Dynamic Model of Beer Pricing and Buyouts

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Abstract

The beer industry in the US is in a period of dramatic transformation. Mergers among mass-production breweries, rapid growth of the craft-brewing sector, and acquisitions of some of the larger craft breweries by major producers means that the industry is at once becoming more consolidated, and more fragmented at the same time. Common to both types of breweries is the observation that the demand for beer is inherently dynamic as beer drinkers exhibit both variety-seeking and habitual behaviors. In this paper, we study the impact of craft-brewer buyout transactions on retail beer prices, and firm profitability in a dynamic, Markov-perfect equilibrium pricing framework. We find that the estimated impact of mergers, or buyouts, is critically dependent upon estimates of the extent of state-dependence in demand and is, in fact, negatively correlated with the initial shock to demand. That is, if the demand shock is positive, the effect of a buyout will be under-estimated by not accounting for state-dependence in demand, while it is over-estimated if the demand shock is negative. This finding is intuitive as the static model will not properly account for the long-term positive effects of a demand shock that is initially positive, or the long-term negative effects that are initially negative.

keywords: craft beer, differentiation, Markov-perfect equilibria, mergers, retail pricing, state dependence, strategic behavior.

JEL Codes: D43, L13, M31

1 Introduction

The emergence of the craft brewing industry is one of the most significant developments in the beverage industry in the past 20 years. In a five-year span, the value of craft beer as a share of the overall US beer market rose from 7.8% in 2013, to 12.7% in 2017 (Brewers Association). Unwilling to yield market share to smaller craft breweries, and unsuccessful in creating their own craft brands due to the "stigma effect" (Barlow, Verhaal, and Hoskins 2018), the mass-production breweries have been acquiring some of the more successful craft breweries in order to gain market share. While these add-on acquisitions are each too small to represent a substantial increase in market share, alleviating the usual monopolization-based concerns with mergers common in the literature (Ashenfelter, Hosken, and Weinberg 2015), they nonetheless represent fundamental changes to what had been an emerging, bifurcated industry structure. While mergers typically involve a trade-off between scale-based efficiencies and concentration-based pricing power, craft beer acquisitions represent neither. Therefore, the ultimate effect of craft-brewery buyouts is an empirical question that may hold more general implications for such portfolio acquisitions in other industries.

We address this question using a dynamic structural model of beer demand, and pricing. Accounting for the dynamic nature of beer demand is important, because there are two, conflicting schools of thought as to the nature of beer-drinking preferences. First, there is evidence that beer demand is state dependent, with beer drinkers loyal to at least a particular style of beer, if not a brand or a small set of brands within that style (Barnes, Gartland, and Stack 2004; Calagione 2005; Rossiter and Bellman 2012).[1] On the other hand, others argue that the rise of the craft beer sector is primarily due to a demand for variety (Clemons, Gao, and Hitt 2006; Garavaglia and Swinnen 2017). Either way, whether consumers seek out the same type or brand of beer from one shopping trip to the next, or something completely opposite, beer demand is fundamentally state dependent. If beer demand is state dependent,

[1]Barnes, Gartland, and Stack (2004) argue that "American beer consumers have become habituated to a particular style of beer, and the lock-in of a broad cultural preference for this style has led to an institutional inertia..." (p. 376).

then pricing decisions by the firms in the industry must reflect their expectations of how pricing affects dynamic consumer behavior, market share, and responses by rivals.[2]

How firms respond to changes in demand is likely to determine the success, or failure, of buyouts such as those witnessed in the craft-beer industry. Indeed, commentators in the popular press advance many explanations for the flurry of craft-beer buyouts by large, national breweries in 2015 and 2016. Predominant among these explanations is the "if you can't beat, them, join them" rationale that assumes beer drinkers are sufficiently well-informed to see through the attempts by AB InBev and MillerCoors to develop craft-beer brands organically (Shock Top and Blue Moon, respectively). If craft-beer drinkers do not view these organic brand-development efforts by the major brewers as viable craft-beer substitutes, then the only plausible alternative for the larger breweries to capitalize on the movement to craft beer is to buy into it. Despite assurances from both sides of each transaction that the acquired brewer would remain independent and pursue the owners' carefully-formed craft-beer mission, the geographic dispersion of purchases, expansion of distribution, assured-access to scarce inputs, and aggressive advertising all suggest that rapid growth of the target firms was always the intent (Figure 1). If this is indeed the case, then the question becomes one of how firms with increasing market power can be expected to compete in markets with state dependent demand?

Our expectations are mixed, and depend empirically on the outcome of a complex harvest-invest dynamic among competing brewers. That is, if brewers believe that their customers are forward-looking, and face substantial costs of switching from one brand or style to another, then they face a "harvest or invest" pricing decision – harvest rents from loyal customers in the short run through higher prices, or invest in building the cohort of loyal customers in the long run by reducing prices. If most buyers are loyal, then the harvest effect dominates and

[2]Others study the price-effect of mergers among firms of approximately equal size (Rojas 2008; Ashenfelter, Hosken, and Weinberg 2015) using static modeling approaches. However, if the underlying demand for beer is dynamic, then the conclusions derived from a static model may be wrong, and wrong in dramatic fashion. Moreover, despite the continued dominance of the large, national breweries as measured by sales volume, the fundamental structural changes in the US beer industry are in the craft sector, and its interactions with the macro, or national brands.

prices rise with the perceived difficulty in switching among products. However, if switching costs are relatively low, and consumers instead demand a variety of brands, brewers have an incentive to price discriminate, charging lower prices to switching customers, and higher prices to those shown to be more loyal (Viard 2007; Cabral 2009; Pearcy 2016).

Even absent the ability to price-discriminate, brewers may still have an incentive to invest in building market size, rather than harvesting locked-in customers (Rhodes 2014). In fact, in a more general model that does not assume producers are even forward-looking at all, Arie and Grieco (2014) show that sellers have an incentive to compensate customers willing to switch by offering lower prices. They show that this compensation effect dominates the harvest effect in the short run, and the invest-effect in the long run when sellers are allowed to be forward looking. Although there are a number of potential mechanisms, the conclusion from the recent theoretical literature is the same – that switching costs need not be anti-competitive, and can drive lower equilibrium prices. With our pricing model, we determine whether equilibrium prices are higher, or lower, depending on the nature and extent of state dependence with respect to a particular brand of beer.

We account for market dynamics in two ways. First, we test for state dependence in demand, whether through habituation, loyalty, or a demand for variety, using the dynamic approximation approach of Roy, Chintagunta, and Haldar (1996) and Seetharaman (2004). With this approach, we are able to test whether the demand for beer at the brand level is state dependent at all and, if it is, whether brand preference exhibits inertia (positive state dependence), or a demand for variety (negative state dependence). With this approach, we parameterize the importance of state dependence on consumer choice, and hence market shares for each brand, and beer style.

We then use the estimates from our demand model to parameterize a dynamic model of firm buyouts and pricing. In our pricing model, we assume oligopolistic retailers are forward-looking and play Markov-perfect pricing strategies (Bajari, Benkard, and Levin 2007; Ryan 2012; Pavlidis and Ellickson 2017), where the state of competition evolves according to the share of each brand of craft beer in the market. Optimal price-responses are consistent with a Markov-switching process, conditioned by the degree of inertia expressed by consumers. By conducting counterfactual simulations of brewers' equilibrium pricing decisions, we examine whether acquisitions in the craft-beer industry appear to be pro-competitive, or anti-competitive, and examine the extent and direction of mis-estimation from using a static modeling approach.

Regardless of the more subtle, strategic effects of buyouts on equilibrium pricing, the direct effects are also of empirical interest. While craft-beer drinkers tend to prefer local brands, and therefore reject products associated with national breweries (Hart 2018), the beer-distribution system favors beers owned by national breweries in fundamental ways. That is, most of the large distributors are associated with either of the two major brewers, so tend to face incentives to sell labels under their primary brand-umbrellas. Further, ownership by large breweries confers advantages in terms of brewery-scale and geographic distribution, advertising, input-access, and expertise in other managerial dimensions that most craft breweries do not enjoy. Therefore, whether demand rises or falls after a buyout remains an empirical question.

Our focus on the craft beer sector reflects the behavior of US beer drinkers. Although the 2015 buyout wave arguably reflected an attempt by the national breweries to buy market share in a growing market segment, the continued dominance of the macro beer market means that the aggregate price effects on national-brand prices of these buyouts is likely small, if it exists at all. Moreover, the beer market is segmented by drinkers' preferences. Summary analysis of Nielsen Homescan data shows that the mean macro-share of craft-beer drinkers is only 8.8%, and the mode is 0.0%. On the other hand, the mean craft share of macro drinkers is less than 6.0%, with a mode of 0.0%. There is very little switching between beer categories. Therefore, it is reasonable to assume that beer drinkers are either macro-drinkers (76%), craft drinkers (16%), or import drinkers (8%) for competitive purposes.[3]

[3]These calculations are based on a sample ($N = 3{,}000$) of US beer drinkers drawn from the Kilts-Nielsen Homescan panel between 2014 - 16.

