continues with an investment strategy. Busch's ongoing investment strategy serves to diminish further customer losses, especially of price-sensitive customers in the lower income segment. In the high-income segment, Busch still loses a larger share of customers since those customers are less price sensitive and less likely to switch from the high-quality to the low-quality product.

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 of 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 formerly chosen brands. It is noteworthy that Samuel Adams' price surpasses the price without switching costs while Busch's price remains below that price without switching costs. Hence, switching costs raise prices only for the high-quality 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 due to their lower price sensitivity. However, it provides incentives for the more price sensitive customers in the low-income segment to switch to Busch. Figure 3 shows that Samuel Adams' profits increase by 5.4 percent when switching costs increase from 1 to 1.5. Its profits eventually exceed profits that were earned in the absence of switching costs. Busch's profits increase by 10 percent but still remain below the profits when switching costs are non-existent.

We conducted 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-quality beer brand Busch with a different low-quality brand. We chose Miller Lite as it is characterized by a similar quality rating and average price per ounce as Busch, see the right panel of Table 2. Therefore, the use of Miller Lite serves as a robustness check whether our effects are representative to beer brands in the low-quality 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-quality, intermediate-quality, and high-quality segment, respectively. Details on the selection criteria, the setting, and the results are relegated to Appendix B; the results are also illustrated in Figures 7-9. The robustness checks show that 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-quality 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-quality beer brands have little incentives to invest in loyal customers. Instead, they adopt harvesting strategies and increase prices. In contrast, the firm with the intermediate-quality brand adopts an investment strategy to steal customers from its competitors, particularly from the low-quality brand.

In general, as switching costs increase, the profit of the high-quality (low-quality) firm increases (declines), while the profit of the firm with the intermediate-quality brand follows a U-shaped pattern. The competitive pressure imposed on the low-quality brand is immense and causes large losses for that firm. Overall, the results confirm close similarities to our results presented above.

7 Conclusion

The prevalence of switching cost can result in persistent consumer brand choices over time. This implies that firms adopt dynamic pricing strategies since current brand purchases increase the probability of repeat purchases. These dynamic pricing decisions can become computationally highly complex, especially when firms operate in competitive environments such as oligopolistic markets. Our study provides further insights into differential effects of switching costs on firms' pricing strategies, 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 individual beer purchase information. Summary statistics show that customers often repeatedly purchase the same brands. Our demand estimations show that low-income customers, and low-quality beer brands exhibit higher price sensitivities and higher switching costs than high-income consumers and high-quality beer brands.

On the supply side, we consider a dynamic oligopoly model and vary switching costs to simulate prices, market shares, and profits of firms offering beer brands that are differentiated in quality and so they target different customer segments. We show that the firm with the low-quality brand serves more price-elastic customers who more easily switch to competing brands compared with the high-quality brand firm that sells to less price-elastic consumers. The presence of customer segments with differential price elasticities implies asymmetric switching behavior of customers since more price-elastic customers purchasing the low-quality brand more easily switch away to purchasing the high-quality brand than vice versa. Therefore, the low-quality firm experiences a higher competitive pressure, especially when switching costs are relatively low. The high-quality firm is able to steal consumers from the low-quality firm, which requires only smaller price reductions and implies a relatively higher profit. Hence, switching costs have more adverse effects on the price and profit of the low-quality firm while the high-quality firm is better shielded against competitive effects originated by switching costs since it serves less price sensitive consumers. Overall, we find that switching costs have mostly adverse effects on prices and profits with the exception of the high-quality provider when switching costs are rather large.

Our study emphasizes that an oligopolistic market focus can reveal further insights into the effects of switching cost on firm and market performance. In this regard, we show that the business stealing effect and asymmetric switching of customers is a relevant driving force. As a result, our results show that the low-quality provider loses customers even after reducing price. This result is novel to the oligopolistic set up and explained by the fact the high-quality provider reduces price as well and more successfully attracts customers.

This study faces its computational limits. 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. We provide several robustness checks and also provide robust results when three brands are offered on the market. Further work, however, would be desired, which requires the adoption of a different dynamic methodology and we leave this topic for future research.