Our empirical analysis focuses on two buyouts that occurred in 2015. Using these buyouts as case-studies, we find that the impact of buyouts on equilibrium pricing, and margins, in the craft beer industry are significantly misestimated if state dependence is not properly taken into account. Specifically, we find the direction of mis-estimation with respect to equilibrium margins is negative correlated with the initial shock to demand. That is, if the net effect of a buyout is to reduce demand for the brand in question, then pricing models conditioned on static demand assumptions will over-estimate the impact on equilibrium margins, while if the initial demand shock is positive, the effect will be under-estimated. In terms of the harvest-invest mechanism described above, we find that firms that experience a positive shock to demand tend to exploit state dependence by raising margins, while a negative shock to demand leads to pro-competitive pricing. In this sense, our empirical findings are consistent with the theoretical literature that emphasizes the "knife's edge" nature of state dependence and equilibrium pricing: Whether loyalty is pro- or anti-competitive depends critically on the economic environment, including the relative size of firms, or the length of time over which price-response is measured (Rhodes 2014; Arie and Grieco 2014; Pearcy 2016).

We contribute to the substantive literature on pricing behavior in the US beer industry, and to the empirical literature on the dynamic effects of buyouts more generally. While Rojas (2008) and Ashenfelter, Hosken, and Weinberg (2015) consider the effect of mergers in the beer industry in a static context, our dynamic, craft-oriented setting more accurately reflects the way pricing decisions are made in the industry, as all players may condition their decisions on the realization that beer demand is dynamic. Empirical models of MPE are by now well-understood, but there are no applications in an acquisition-context similar to the US craft beer industry. If the demand for beer is state dependent, then the competitive effects of craft-brewery buyouts on the craft sector must reflect the underlying harvest-invest dynamic faced by managers of both the firms that were bought, and their competitors.

The rest of the paper is organized as follows. In the next section, we provide a brief discussion of the nature of the craft beer industry, and state dependent demand in order to make the case more carefully as to why habits and loyalty need to be taken into account in any empirical analysis of beer demand. We then describe our panel-scanner data set, and provide some model-free evidence as to the importance of state dependence, and the effect of the 2015 buyouts on pricing and market share. In the fourth section we provide more detail on the structural econometric model that we use to estimate the dynamic effect of buyouts on equilibrium pricing, both on the demand- and pricing-side of the market. We explain our findings in the fifth section, and draw some more general conclusions and implications in the final, concluding section.

2 The Beer Industry and State Dependent Demand

Craft brewing is one of the most dynamic industries in the US. While beer sales declined by 0.8% in 2018, the craft-beer segment continued to grow at a 3.9% rate (Brewers' Association 2019). Nearly 1 out of every 8 barrels of beer sold in 2018 was produced by a craft brewery.[4] Growth, however, does not necessarily imply consistent profitability for all firms as smaller breweries continue to come, and go.

Unlike earlier, and weaker, periods of growth in the craft-beer industry (Hindy 2014), growth in the late 2010s lead to a wave of mergers, or buyouts, between craft breweries and their newly-threatened national-brand competitors. Why? There are several reasons, but they all come down to maintaining brand equity (Herron 2017). As the national breweries watch the erosion of their brand equity caused by the growth of craft breweries, and craft beer in general, adding high-margin, under-capitalized brands that are popular with loyal consumers seems a clear solution. One of the reasons why craft breweries tend to be attractive buyout targets is that intensive beer drinkers tend to be highly engaged, or involved in the purchase decision, which is very much different from consumers in other packaged-goods markets. How this level of engagement affects patterns of demand and repeat-purchase, however, is a subject for the empirical research considered here.

[4]A craft brewery produces less than 6.0 million barrels of beer per year, and is at most 25% owned or controlled by an entity that is not itself a craft brewery (Brewers' Association).

More importantly for the structure of the US beer industry, the 2014 - 2016 time period saw a turning point in which the major brewers recognized the importance of the craft beer movement, and their inability to develop craft brands organically. AB-InBev and, to a lesser extent, Miller-Coors, Heineken, Constellation Brands, and others, initiated a buyout spree that saw over a dozen of the most successful craft breweries, geographically disparate, become part of their one-time rivals. From the buyers' perspective, purchasing craft breweries represented an attempt to buy into a rapidly-growing market segment that was taking market share (Solomon 2015). From the sellers' perspective, becoming part of a major brewery helps alleviate constraints associated with capital, access to key inputs, marketing expertise, and growth potential. Moreover, selling to a major brewer provided many of the craft-brewery founders an opportunity to cash-out, and monetize some of the wealth they had invested in the business for, in most cases, many years.

Whether these acquisitions prove to be profitable in the long run depends on their impact on demand, and how they are perceived in the market. In our model, we carefully differentiate between different sources of state dependence in demand while estimating the marginal impact of the buyout event. In the early literature on testing for dynamics in demand, Heckman (1981) argued for the importance of controlling for multiple potential sources of state dependence, but the distinction is perhaps more clear in marketing. For example, Liu-Thompkins and Tam (2013) draw a sharp distinction between "attitudinal loyalty" and habitual purchase. While both can generate observed repeat-purchase behavior, they derive from fundamentally different behavioral sources as attitudinal loyalty reflects a much deeper commitment to a brand or firm, and is often borne of careful reconsideration on each purchase occasion, while habit is more to derive from a desire to maximize convenience and minimize transactions cost. Because these behaviors differ in the level of consideration that underlies each purchase, they have dramatically different implications for cross-selling. While attitudinal loyalty is likely to generate many opportunities for cross-selling, habit is exactly the opposite as the buyer is not likely to consider the salience of attributes of the purchased product for other, related purchases.

Based on previous research on dynamic demand, and equilibrium pricing, we argue that previous analyses of merger activity in the beer industry may be missing the fundamental characteristic of the beer market that distinguishes it from other CPG markets: State dependence in demand. For the reasons cited above, mergers, or buyouts in this case, may lead to either higher or lower equilibrium prices in the industry, depending on whether the merged entities intend to harvest loyal consumers, and exploit their enhanced market position, or compete more aggressively for the pool of loyal consumers by reducing prices. We analyze this problem using the data described next.

3 Data and Identification

3.1 Data

Our primary data source for our analysis is a consumer-panel data set from Nielsen, Inc., which describes all retail beer purchases from some 50,000 households annually over the 2014 - 2016 time period in the full, national sample. We supplement this consumer panel data set with store-level Nielsen Scantrak data in order to impute prices and promotional activity for brands that were available to each household on each purchase occasion, but were not purchased.

Importantly, however, the demand for craft beer is largely a hyper-local phenomenon (Hart 2018). That is, craft drinkers prefer to drink beer that they identify as clearly local. This assumption is supported by survey evidence (Brewers Association 2018), and has possibly dramatic implications for the effect of the buyouts of 2015 - 16. If the breweries that were bought out are no longer perceived as local, then the demand for their beer is likely to fall in the region in which they were originally brewed. Craft-beer purists, or those who follow the Brewers Association definition of craft beer as "independently brewed," may also reduce their demand for the beer from buyout targets, and shift to craft beers from truly independent brewers. On the other hand, one of the benefits of being acquired meant access to a larger distribution system, and even brewing operations far from the original market. For purposes of our analysis, we focus on pricing and competition for craft beer market-share on a regional level. Therefore, we use a subset of the 50,000 Nielsen households who reside in a single state, and focus our attention on the buyouts of two breweries from that state: Brewery A and Brewery B.[5]

Our sample consists of households in a single state that make at least 50 purchases over the three-year period, specifically within the beer category. Our data represent purchases made from all channels through which consumers purchase retail beer (grocery, liquor, mass merchandisers, club stores, convenience, and drug stores), including items from the major breweries (non-craft, or macro-beers such as Budweiser and Coors), import, and craft beers. Our sample consists of some $45,470$ beer purchases from 176 households over the three-year period, $7,000$ of which are from the craft-beer category, and the remainder from the "outside option," or beers other than craft. Table 1 summarizes the purchase habits of our sample households, their demographic attributes, and other variables used in the demand model. Relative to the population of the state as a whole, the households in our sample are relatively high income (mean = $\$87,600$ versus $\$67,400$), considerably older (mean = 58.9 years versus 36.2 years), live in slightly smaller households (mean = 2.7 persons versus 3.0 persons), but are equally well-educated (mean = 13.7 years versus 13.8 years). Consequently, all of our estimates are to be interpreted conditional on the fact that we describe the state's craft-beer market, and not the general population of the state.

[Table 1 in here]

As a category, craft beer is highly differentiated. Each brewery offers many stock-keeping units (SKUs), and continually experiments with new tastes, and hop-malt combinations. Consequently, the category is highly fragmented, with only a handful of SKUs garnering national recognition. In our data, for example, there were some $2,400$ labels in 2016, and the top two brands earn craft-market shares of only 13.4% and 5.7%, respectively. Estimating

[5] The identities of the two breweries, and the state, are masked as required by our data agreement with Nielsen, Inc.

a structural model of demand and pricing at the individual SKU (or UPC) level is not only impractical, but undesirable as breweries do not price by the label, and tend to use product-line pricing. Moreover, our objective is to study the impact of loyalty on demand and pricing, and beer drinkers tend to be loyal to a brand and not to a specific label within that brand (Barnes, Gartland, and Stack 2004). Therefore, we focus our model at the brand level, and aggregate the panel data up to describe prices and market shares for each of the 14 largest craft beer brands sold in retail stores, aggregate all other craft brands into an "all-other brand" designation, and consider all other beer-purchase occasions as the outside option.

Separating craft beer from brands sold by national (macro) breweries, and import beers, allows us to focus on craft-brands specifically, and allows for expansion of the craft category as it takes share away from the outside-option brands (Toro-González, McCluskey, and Mittelhammer 2014). Table 2 provides more detailed information on the structure of prices, and market shares, among the craft brands in our sample. Clearly, there is considerable variation in pricing and market share, both among brands, within each brand over time, and across retailers.

[Table 2 in here]

We chose the 2014 - 16 time period in order to bracket the buyout wave that took place between late 2014 and late 2015. Within a 12-month period, there were at least 6 major buyouts that likely impacted regional craft-beer markets (Table 3). For purposes of this study, the buyouts of Brewery A by Parent A and of Brewery B by Parent B in 2015 were likely to be of some consequence to many of the state's craft beer drinkers. Not only were these two brands significant in craft-market share, but they were also fast-growing, and each had several highly-rated craft beers. Importantly, the management of each brewery were amenable to the vision that their acquirors had for them: Continue their fast-growth strategies in order to provide the parent company with a toe-hold in the craft beer market, without constraining operations (Solomon 2015).

[Table 3 in here]

3.2 Identification

Whether buyouts have an impact on pricing, and market share, in this setting remains an empirical question. Testing this hypothesis formally requires a complete econometric model of demand (described in the next section), but we first examine the summary data for any model-free evidence that the structure of the state craft beer market changed as a result of the buyouts in 2015, or at least the two captured here. In Table 4, we show simple summary statistics of the average prices and market shares for our two focal brands, before and after their respective buyouts by macro breweries. For this purpose, we use the Kilts-Nielsen Retail Scanner data, as opposed to the panel data used in the estimation stage. In the upper panel of Table 4, we show that the average price for Brewery A-brand beers did not change pre- and post-buyout, but the price of Brewery B beers increased significantly. In the lower panel, the retail scanner data shows that both brands increased their share of the state craft beer market significantly, whether due to increased distribution, advertising, or simply the buzz surrounding the buyouts. Again, however, it may be the case that, despite the gains in market share, the segment of the craft-beer market that regards itself as particularly engaged may still harbor a negative sentiment toward those breweries that "sold out" to the larger breweries.

[Table 4 in here]

Our primary assumption in modeling the demand for craft beer is that beer drinkers, particularly craft-beer drinkers, tend to be state dependent, or their choice depends on the previous choice. If this is the case, then any demand model brought to the panel data has to explicitly account for the state dependence of demand. Again using simple summary statistics, Table 5 examines the extent of loyalty among our included brands in a model-free way. Defining loyalty simply as the number of repeat-purchases from the same brand, we find that four brands have loyalty metrics above 0.5, meaning that there is more than a 50% probability that the household will buy the same brand on successive visits to the store (Keane 1997; Seetharaman 2004). Moreover, the average re-purchase probability, which we interpret as a measure of loyalty, is over 34%. While summary statistics cannot disentangle the motives for purchasing the same brand each time a consumer visits the store, we interpret these statistics as powerful evidence in favor of state dependent demand for craft beer. In the next section, we develop a model in which we formally test for two different forms of state dependence, differentiating loyalty from habituation, or mere unobserved heterogeneity in preferences.

[Table 5 in here]

4 Econometric Model

4.1 Overview

Our empirical model of brewery acquisitions and pricing consists of two parts. In the first part, we estimate a discrete-choice model of the demand for beer as a function of its price, and other marketing-mix elements, as well as observed attributes of the beer, and unobserved heterogeneity among beer-drinking households. In the second part, we estimate brand-level marginal costs assuming beer sellers arrive at a Markov-perfect equilibrium (MPE) in their pricing decisions.

4.2 Empirical Model of Beer Demand

Our objective is to determine the impact of buyouts in the craft beer industry on pricing behavior among firms in the craft beer industry. We recognize the brewers understand the inherent state dependence of demand for their product, and price accordingly. That is, conventional theory suggests that products with habitual demand are subject to a "harvest - invest" pricing mechanism. That is, firms with market power can either set relatively high prices in order to harvest rents from habituated customers, or can set relatively low price points in order to invest in building a larger market for later rent-extraction. Which dominates is clearly a dynamic decision process, one that is influenced by both the structure of the output market, and the strength of habituation among consumers. In our model, we assume a Markov-perfect pricing equilibrium (MPE) among competing brewers, and condition their pricing decisions on a structural model of state dependent beer demand.[6]

We assume the demand for beer is inherently state dependent, driven by either loyalty or habituation to both a brand, or a class (style) of beer. Therefore, a consumer's choice of beer today depends on their purchase history for all brands, and styles. We account for three forms of state dependence (Roy, Chintagunta, and Haldar 1996; Seetharaman 2004): (1) structural state dependence, or the effect of previous choices on the decision made on the current purchase occasion, (2) habituation, in the sense of Seetharaman (2004) that captures a second form of serial correlation in choices actually made by households, and (3) unobserved heterogeneity, or the notion that factors unique to the individual, yet unobserved, may mean that the consumer purchases the same item on subsequent trips simply out of idiosyncratic preference (Keane 1997).[7] Accounting for all three sources of state dependence is necessary in order to isolate the factor of concern here, structural state dependence, without bias.

Our empirical model follows Roy, Chintagunta and Haldar (1996) by accounting for each of these potential sources of observed state dependence in a single, integrated framework. They differentiate between state dependence (feedback), habit (inertia), and unobserved heterogeneity in explaining repeat purchases of consumer packaged goods. Simple habituation is not state dependence as it implies the consumer does the same thing as before, in the absence of any other evidence or experience that may change his behavior. State dependence, on the other hand, allows for elements of the environment, the state of the system, to generate feedback that may influence the decision. Roy, Chintagunta, and Haldar (1996) explain that "...in general, three notions of temporal dependence are invoked in models of dynamic choice behavior-habit persistence, state dependence, and unobserved heterogeneity." They differ-

[6]Our demand model is structural in the sense that we explicitly account for state-dependence in demand, but our demand model is not structural in the sense of Erdem and Keane (1996) or Ching, Erdem, and Keane (2014) by allowing consumers to follow a purposefully-dynamic, optimal learning process over time.

[7]Heckman (1981) refers to this second source of state dependence as habit-persistence, so our approach is able to distinguish between what is commonly understood to represent habituation from state-dependence due to loyalty in the sense of Guadagni and Little (1983). We estimated a version of the model that included incidential state depdenence, or the serial correlation in utility between subsequent purchase occasions (Seetharaman 2004), but this model was not identified in our data.

entiate between state dependence and habit persistence as explaining that structural state dependence is the influence of past experiences – learning about quality, for example – while habituation is simply repeating a past experience, perhaps in order to minimize cognition cost, as manifest in the serial correlation of model error terms.

In a random-utility framework, the errors between one decision and the next are assumed to be independent. Consequently, allowing for serial correlation in the error process violates the underlying assumption of the framework. Therefore, we follow Resnick and Roy (1990); Roy, Chintagunta, and Haldar (1996) and Seetharaman (2004) and assume that the arrival of unobserved demand shocks at the household level follows a Poisson process, which causes serial correlation in the decision-errors on choices in subsequent purchase occasions if consumers choose the option that provides the maximum shock at each purchase occasion. Resnick and Roy (1990) show how this process results in a sequence of choices that are described by an extreme-value distribution.

Specifically, households in our model are assumed to purchase one alternative from a consideration set that is unique to their local market. As described above, we define our example market as consisting of the top 14 brands of craft beer purchased by households in the state between January 1, 2014 and December 31, 2016, plus an all-other craft brand, and an outside option. From this consideration set, households choose the item that provides the most utility from all alternatives available, subject our assumption regarding the unobserved heterogeneity in beer-preference. We introduce state dependence following the dynamic Markov method developed by Roy and Resnick (1990) explained above, controlling for other measures of state dependence that capture the evolution of purchase-intensity at the household level (Briesch, Chintagunta, and Fox 2009).[8] Let $h = 1, 2, ..., H$ index consumers, $j = 1, 2, ..., J$ index the brands offered on purchase occasion $t = 1, 2, ..., T$, so the

[8]Such inventory-type measures are commonly used to capture purchase-incidence at the category level, but preliminary analysis of the data suggested that brand-choice in our context was also strongly dependent upon measures of purchase-frequency, and consumption intensity. In our context, these measures likely capture consumers' level of engagement with beer in general, than the usual need-based interpretations.

indirect utility function is written:

$$U_{hjt} = \psi_j + \alpha_h p_{jt} + \boldsymbol{\beta}\mathbf{X}_{jt} + \gamma\mathbf{Z}_h + \tau I_{hj,t-1} + \varepsilon_{hjt}, \quad (1)$$

where: ψ_j is a brand-specific constant term, $\mathbf{X}_{jt}$ is a k-vector of covariates that describe item-specific marketing-mix activity specific to brand j, $\mathbf{Z}_h$ is a vector of household-specific variables, including those that capture need-based measures of state dependence, $I_{hj,t-1}$ is a lagged-choice indicator variable that assumes a value of 1 if household h purchased brand j on the previous purchase occasion, and ε_{hjt} is a random variable, assumed to be unobserved, and uncorrelated with any of the other elements of the utility function.