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Appendix A

Simulation Algorithm

We solve the dynamic game by adopting a two-stage approach that consists of value function and policy function iterations.It should be noted that the algorithm is still complex and the program runs for several days. The entire simulation process can be decomposed into inner loops and outer loops. The indexes for the rounds in the inner and outer loops 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 factor β is 0.98. We normalize the market size to 1,000 and, in following earlier studies, we set the brand-specific unit cost c_j at 60% of the lowest brand-specific retail price observed in the dataset see, for example, Linde, Norton, and Siebert (2021).[22]

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 the initial tolerance threshold for prediction at $\epsilon_1^0 = 0$, where the subscript 1 refers to the first stage and the superscript zero declares the starting round. 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 the state space.

1.2) If the difference between TV^l and V^{l-1} is larger than the tolerance level (i.e. $|TV^l - V^{l-1}| > \epsilon_1^0$), we assign $\epsilon_1 = |TV^l - V^{l-1}|$ and V^l is set to TV^l and we then 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 the initial tolerance thresholds for prediction to $\eta_2^0 = 0$ and $\epsilon_2^0 = 0$ (where the subscript 2 refers to the second stage).

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 $|V^{l-1} - TV^*| > \epsilon_2^0$, we set $\epsilon_2 = |V^{l-1} - TV^*|$ and compare the difference between p^* and p^{L-1}. If $|p^* - p^{L-1}| > \eta_2^0$, 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.

[22] Note that the choice of a different percentage term would rather reflect a monotonic shift in outcomes and leave the differential effects of switching costs largely unaffected.

Appendix B

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

B.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 Lite 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 brand with intermediate quality (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-quality brands adopt a harvesting strategy and increase prices, the firm with the intermediate-quality brand engages in an investment strategy and reduces price.

B.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-quality 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 Lite, which loses a drastic number of low-income customers.

Turning to Budweiser and Miller Lite (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 Lite both reduced prices, customers switched to the premium brand, whose price reduction became more attractive to customers. The fact that Budweiser and Miller Lite 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 Lite) continue losing high-income customers to the high-quality brand. In contrast, both firms gain low-income customers at the expense of the high-quality 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 Lite.

If switching costs are high, Miller Lite 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 Lite 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 Lite's harvesting strategy reduces its share of low-income customers. Miller Lite'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 high-quality firm 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-quality brand's price increase results in market share gains that are explained by low-income customers that were loyal to the low-quality brand and switch to the high-quality brand. The switching is explained by low-income consumers facing lower switching costs. The loss of the low-quality brand's consumers is further explained by the investment strategy of the intermediate-quality 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-quality brand.

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

B.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 increasing share 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 and less price sensitive customers.

The profits of Budweiser and Miller Lite (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 Lite'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 Lite's profits decline for large switching costs, as explained by the harvesting strategy and more price sensitive customers 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-quality beer brand Miller Lite with Coors. The main results continue to hold.

Table 1: Beer Prices, Market Shares, and Attributes

Brand Name (1)	Headquarter (2)	Avg. Price (cents/oz) (3)	Market Share (%) (4)	Alcohol (5)	IBU (6)	Carbohydrates (7)	Calories (8)	Sugar (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, Quality, and Mean Utility