Our set of marketing-mix variables includes the shelf price, a binary indicator of whether a particular item was on display, and an indicator of whether it was featured at the time of purchase. Our household-specific variables capture observed heterogeneity in brand-choices, and includes household-head age, education, income, and the number of individuals in the household. Among the set of household-specific variables, our measures of purchase-intensity include the household's average beer-consumption rate, the amount purchased on the previous visit, and the number of days since the previous beer purchase. Further, we include a set of manufacturer, or brand, fixed effects (ψ_j), and a control function to address the issue of price-endogeneity.

We account for an outside option in order to capture the impact of aggregate demand shocks on the size of the craft beer market. In our application, the outside option consists of all other beer purchases by the household on each purchase occasion. That is, we implicitly assume that the consumer enters the store seeking some sort of beer, so if they are not satisfied with anything in the beer selection at the store, they will purchase a different type of beverage. If they do so, we assume they earn an indirect utility that is also Extreme Value distributed such that: $U_{hot} = \varepsilon_{hot}$. We also account for unobserved heterogeneity in consumer preferences by allowing the marginal utility of income to be randomly distributed, and a function of household-demographics in a manner similar to Keane (1997) so:

$$\alpha_h = \alpha_o + \sum_k \alpha_k \mathbf{Z}_{hk} + \alpha_{k+1}\nu_h,\ \nu_h \sim N(0, \sigma_\nu) \tag{2}$$

where v is a vector of random normal error terms. In this way, the response to the most important marketing-mix element (price) captures both observed and unobserved heterogeneity.

Although the underlying utility model is a relatively standard multinomial logit model (MNL), the fact that we allow for heterogeneity in horizontal item-preferences (ε_{hjt}), and unobserved heterogeneity in the response to variation in item-prices, means that we integrate over all distributions in order to estimate the probability of purchase for household h, and item j. In this sense, our model is a mixed-logit model, which we estimate using simulated maximum likelihood in the absence of closed-form expressions for the probability-of-purchase variable. Therefore, we write the probability for each household-item as:

$$s_{hjt}(\Omega) = \int_{A_{jrt}} dF\varepsilon(\varepsilon) dF_v(v), \tag{3}$$

for parameters Ω, where:

$$A_{hjt} = [(\varepsilon, \nu) \mid U_{hjt}(X_{kjt}, I_{hj,t-1}) \geqslant U_{hmt}(X_{lmt}, I_{hm,t-1})],$$

represents the set of items that are chosen by our sample households. With our assumption that ε is EV distributed, we simplify this expression by including the known functional form for the EV density to arrive at the estimated probability function:

$$s_{hjt}(\Omega) = \int_{A_{hjt}} \left(\frac{\exp(\eta_{hjt})}{\sum_{m=1}^{M} \exp(\eta_{hmt})} \right) dF_\nu(\nu), \tag{4}$$

where η_{hjt} is the mean utility for item j for household h in week t.

To this point, our definition of habit persistence follows the "Type I" definition of Seetharaman (2004) by capturing only the serial correlation in utility between successive purchase occasions. When we allow for the Poisson arrival of individual-information shocks, however, such as an unobserved national advertisement, article on a local-beverage website or beer-blog, or similar, we observe an additional serial correlation among choices, or "Type II" habit persistence. We capture Type II habit persistence using the Markov model of Roy and Resnick (1990) such that:

$$S_{hjt} = \begin{Bmatrix} \rho + (1-\rho)s_{hjt} & if\ I_{hj,t} = I_{hj,t-1} \\ (1-\rho)s_{hjt} & if\ I_{hj,t} \neq I_{hj,t-1} \end{Bmatrix}, \tag{5}$$

where ρ is the measure of Type II habit-persistence. In this model, the value of ρ is also allowed to lie on [-1,+1] in order to accommodate both habit persistence, and consumers' revealed preference for variety between trips. The expression for the aggregate market share in (5) represents the critical measure of market-share dynamics in the model because it allows the share of each brewery to evolve with the Markov property necessary for the pricing model developed in the next section. The value of this parameter is also critical from a managerial perspective as $\rho > 0$ suggests that, controlling for all other possible explanations for state dependence, habit persistence dominates so exposure to the item is more likely to lead to repeat purchase. Appearances at beer-festivals, rotating-tap nights, or other sampling experiences are likely to be effective marketing tools. On the other hand, if $\rho < 0$, then variety-seeking is likely to dominate, after controlling for other forms of state dependence, so consumers are more likely to move from item to item from one occasion to the next, and activities designed to attract trial-purchases are not likely to be profitable in the long run. Rather, a diverse and changing product line is recommended as a preferred strategy.

It is also important to emphasize the source of market-dynamics with this demand model. Because we control for unobserved heterogeneity, intertemporal spillover effects from marketing-mix elements, and serial correlation in utility, we assume that the evolution of market share over time is due to the Markov property of the unobserved demand shocks arriving at each household. While this assumption is reduced-form in nature, it is consistent with the Markov-perfect equilibrium pricing strategy described in the next section.

Estimating (5) is complicated by the fact that the underlying probability-of-choice function has no closed-form. Therefore, we simulate the likelihood function over the assumed distributions for each. Defining δ_{hjt} as a binary-purchase indicator for each household-occasion observation, the log-likelihood function is written:

$$\pounds(X_{kjt}, I_{hj,t-1} \mid \Omega) = \sum_{h=1}^{H} \sum_{t=1}^{T} \sum_{j=1}^{J} \delta_{hjt} \log S_{hjt}(\cdot, \Omega),$$

which we simulate using Halton draws ($H = 50$) in order to improve the efficiency of the simulation process (Bhat 2003).

Prices in our model are likely to be endogenous. Although household-level prices are not endogenous for the usual, market-clearing reasons, there are still unobservables at the household level that are correlated with observed prices (Villas-Boas and Winer 1999). Therefore, we estimate the model using a control function approach (Petrin and Train 2010) in order to control for the bias that would otherwise result. As the control-function approach is of the general class of instrumental-variables methods, the quality of our estimator depends on both the strength of our instruments, and their independence from the error term in the equation of interest. As is well understood, quality instruments have to be correlated with the endogenous variable, and mean independent of the error term. While we can formally test instrument strength in a number of ways (Staiger and Stock 1997), we evaluate independence on first principles, that is, whether there is no logical correlation between the instrument and the unobservables in the estimating equation.

We use input prices for the beer production-and-marketing process as instruments for endogenous prices. Input prices are not likely be correlated with unobservables in the demand equation because each price is determined in a market that is larger than the state craft-beer market, so is at least plausibly exogenous. The primary production ingredients for beer are water, malt (barley), yeast, and hops. However, there are no reliable price series for yeast or hops, so we include only water, barley, and malt.[9] We capture other costs in the beer-production process by including price indices for energy (diesel fuel and commercial electricity) and beverage-production wages. Further, because packaging and marketing form

[9]Malt prices are not perfectly correlated with barley prices as a production process converts barley to malt, and barley has alternative uses, generally livestock feed.

a substantial part of the total cost of producing beer, we include indices for glass, aluminum, cardboard, and advertising services. All price indices are from the US Bureau of Labor Statistics. Based on estimates from a first-stage, instrumental-variables regression of beer prices on this set of input-price indices, we can safely conclude the instruments are not weak as the F-statistic is $1,417.2$, relative to the accepted standard of 10.0 (Staiger and Stock 1997).

Based on the estimates from this demand model, we then estimate the marginal cost of beer from each brewery on the assumption that they compete in a dynamic, Markov-perfect equilibrium (MPE) sense. We describe this pricing model in the next section.

4.3 Model of Strategic Pricing

Our model of dynamic strategic pricing follows the approach developed in Bajari, Benkard, and Levin (BBL, 2007). BBL describe an approach to estimating MPE pricing models that avoids the need to compute dynamically-optimal solutions within the estimation algorithm. In our application of this approach, rival firms compete in price, conditioned on the state of the market, where the state is described by the share of the market earned by each firm in the industry. Market share is an indicator of the degree of habituation or loyalty to the products sold by each firm (Pavlidis and Ellickson 2017). Market share, in turn, evolves according to a Markov transition process described in more detail in our explanation of the BBL algorithm below. Ultimately, the model produces estimates of the structural parameters governing each brewery's pricing strategies, which are marginal costs in this application. By simulating the equilibrium model over a range of assumptions regarding the presence or absence of buyouts, and the nature of state dependence in demand, we are able to reveal the impact of buyouts on the incentive to buy a craft brewery, and any mis-estimation that may arise from assuming static demand.