Brand Name (1)	Market Share (%) (2)	Avg. Price (3)	Brand Name (4)	Avg. Price (5)	Min. Price (6)	Max. Price (7)	Quality (8)	MU (9)
Budweiser	9.9	6.9	Stella Artois	12.3	4.5	15.1	2.7	12.5
Modelo	7.4	10.2	Samuel Adams	11.6	9.1	14.9	3.3	12.1
Miller Lite	6.7	4.9	Negra Modelo	10.8	9.0	13.6	2.8	10.7
Corona	6.4	10.8	Corona	10.8	9.2	13.4	2.1	12.9
Miller G	6.0	6.2	Heineken	10.4	8.0	15.1	2.4	10.7
Heineken	4.9	10.4	Modelo	10.2	8.8	14.6	2.3	11.1
Pabst Blue R	4.0	5.1	Dos Equis	10.1	3.7	11.9	2.3	7.3
Icehouse	3.8	4.7	Steel Reserve	9.8	4.2	21.8	1.7	12.1
Busch	3.6	4.8	Beck's	8.2	7.9	13.6	2.4	10.5
Stella Artois	2.9	12.3	Budweiser	6.9	5.6	9.0	1.8	8.3
Samuel Adams	2.7	11.6	Coors	6.5	5.2	9.8	1.6	7.4
Tecate	2.7	6.2	Tecate	6.2	5.4	9.7	1.9	9.7
Coors	2.6	6.5	Miller G	6.2	5.6	10.1	1.8	7.0
Rolling Rock	2.3	4.9	Labatt Blue P	5.9	5.5	7.9	1.8	7.7
Dos Equis	1.6	10.1	Milwaukee's	5.1	3.5	9.7	1.2	7.3
Natural Ice	1.5	4.7	Pabst Blue R	5.1	3.9	8.6	2.1	8.1
Beck's	1.2	8.2	Rolling Rock	4.9	4.2	6.4	2.1	7.6
Labatt Blue P	1.0	5.9	Miller Lite	4.9	4.2	9.7	1.6	7.0
Negra Modelo	0.9	10.8	Busch	4.8	4.1	7.9	1.4	7.8
Milwaukee's	0.8	5.1	Icehouse	4.7	4.0	7.4	1.6	7.8
Steel Reserve	0.2	9.8	Natural Ice	4.7	3.5	10.4	1.3	7.4

This table shows market shares and prices in descending order. Prices are measured in cents/oz. MU indicates the mean utility retrieved from the demand estimation. Sources: AC Nielsen Data, Ratebeer.com.

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	53.8
Miller Lite	4.9	6.7	51.8	48.2
Heineken	10.4	4.9	55.7	44.3
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	2.3
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	Repeat Purchases (%)	Share of Trips	Price (cents/oz)	Market Share (%)	Low-income (%)	High-income (%)
(1)	(2)	(3)	(4)	(5)	(6)	(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: Step One Estimation Result (θ_2 parameters)

	(1)	(2)
BL ($\widetilde{\lambda}$)	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 (α_{H+1})	9.92***	9.73***
	(3.73)	(3.43)
BL x Brand Dummies	Y***	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: Step Two Estimation Result (θ_1 parameters)

	First Stage Results	Second Stage Results
	(1)	(2)
Price (Instrument)	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. Price (Instrument) refers to the price instrument, that is, the average price of the beer brand in adjacent markets. Note, prices are measured in \$/oz. Standard errors are shown in parentheses; *** indicates a significance level of 1%.

Figure 1: Equilibrium Price (cents/oz)