Estimating fully optimal models of dynamic pricing-interactions of the sort described here are complicated by two, related problems (BBL, 2007). First, to ensure that the decisions of each agent are fully optimal, complete solutions to the firms' dynamic programming problems must be embedded within the estimation routine (Rust 1987; Pakes and McGuire 1994; Ericson and Pakes 1995). While there are many examples of successful implementation of these models, their inherent complexity limits researchers to somewhat simplified versions of the underlying economic problem. Second, there is the possibility of multiple equilibria, so we can never be absolutely confident that the estimated parameters describe behavior that is fully optimal. The BBL method circumvents these two problems in an elegant way – by assuming the data reflects optimal behavior on the part of the agents, and accurate beliefs about not only the decisions of other agents, but about the state of the economic environment. With this assumption, the approach "...effectively recover[s] the agents' equilibrium beliefs" (p. 1332, BBL). Our solution concept is MPE as the equilibrium decisions are Markov reactions by each player, meaning reactions that are only conditioned on the state of the game. While there are many examples in the literature of dynamic discrete games that use the logic of BBL (Aguirregabiria and Mira 2007; Aguirregabiria, Mira, and Roman 2007; Pakes, Ostrovsky, and Berry 2007; Ellickson, Misra, and Nair 2012; Ryan 2012; Arcidiacono, et al. 2016), the paper that is closest to ours methodologically, and one that we follow closely, is Pavlidis and Ellickson (2017).

The BBL method is, conceptually, a two-stage estimation approach. In the first stage, we estimate policy functions that describe how each agent chooses values of the control variable in response to different states of the market. In an oligopoly setting such as ours, own-loyalty is less important than how the firm perceives loyalty to other brands. Therefore, the state of the system is captured by rival loyalty, or the degree of loyalty consumers express to brands other than the own-brand. We expect this relationship to be non-linear as a brand's prices are likely to be relatively insensitive to the degree of loyalty a brewer perceives the other brands to hold when rival-loyalty is low, but then fall when the brewer feels that consumers are relatively more loyal to other brands.

In the second stage, we use these policy functions to forward-simulate continuation values for each firm, where the continuation value is defined as the present value of a future stream of likely profit. By considering a range of "perturbations" from these optimal, or observed, continuation values, we use the equilibrium conditions for a MPE to formulate a minimum-distance estimator that recovers the unobserved structural parameters of the model. That is, the equilibrium requires that the observed data reflect fully optimal decisions by the agent, so the parameters can be recovered by comparing the observed and simulated, non-optimal, decisions. The structural parameters are the ones that fully reconcile the observed data with the simulated data that does not capture the same optimal decisions.

We then use the structural model estimated in this second stage to conduct a series of counterfactual simulations that allow us to compare equilibrium prices under alternative buyout scenarios. That is, conditional on our estimated loyalty parameters, we calculate equilibrium prices under a base-case scenario that assumes demand conditions with no buyouts. We then compare these baseline prices to equilibrium prices calculated assuming Brewery A is bought out, but not Brewery B, and then the opposite: Brewery B is purchased, but not Brewery A. We interpret the difference in prices among these scenarios as showing the impact of the major breweries' buyouts, conditional on the exercise of loyalty by craft-beer consumers.

More formally, assume the brewing industry consists of $r = 1, 2, ..., N$ firms, each with state $S^*_{r,t}$ in period t such that the state of the system is described as the vector $\mathbf{S}_t = (S^*_{1,t}, S^*_{2,t}, ..., S^*_{N,t})$. Each period, firms adopt actions in the current period by choosing brand-average prices: $p_{r,t}$. Further, define private shocks to the profitability of each firm as υ_r and a set of Markov strategies as $\boldsymbol{\sigma} = (\sigma_1, \sigma_2, ..., \sigma_N)$ that map states into actions such that: $p_{r,t} = \sigma_r(\mathbf{S}_t, \mathbf{v})$. With this structure, define the expected value of firm r as the Bellman equation (BBL, 2007):

$$V_r(\mathbf{S}_t; \boldsymbol{\sigma}) = E_v[\pi_r(\boldsymbol{\sigma}(\mathbf{S}_t, \boldsymbol{\upsilon}), \mathbf{S}_t, \upsilon_r) + \beta \int V_r(\mathbf{S}'_t; \boldsymbol{\sigma}) dP(\mathbf{S}'_t | \boldsymbol{\sigma}(\mathbf{S}_t, \boldsymbol{\upsilon}), \mathbf{S}_t | \mathbf{S}_t], \tag{6}$$

where $dP(\mathbf{S}'_t | \boldsymbol{\sigma}(\mathbf{S}_t, \boldsymbol{\upsilon}), \mathbf{S}_t)$ defines the Markov transition process underlying the set of state variables. With each firm value given by (6), a MPE is defined as the set of strategies that are preferred to all others for the given states, or:

$$
\begin{aligned}
V_r(\mathbf{S}_t;\boldsymbol{\sigma}) \geqslant & V_r(\mathbf{S}_t;\sigma'_r,\boldsymbol{\sigma}_{-r}) \\
& = E_v[\pi_r(\boldsymbol{\sigma}'_r(\mathbf{S}_t,\upsilon_r),\boldsymbol{\sigma}_{-r}(\mathbf{S}_t,\boldsymbol{\upsilon}_{-r}),\mathbf{S}_t,\upsilon_r) \\
& + \beta\int V_r(\mathbf{S}'_t;\sigma'_r;\boldsymbol{\sigma}_{-r})dP(\mathbf{S}'_t|\sigma'_r(\mathbf{S}_t,\upsilon_r),\boldsymbol{\sigma}_{-r}(\mathbf{S}_t,\boldsymbol{\upsilon}_{-r}),\mathbf{S}_t)|\mathbf{S}_t],
\end{aligned} \tag{7}
$$

for each firm r. In our empirical application, therefore, we seek to estimate the parameters of the profit function, π_r, the transition probabilities $P(.)$ and the distribution of private shocks facing each firm. We assume the discount factor, β, is fixed and known to all firms.

Despite the two-stage nature of the of the BBL approach, we estimate the unknown parameters in (7) following five steps (Pavlidis and Ellickson 2017). For clarity, we describe each step of this approach in detail here. In the first step, as explained above, we estimate flexible policy functions in order to recover the price-response of each firm with respect to rival-loyalty, or the average percentage of consumers each week who express loyalty to brands other than r. Because we expect each firm's response to the perceived loyalty of the other firms to be non-linear, we allow each firm's price to be a quadratic function of the extent of rival-loyalty. In our multi-firm case, we follow BBL in estimating local non-linear regressions of each firm's price on the loyalty to other brewers $(-r)$, such that:

$$p_{rt} = \gamma_0 + \gamma_1 S_{-r} + \gamma_2 S^2_{-rt} + \varepsilon_{rt}, \tag{8}$$

where ε_{rt} is an iid normal error term. In this way, we allow the data to determine how each firm is likely to set prices in response to the revealed loyalty consumers express toward other firms, assuming equilibrium responses.

In the second step, we estimate Markov-transition probabilities for each state variable (separately) as a function of all firms' policy variables. In this regard, we follow the logic of Pavlidis and Ellickson (2017) and estimate conditional choice probabilities, defined as the probability a consumer will remain loyal to the brand in question, given that he or she was loyal in the previous period. These are conditional probabilities, as we estimate the probability a consumer buys a particular brand, conditional on their revealed loyalty to the brand.

For each firm, therefore, we estimate transition probabilities using (4) above, conditional on the observed loyalty for each brand, each week. We then use the resulting parameter estimates from the demand model to calculate each element of the Markov-transition matrix, $\mathbf{Q}(\mathbf{p}_t, \mathbf{S}_t)$. That is, each element Q_{ij} represents the marginal probability of remaining loyal to the current brand, conditional on being loyal to the own-brand (diagonal of $\mathbf{Q}$) and all other brands (off-diagonals of $\mathbf{Q}$).[10] We then calculate new values for the state variable using the Markov transition matrix according to:

$$S_r^{t+1} = S_r^t * \mathbf{Q}(\mathbf{p}_t, \mathbf{S}_t), \tag{9}$$

for each firm, r. Based on the estimates from the Nielsen retail-beer data, we find that the Markov process reaches a steady-state after approximately 20 weeks, and remains constant thereafter.

In the third step, we define the initial state values, and forward-simulate profit using the state transitions defined in the second step above. For this purpose, we allow the state vectors to include the random shock from the step 1 policy-function regressions, which is the idiosyncratic shock, υ_r. After defining the initial state variable values, we calculate optimal policies for the estimated policy functions for the initial states, calculate the associated profits with those initial states, calculate the forward-simulated states based on the Markov-transition matrix ($\mathbf{Q}$) from the second step, and calculate the profit associated with each of those forward-simulated states. Each increment of the forward-simulated profit depends on the updated state in a Markov-perfect equilibrium (MPE), and prices are consistent with each state by the policy functions estimated in step 1. Therefore, profit in each forward-simulated period depends not only upon the state, but each firm's optimal response to the state based on observed rival behavior. Profit in each period is discounted to current period using a cost of capital ($r = 0.05$) that implies a negligible increment to the current value of the firm beyond week 2,000. We conduct the exercise with a range of discount values, and

[10]Recall that the elements of a Markov transition matrix are interpreted as representing the probability that the agent who is currently in the row-state will be the column-state in the next period. Clearly, each row must sum to one for logical consistency.

our findings are not sensitive to our choice.

In step 4, we conduct the forward-simulation process for a large number of "perturbed" or hypothetical responses in which the policy functions for each firm are defined as deviates from the optimal responses defined in Steps 1 - 3 by small amounts. For this purpose, we follow Ryan (2012) and define each perturbed value as a random, standard normal variate from the optimal policy functions. We define the number of perturbed states, H, as 2,500 in order to obtain a sufficient number of observations to identify the unobserved costs in the estimated value functions. Therefore, we forward-simulate 2,500 alternative scenarios in which the value functions are calculated with policy functions that are slight deviations from the observed, and assumed optimal, policy functions. These 2,500 observations then form the data for the structural estimation process described next.

Estimates of the structural parameters of the profit function, which are defined as marginal costs of brewing, θ_r, in our case, are obtained in step 5. BBL note that estimating the cost-parameters of the problem is simplified considerably by exploiting the inherent linearity of the problem. With linear value functions, the forward-simulation process need only be carried out once, and not for every possible value of the unobserved cost vector. For example, the value function in our example is given by (Pavlidis and Ellickson 2017):

$$V_r(S_r^*; \sigma_r; \theta_r) = \sum_{t=0}^{\infty} \beta^t \left(p_{rt} * D_{rt} * M\right) - \left(\sum_{t=0}^{\infty} \beta^t (D_{rt} * M)\right) * \theta_r, \tag{10}$$

where D_{rt} is the market share of brewery r in week t (and a function of the state and policy variables), and M is the size of the market. Step 5 embodies the core of the BBL estimation logic as the intent is to find the value of θ_r that reconciles the optimal with the "perturbed" value-functions − there is a cost parameter that ensures the optimal value function does indeed represent a MPE, or the optimal policy-path given the choices of the rival firm over time. Although BBL (2007) use a minimum-distance estimator to find the value of θ_r that rationalizes the observed data, we follow Pesendorfer and Schmidt-Dengler (2008) and interpret the second-stage estimates in the BBL algorithm as least-squares estimates, minimizing the squared deviations between the value functions, subject to the observations where the perturbed value exceeds the observed value. We then calculate equilibrium price estimates from this structural model to determine the effect of buyout activity on optimal pricing by each retailer, conditional on the degree of loyalty expressed toward each beer-brand.

Specifically, we conduct a number of counterfactual simulations of the pricing model under different assumptions regarding the presence or absence of buyouts, and examine whether equilibrium prices at the brewery level are higher, or lower, than the benchmark scenario of no buyouts. We compare equilibrium prices under three scenarios: (1) the base-case solution with no buyout activity, (2) Brand 2 (produced by Brewery A) is purchased by a major brewery in August of 2015, and (3) Brand 9 (produced by Brewery B) is purchased in November of 2015. We then repeat this process, while removing the effect of loyalty on the demand for each brand, and compare the resulting equilibrium prices. With this approach, we are able to answer two questions: How buyouts affect equilibrium prices under observed loyalty, and how buyouts affect equilibrium pricing the absence of loyalty. Comparing equilibrium prices in this "difference-in-difference" framework provides the core insights of our paper.

5 Results and Discussion

We begin by presenting the results of the dynamic demand model, and then interpret the results from the MPE pricing model.

Table 6 presents the estimates from three versions of our maintained demand model: Model 1 is a fixed-parameter version of the model with only structural state dependence, or only the lagged-purchase indicator, Model 2 is a fixed-parameter version that accounts for both structural state dependence, and the loyalty in the sense of Resnick and Roy (1990), while Model 3 accounts for both forms of state dependence, and unobserved heterogeneity in brand preference. Because these models are nested, we compare their goodness of fit using a series of likelihood-ratio (LR) tests. By this criteria, the most comprehensive model is preferred as the Chi-square statistic of $2,768.8$ is greater than the critical Chi-square value of 7.81 (with 3 degrees of freedom). Therefore, we use Model 3 to calculate MPE prices below.

[Table 6 in here]

Before presenting the results from the dynamic pricing model, however, there are several findings of note from the demand model. First, the measure of structural state dependence ("Loyalty" in Table 6) is consistently the most important variable explaining brand choice across all of the three specifications. Intuitively, the best predictor of the brand of beer a consumer purchases on the current shopping trip is the identity of the brand purchased on the previous trip. Second, each of the three measures of beer-preference intensity ("Consumption Rate," "Lagged Purchase," and "Interpurchase Time") are statistically significant, and clearly important in beer-brand choice. Third, controlling for all other factors, the purchase of Brand 2 by a major brewery had a significantly negative effect on the demand for Brand 2 beers. While each buyout is likely to entail positive distribution, advertising, and scale-effects, craft-beer drinkers, and local-beer drinkers more generally, may discount the "craftiness" of beer brands that are no longer independently owned. At least for Brand 2, the net effect of the buyout is negative.[11]

On the other hand, the purchase of Brand 9 appears to have had a positive effect on demand. Although statistically less significant in Model 3 relative to Models 2 and 1, the estimate nonetheless shows that consumers were more likely to purchase Brand 9 after being purchased by a major brewery. In this case, we interpret this finding as capturing the strong distributional effect associated with the purchase, and perhaps weak knowledge on the part of consumers that the brewery was purchased. In each case, our market-estimates reflect the relative proportions of informed and non-informed craft-beer consumers, so it may be the case that too few buyers were aware that Brand 9 was purchased by a non-craft brewery. Regardless of the mechanism, the net direct-effect in the case of Brand 9 is positive.

[11] We attempted to estimate the model with an interaction term between each buyout variable, and brand loyalty, but, perhaps due to the relatively small number of purchases per household per brand, the model would not converge.

Conditional on these demand effects, Table 7 shows our estimates of the equilibrium marginal cost of producing each beer-brand. That is, these estimates reconcile the observed prices in our data, with the expected prices based on the dynamic expectations of each brewery in our data. Not surprisingly, the marginal cost of producing beer is similar in each case, with Brand 8 representing a high marginal-cost producer ($0.0226 / oz) while Brand 9 is a relatively low-marginal cost beer ($0.0105 / oz). Brand 15, as the composite, or "all other" brand, reflects an approximation of the average marginal cost of production at $0.0153 / oz. In each case, note that these are marginal costs of production, and not average costs.

[Table 7 in here]

We use these marginal cost estimates to calculate equilibrium prices, and price-cost margins (expressed as a percentage of the selling price, or the Lerner Ratio), under a number of counter-factual scenarios. Table 8 shows the equilibrium prices estimated under the base-case scenario of no buyout activity, but full state dependence, from all sources included in the model. First, it is important to note that the estimates in this table, compared to the marginal cost estimates in Table 7, show substantial variation in equilibrium prices. Second, in this table, Brands 1, 2, and 4 have the highest equilibrium prices, while Brands 3, 12, and 15 (all other) are clearly lower-priced brands. Once we introduce the estimated buyout parameter for Brand 2, however, a different set of equilibrium prices emerges. Because of the negative shock to demand, the equilibrium price for Brand 2 falls by some 9.73% relative to the base-case scenario. Each of the other brands is, to a certain extent, a substitute for Brand 2, so their equilibrium prices are generally higher. Among all of the substitute brands, Brand 1, which is the largest market-share brand in our data, is a clear beneficiary as its equilibrium price rises from $0.1760 / oz to some $0.1785 / oz. In percentage terms, the prices for Brands 4 and 11 rise the most – 2.17% and 2.72%, respectively. Introducing the positive shock to Brand 9 demand due to its buyout, equilibrium prices again change. In this case, due to the relative strength of the positive demand effect, the equilibrium price of

Brand 9 rises by over 7.7%. If consumers were aware of the lost craft status, the impact is outweighed by improvements in distribution, advertising, and other anticipated demand-side benefits of the buyout. Interestingly, prices for most other brands rise, perhaps in response to the category-expansion effects of the announcement, except for Brand 2, which is a major competitor.

[Table 8 in here]

Each of these outcomes, however, would likely have prevailed in a static model of demand, and pricing. We demonstrate the importance of accounting for forward-looking behavior in equilibrium pricing by conducting the analysis in Table 8, but removing the dynamic elements of demand, and re-solving for equilibrium prices. The results of this experiment are in Table 9 below. In this table, we see that the directional impacts on equilibrium prices are the same, namely prices for Brand 2 fall in response to its buyout, and those for Brand 9 rise. However, the estimates in this table suggest that static models of demand misestimate prices in a positive direction relative to the theoretically-consistent estimates in Table 8. In Table 9, the equilibrium prices for both Brand 2 and Brand 9 are higher than they would otherwise be. Based only on prices, this finding is consistent with a pro-competitive effect of state dependence – if each firm takes future market share into account, it is likely to invest by reducing prices in the current period below what a static model would suggest.