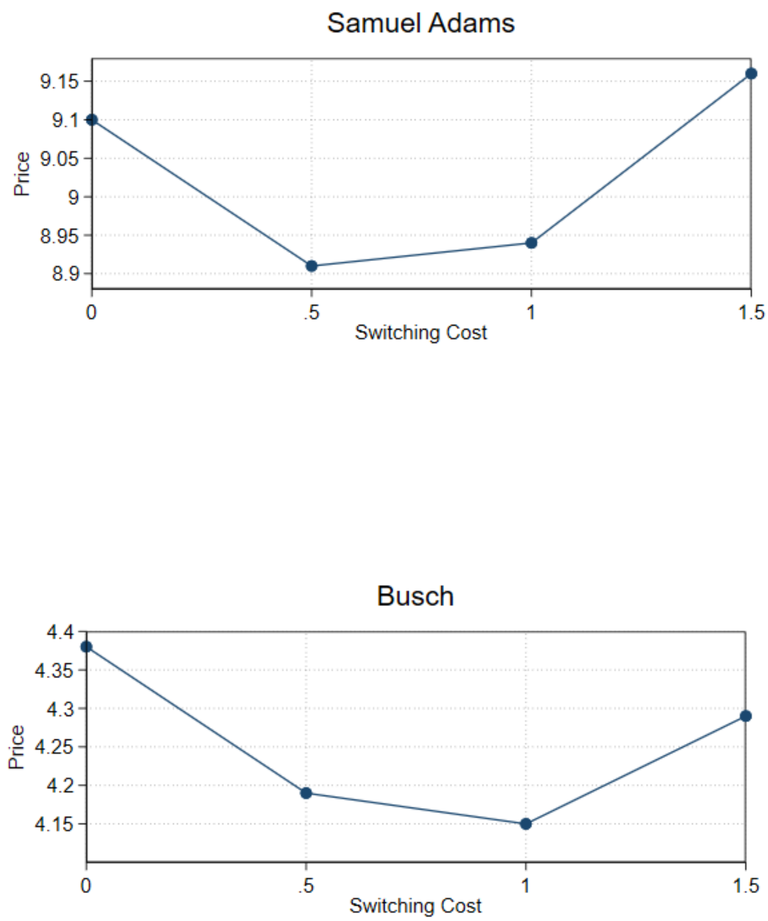


Figure 2: Market Share (%)

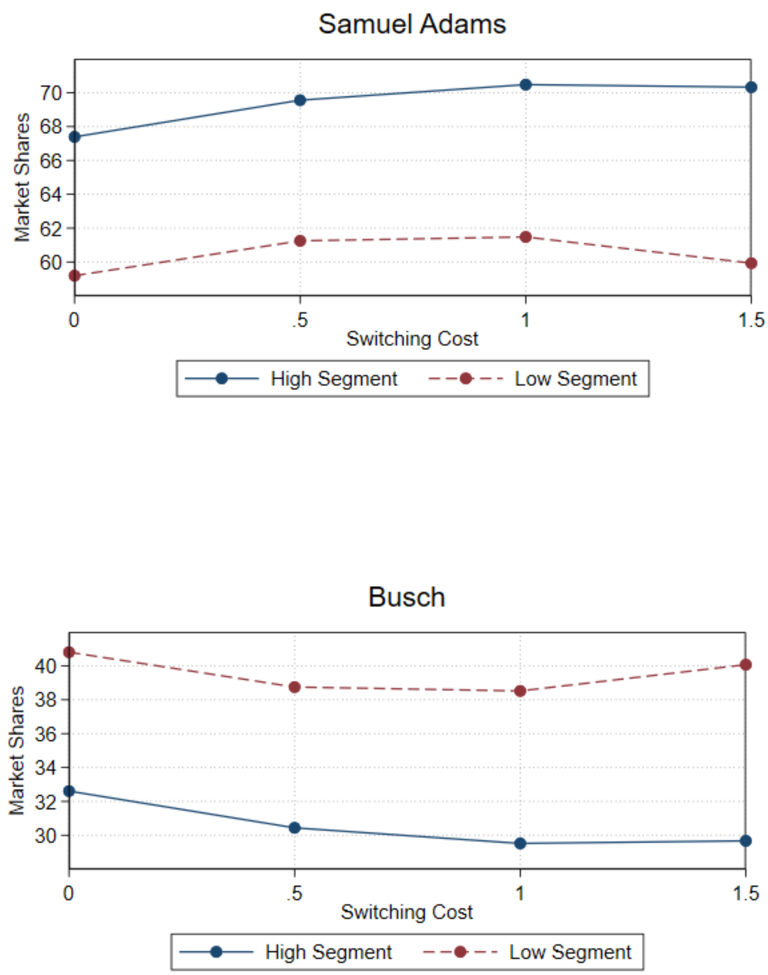


Figure 3: Value Function

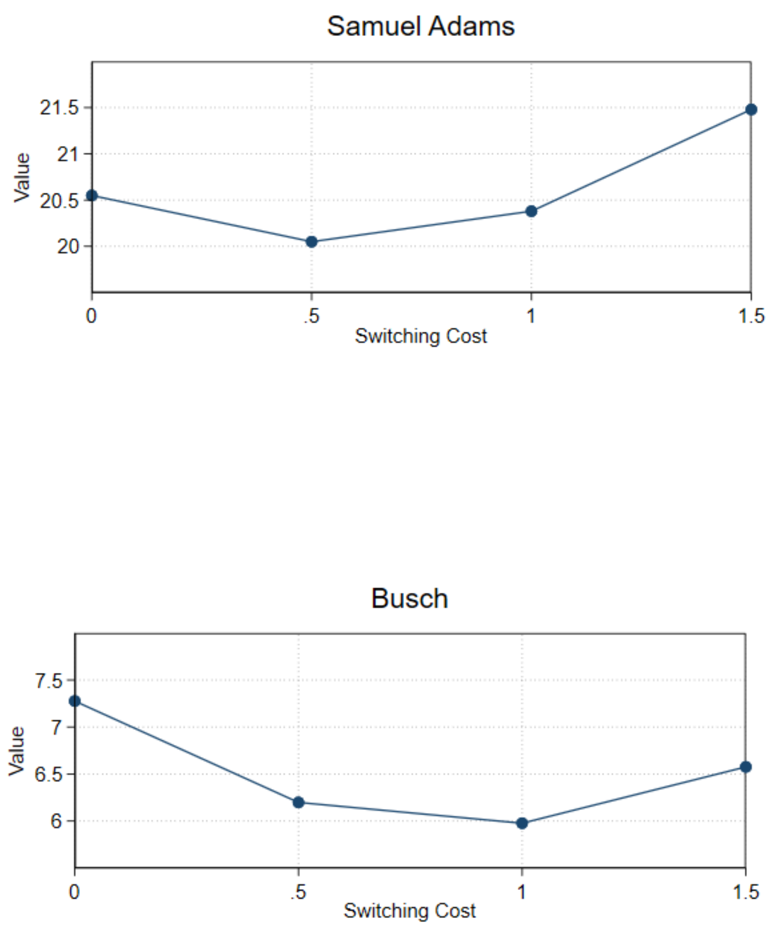
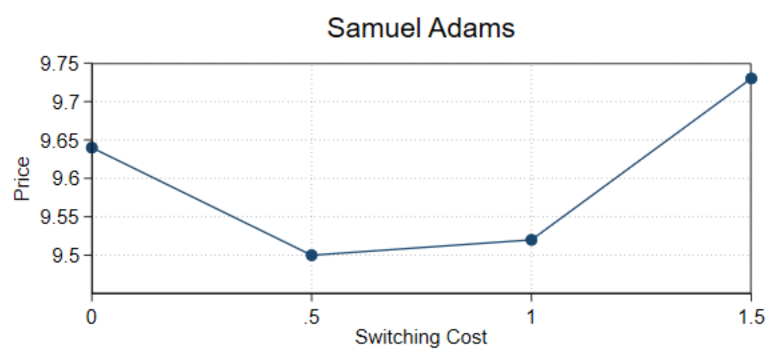


Figure 4: Equilibrium Price (cents/oz)



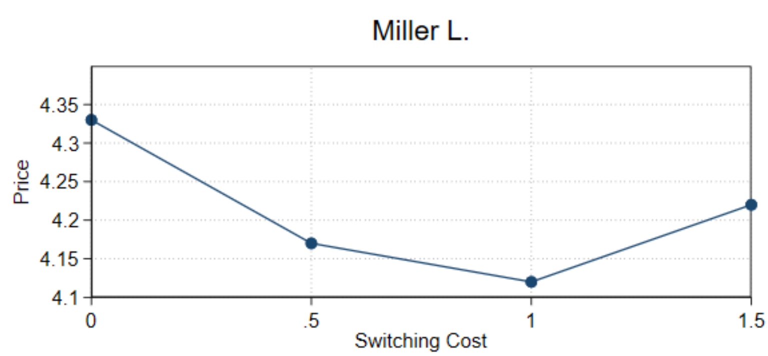


Figure 5: Market Share (%)