[Table 9 in here]

Equilibrium prices are only part of the story, as buyouts could entail substantial changes in margin. Tables 10 and 11 compare margin estimates before and after the Brand 2 and 9 buyouts, both with state dependence (table 10), and without (table 11). Compared to the estimates in table 8, the estimates in table 10 show that the high-price brands are not necessarily the most profitable as Brands 3, 9, and 12 have higher equilibrium margins, while Brands 10, 11, and 13 are low-margin brands. After the Brand 2 buyout, its margin falls by over 2.0%, consistent with its lower price. In this case, demand erosion, perhaps due to buyers' perceptions that the brand is no longer "craft" dominates any advantage in cost or distribution. Among the other brands, many experience margin erosion despite higher prices, because the marginal cost of expansion rises quickly in small, craft enterprises. For Brand 9, we see that its equilibrium margin erodes by an amount similar to the *rise* in its price. Despite the fact that prices rise, costs rise substantially, likely due to the inherent difficulties in growing small brands quickly. In fact, this result, estimated with data over 2014 - 2016 is supported by subsequent events: In 2019, the parent firm of Brand 9 declared an "impairment" of the Brand 9 value, citing higher costs, and closed two breweries that were opened in 2016 (Furnari 2019). Our model predicts exactly this outcome.

[Table 10 in here]

We again remove the state dependent elements of the model, and re-solve for equilibrium margins to demonstrate the importance of accounting for dynamics in buyout analysis. These results are in table 11 below. Focusing on the Brand 2 buyout event, we find that equilibrium margins rise once we remove state dependence, which implies that much of the negative-profit effect show in Table 10 may be due to the pro-competitive effects of state dependence (Dube, Hitsch, and Rossi 2009). Because prices are uniformly lower without state dependence, this outcome is more likely due to the compensation effect of Arie and Greico (2014) than the harvest-invest mechanism suggested by Cabral (2009) and others. However, in terms of the Brand 9 buyout, we find that margins are substantially lower in the absence of state dependence, despite higher prices. This case supports a more conventional interpretation of state dependence – market power falls with fewer loyal consumers. Said differently, the parent of Brand 9 chose to "harvest" loyal consumers, instead of investing in future market share, apparently to their detriment, given the evidence provided above.

[Table 11 in here]

Importantly, comparing the results in table 11 with those in table 10, we see that the direction of the mis-estimation by not accounting for state dependence is related to the nature of the initial demand shock. That is, when we remove state dependence from the model (table 11), the estimated margin for Brand 2 rises relative to the base case with state dependence in table 10. The direction of mis-estimation with a static model is positive. On the other hand, the estimated margin without state dependence for Brand 9 is significantly smaller, suggesting that the direction of mis-estimation in this case is negative. Recall that Brand 2 experiences a negative shock to demand due to the buyout, and Brand 9 experiences a positive shock. Therefore, the direction of mis-estimation appears to be negatively correlated with the initial demand shock: Margins will be over-estimated if the shock is negative, and under-estimated if the shock is positive. This is intuitive as the static model will not properly account for the long-term positive effects of a demand shock that is initially positive, or the long-term negative effects that are initially negative.

Our findings are important both for our substantive conclusions regarding the impact of craft-beer buyouts, and the importance of accounting for dynamic effects in merger-analysis more generally. First, we find that neither of the buyouts in 2015 were likely to be profit-enhancing, despite the net-positive impact to demand experienced by one of the brands. Second, we find that margin-impact estimates from a model with state dependence differ substantially from one that does not account for loyalty. When evaluating the potential profitability of mergers, or buyouts in this case, whether from a business or anti-trust perspective, it is clearly critical to account appropriately for state dependence in demand.

6 Conclusion and Implications

In this paper, we estimate the impact of craft-brewery buyouts on dynamic equilibrium pricing behavior in the US beer industry. We frame our empirical analysis in terms of a dynamic model of demand, and Markov-perfect equilibrium pricing. *A priori*, our expectations are inconclusive as there are two competing theories as to how state dependence is likely to effect the outcome of a merger. While a firm with enhanced market power may choose to raise prices to loyal consumers, and not invest in growing market share (Farrell and Klemperer 2007), others suggest that loyalty, and higher switching costs, lead to lower margins as firms compete for potential switchers (Cabral 2009; Rhodes 2014, Arie and Grieco 2014).

We find that accounting for state dependence is critical in estimating the impact of mergers. In our setting, we find one case in which margins are over-estimated by not accounting for state dependence (Brand 9), while the other is under-estimated (Brand 2). We interpret the difference in terms of the direction of the initial impact on demand: If the demand shock due to the buyout is negative (Brand 2), the effect will be over-estimated, while if the demand shock is positive (Brand 9), the effect is under-estimated. In other words, the extent of mis-estimation is negatively correlated with the initial shock to demand. This type of error is to be expected as a static model will not take into account the longer-term impacts of a one-time shock to demand.

Our findings with respect to the harvest-invest mechanism are similarly intuitive. That is, our results suggest that the pro- versus anti-competitive effects of state dependence is subject to some asymmetry, as perhaps to be expected. If managers experience lower demand in response to a merger, they are likely to respond by reducing prices, which appears to be a pro-competitive response, while if the shock is positive, the opposite will occur.

Our findings are likely to go beyond the context of craft beer considered here. Many product categories are subject to state dependence in demand, from either loyalty, habituation, or addiction, so merger analysis must be framed in terms of explicitly dynamic empirical models. Mergers in the pharmaceutical, media, communications, and technology industries may all be subject to the same mechanism we find in this analysis of the craft beer industry.

Future research in this area may want to consider other models of dynamic demand than the one used here. Because of the importance of demand-response to empirical estimates in dynamic models, and the range of potential options for estimating demand, there should be considerable interest in research that studies the sensitivity of MPE estimates with respect to the form of demand. Second, we restricted our sample to a limited set of brands, and geographies, for reasons of tractability. A more general analysis would expand the scope of brands under consideration, over perhaps a broader geographic range. Third, our subject-matter interest focused on the craft-beer industry, but there has been a number of mergers among macro-breweries that may be subject to the same dynamics considered here. Future research may want to look back to these merger cases.

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Figure 1: Buyout Brewery Growth

Table 1. Summary of Demand and Pricing Model Data

Variable	Units	Mean	Std. Dev.	Min	Max	Variable	Units	Mean	Std. Dev.	Min	Max
Cons. Rate	Units / day	2.027	6.000	0.000	39.507	Malt Barley	Index	5.773	0.361	5.130	6.520
Lag Quantity	# Units	15.404	52.652	0.000	1690.000	Water	Index	87.183	2.600	83.800	91.700
Interpurchase	Days	1.495	7.772	0.000	327.000	Aluminum	Index	104.651	2.158	101.600	108.600
Age	Years	58.863	11.090	23.000	87.000	Glass	Index	105.540	0.571	104.500	106.400
Income	$,000	87.621	36.700	12.532	125.492	Cardboard	Index	120.725	1.915	117.200	123.900
Household Size	#	2.709	1.245	1.000	9.000	Diesel	Index	260.597	86.960	141.900	403.100
Education	Years	13.714	1.639	8.000	24.000	Electricity	Index	170.351	5.771	162.900	180.500
Malt	Index	176.401	3.760	169.500	184.900	Wages	Index	1009.278	28.815	949.020	1072.400
Barley	Index	186.662	26.456	141.600	243.800	Advertising	Index	104.329	1.378	102.500	109.500

Note: Source, Kilts Center - Nielsen Panel Data. Input price data from Bureau of Labor Statistics, Department of Commerce.
"Units" are defined as 12 oz cans or bottles.