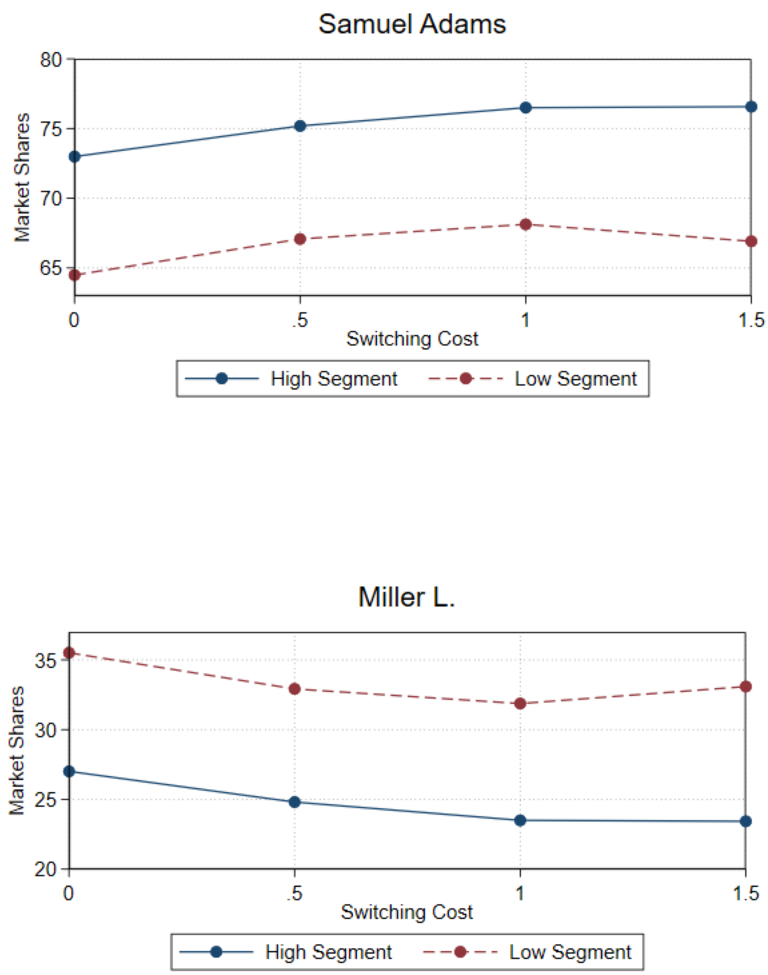


Figure 6: Value Function

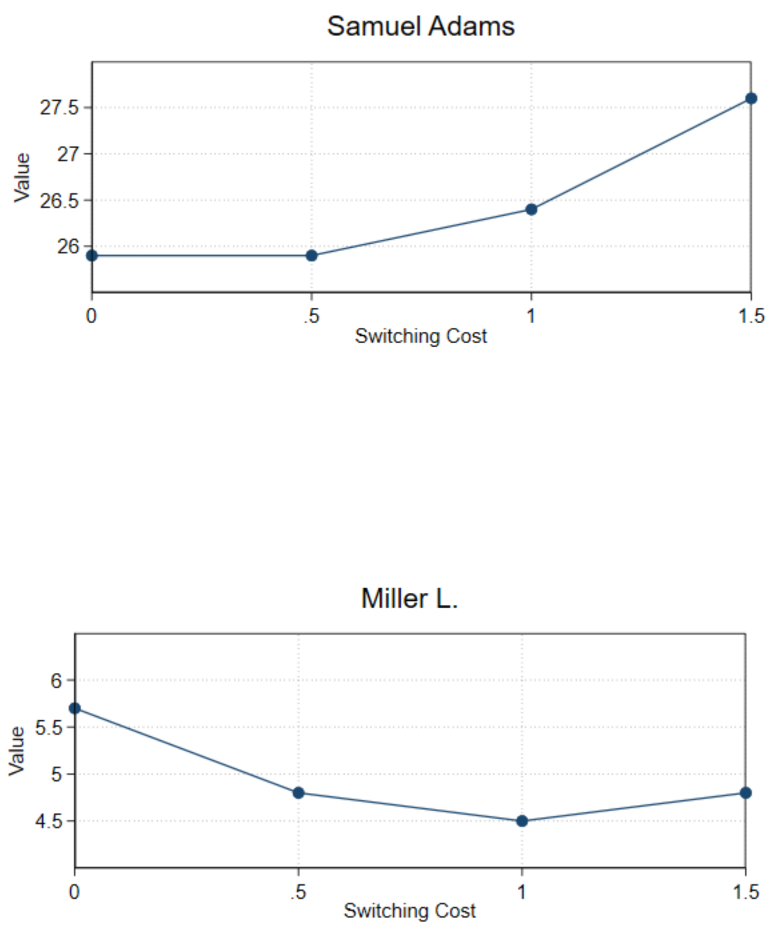


Figure 7: Equilibrium Price (cents/oz)

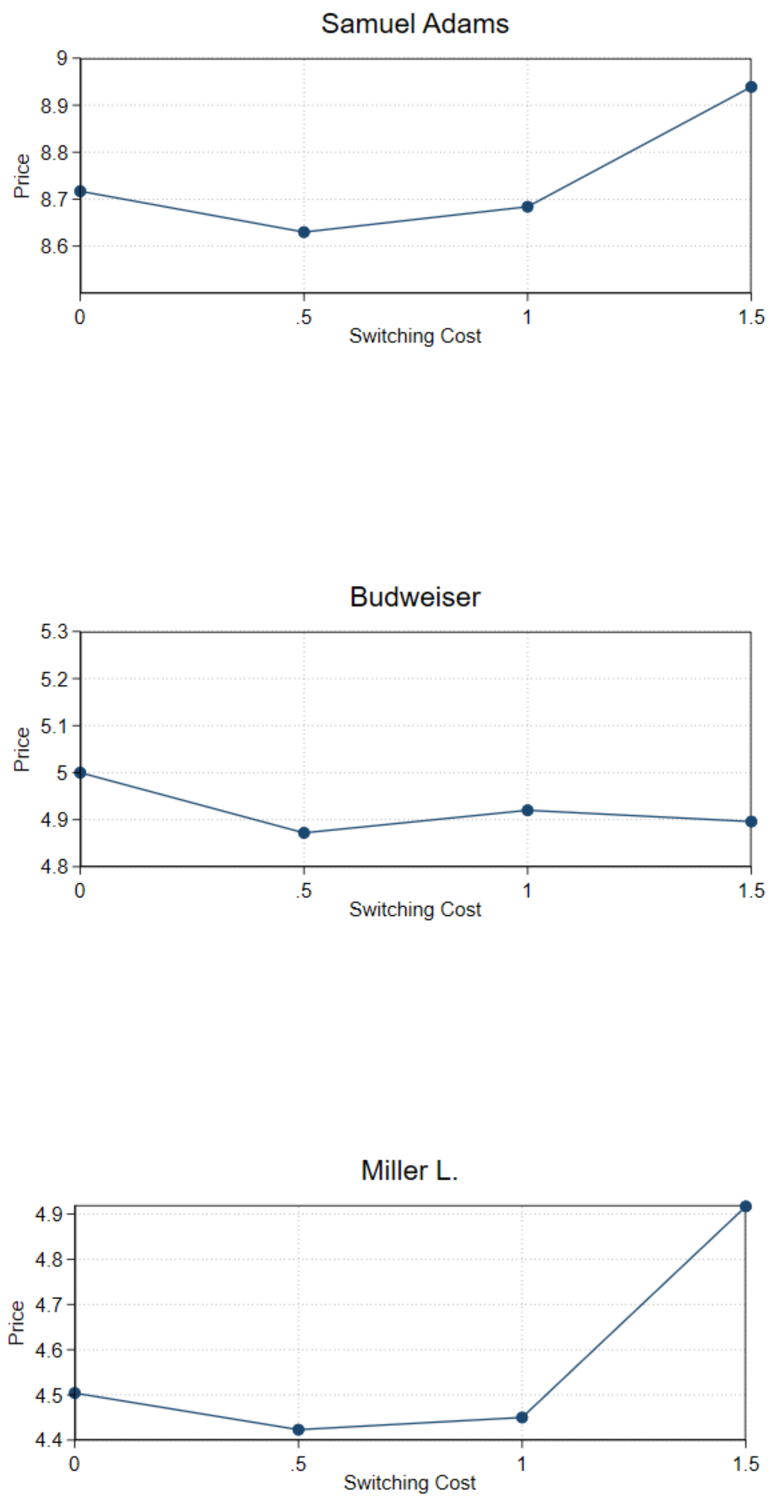


Figure 8: Market Share

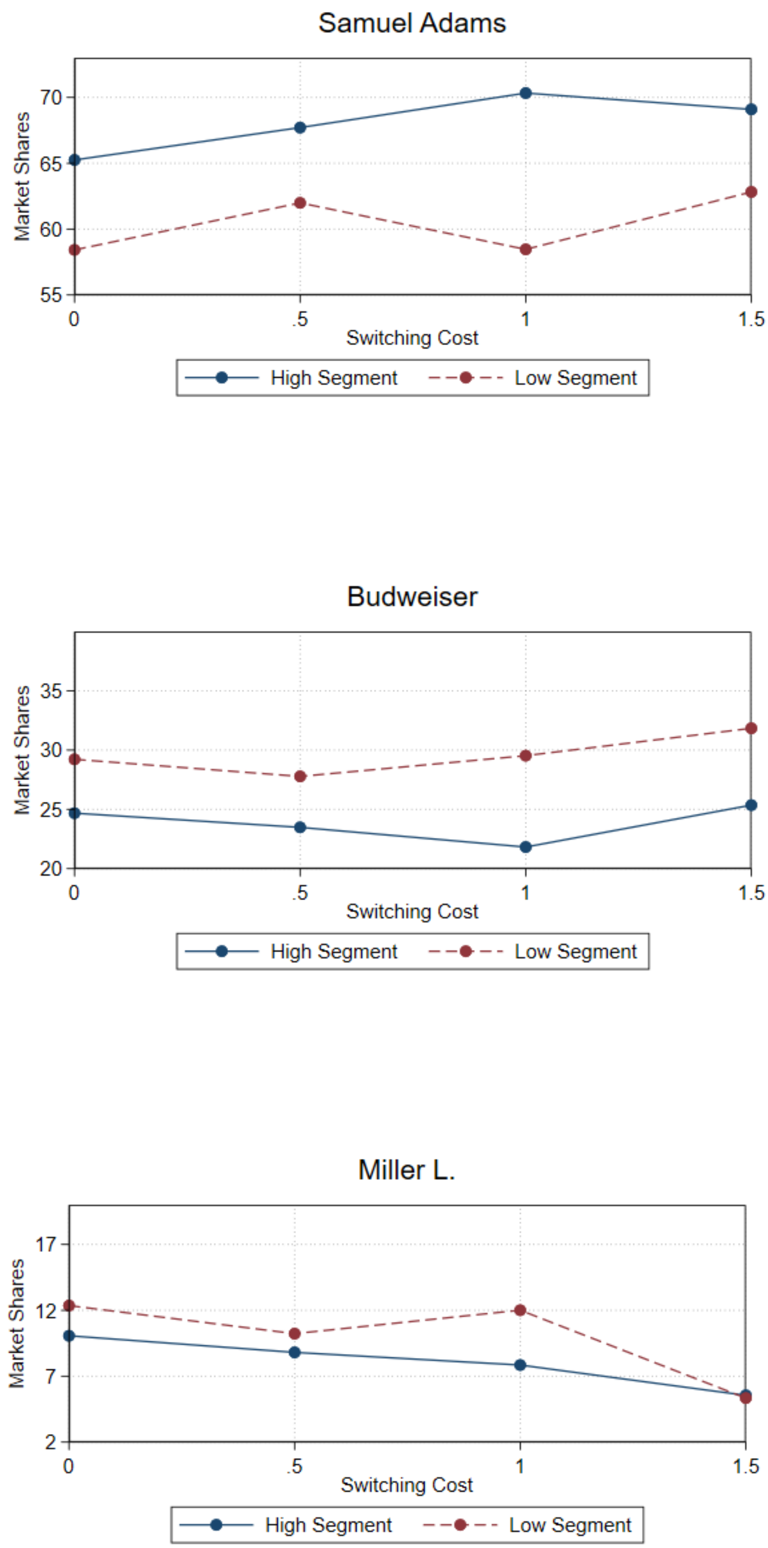


Figure 9: Value Function