Table 2. Summary of Demand Data

Variable	Units	Mean	Std. Dev.	Min	Max	Variable	Units	Mean	Std. Dev.	Min	Max
Price 1	$ / oz	0.117	0.014	0.054	0.666	Share 1	%	13.35%	14.18%	0.00%	100.00%
Price 2	$ / oz	0.123	0.033	0.062	0.927	Share 2	%	11.89%	13.40%	0.00%	100.00%
Price 3	$ / oz	0.117	0.019	0.052	0.772	Share 3	%	5.72%	9.34%	0.00%	100.00%
Price 4	$ / oz	0.069	0.018	0.032	0.333	Share 4	%	2.87%	6.63%	0.00%	100.00%
Price 5	$ / oz	0.125	0.033	0.042	0.749	Share 5	%	3.37%	7.19%	0.00%	100.00%
Price 6	$ / oz	0.113	0.098	0.028	0.902	Share 6	%	2.39%	6.05%	0.00%	100.00%
Price 7	$ / oz	0.112	0.007	0.069	0.453	Share 7	%	1.63%	5.00%	0.00%	100.00%
Price 8	$ / oz	0.127	0.011	0.014	0.340	Share 8	%	1.46%	4.73%	0.00%	100.00%
Price 9	$ / oz	0.162	0.033	0.062	0.454	Share 9	%	3.07%	6.86%	0.00%	100.00%
Price 10	$ / oz	0.123	0.026	0.000	0.681	Share 10	%	1.89%	5.38%	0.00%	100.00%
Price 11	$ / oz	0.073	0.004	0.046	0.167	Share 11	%	2.67%	6.40%	0.00%	100.00%
Price 12	$ / oz	0.118	0.005	0.076	0.260	Share 12	%	1.20%	4.29%	0.00%	100.00%
Price 13	$ / oz	0.115	0.004	0.037	0.222	Share 13	%	1.10%	4.11%	0.00%	100.00%
Price 14	$ / oz	0.141	0.030	0.097	0.547	Share 14	%	1.27%	4.42%	0.00%	100.00%
Price 15	$ / oz	0.106	0.051	0.000	0.838	Share 15	%	46.12%	25.68%	0.00%	100.00%

Note: Source: Kilts Center - Nielsen Panel Data, 2014 - 2016 state X craft beer market

Table 3. Buyouts in the Craft Beer Industry: 2014 - 2016

Target	Acquiror	Month	State	Price ($ m)	Price / Bbl
Brewery A	Parent A	August, 2015	X	$500	$1,264
Brewery B	Parent B	November, 2015	X	$1,000	$3,608
Brewery C	Parent C	December , 2014	Y	N.D.	
Brewery D	Parent D	January, 2015	Z	$60	$818
Brewery E	Parent D	November, 2014	A	$50	$1,250
Brewery F	Parent D	December, 2015	B	$80	$1,186

Note: Value for Parent D inferred from industry sources and trade-press reports. Parent A acquired remainder of Brewery A for $500.0 million. N.D. = not disclosed.

Table 4. Beer Pricing Pre- and Post-Buyouts

		Pre-Buyout	Std. Dev.	N	Post-Buyout	Std. Dev.	N	t-ratio
Prices	Brewery A	0.1185	0.0059	83	0.1177	0.0045	75	-0.9694
	Brewery B	0.1451	0.0057	98	0.1767	0.0136	55	16.4501
Share	Brewery A	0.0164	0.0085	83	0.0304	0.0069	75	11.3820
	Brewery B	0.0184	0.0086	98	0.0306	0.0072	55	9.3033

Note: Price calculations from Nielsen Retail Panel data,
prices expressed per ounce. Volume from Panel data, in share of top brands.

Table 5. Summary Evidence of Loyalty

Brand	Loyalty	Std. Dev.	N
1	0.495	0.500	934
2	0.359	0.480	832
3	0.535	0.499	400
4	0.836	0.371	201
5	0.284	0.452	236
6	0.174	0.380	167
7	0.526	0.502	114
8	0.186	0.391	102
9	0.237	0.426	215
10	0.091	0.289	132
11	0.652	0.477	187
12	0.190	0.395	84
13	0.117	0.323	77
14	0.135	0.343	89
15	0.306	0.461	3227
Average	0.344	0.416	269

Note: Loyalty defined as re-purchased last brand. Brand 15 is "all other brands." Average is from the top 14 brands.

Table 6. Structural Demand Model Estimates

	Model 1		Model 2		Model 3	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Brand 1	0.2602	0.3307	-1.0442	0.4106	1.9240	0.5656
Brand 2	-2.1884	0.3735	0.4559	0.3860	1.9115	0.5700
Brand 3	-0.4877	0.3309	-2.4236	0.5989	1.1318	0.5642
Brand 4	-0.8009	0.3308	-3.2336	0.7445	-0.8754	0.5578
Brand 5	-1.1130	0.3349	-1.3489	0.3897	0.4130	0.5679
Brand 6	-1.1144	0.3414	-1.8097	0.4014	-7.3806	2.0611
Brand 7	-2.6027	0.3628	-1.0181	0.3867	0.5161	0.5672
Brand 8	-4.1081	0.4709	-0.7345	0.3867	0.1550	0.5714
Brand 9	-1.6352	0.3531	-1.7556	0.4231	-4.5310	0.8788
Brand 10	-2.2508	0.3556	0.4274	0.3822	-0.5201	0.5766
Brand 11	-0.7267	0.3305	-4.4031	0.8666	-0.9583	0.5640
Brand 12	-1.5548	0.3396	-0.0982	0.3830	-4.8287	1.2646
Brand 13	-1.4132	0.3407	-2.9524	0.4283	0.7527	0.5692
Brand 14	-0.5691	0.3326	-1.4235	0.3934	-0.6425	0.5727
Brand 15	2.0243	0.3293	2.1053	0.3832	3.1363	0.5669
Price	-1.8539	0.2211	-6.0141	0.3119	-5.0302	0.7369
Display	-10.0095	1.0441	-17.3905	2.5035	-1.6218	3.5377
Feature	0.4949	2.4027	0.7248	0.8392	-0.9557	0.9940
Loyalty	3.0893	0.1439	6.3699	0.2190	9.9024	1.3175
Control	6.8520	0.6945	8.1182	0.8144	-24.2200	1.2261
Age	-0.0566	0.0034	-0.0483	0.0040	-0.0973	0.0068
Income	0.0020	0.0010	0.0036	0.0012	-0.0005	0.0022
Education	-0.2451	0.0179	-0.2884	0.0206	-0.2236	0.0337
HH Size	1.8410	0.2389	2.3509	0.2748	-1.1735	0.4446
Cons. Rate	7.6961	0.2039	9.8350	0.2683	10.8668	0.3576
Lag Purchase	1.4505	0.1695	2.5779	0.2351	4.1776	0.3648
Int. Pur. Time	4.6944	0.4210	-0.3575	0.2700	2.3313	0.5622
Buyout (Brand 2)	-4.5320	1.5494	-1.0542	0.1293	-0.1750	0.0864
Buyout (Brand 9)	3.5359	0.1860	2.9919	0.2109	1.4797	0.8785
Rho			0.0213	0.0907	0.0142	0.0518
Price (Demos)	No		No		Yes	
LLF	-27,067.2		-18,234.0		-16,849.6	
Chi-Square	8,400.2		26,066.6		28,835.4	

Note: A single asterisk indicates significance at 5%. Chi-square compares each model to a naive model with only brand-level fixed effects.

Table 7. Markov-Perfect Cost Structure

	MC	Se	LLF	χ^2
Brand 1	0.1153*	0.0002	25.74	51.48
Brand 2	0.1106*	0.0008	49.55	99.11
Brand 3	0.0924*	0.0002	27.89	55.77
Brand 4	0.1153*	0.0007	4.99	9.99
Brand 5	0.1071*	0.0014	7.99	15.98
Brand 6	0.1052*	0.0185	0.48	0.96
Brand 7	0.0998*	0.0090	0.41	0.81
Brand 8	0.1074*	0.0003	79.61	159.23
Brand 9	0.0934*	0.0003	79.49	158.98
Brand 10	0.1079*	0.0026	10.28	20.57
Brand 11	0.1002*	0.0009	149.39	298.78
Brand 12	0.0950*	0.1410	0.04	0.07
Brand 13	0.1056*	0.0003	77.57	155.14
Brand 14	0.1013*	0.0096	1.90	3.79
Brand 15	0.0959*	0.0000	8,008.49	16,016.97

Note: A single asterisk indicates significance at 5%.
Models estimated separately. MC = marginal cost.

Table 8. Buyout Simulations: Pricing with and Without Brand 2 and 9 Buyouts

	Model 1: Base		Model 2: Brand 2 Buyout				Model 3: Brand 9 Buyout			
Brand	Price	Se	Price	%Δ	Se	t-ratio	Price	%Δ	Se	t-ratio
1	0.1760	0.0389	0.1785	1.38%	0.0389	2.2038	0.1749	-0.63%	0.0389	3.0853
2	0.1692	0.0338	0.1528	-9.73%	0.0338	-17.2447	0.1682	-0.62%	0.0338	0.3897
3	0.1506	0.0701	0.1509	0.23%	0.0701	0.1746	0.1506	-0.03%	0.0701	21.3931
4	0.1734	0.0297	0.1771	2.17%	0.0297	4.4752	0.1725	-0.51%	0.0297	1.5954
5	0.1618	0.0497	0.1625	0.41%	0.0497	0.4718	0.1617	-0.11%	0.0497	11.8021
6	0.1541	0.0316	0.1543	0.12%	0.0316	0.2038	0.1539	-0.15%	0.0316	29.6543
7	0.1561	0.0752	0.1566	0.35%	0.0752	0.2544	0.1556	-0.30%	0.0752	15.1630
8	0.1532	0.0337	0.1534	0.09%	0.0337	0.1384	0.1532	-0.01%	0.0337	41.9467
9	0.1588	0.0433	0.1601	0.84%	0.0433	1.0877	0.1710	7.70%	0.0433	5.8656
10	0.1531	0.0257	0.1534	0.17%	0.0257	0.3530	0.1529	-0.13%	0.0257	17.9671
11	0.1621	0.0437	0.1665	2.72%	0.0437	3.5742	0.1615	-0.33%	0.0437	1.6488
12	0.1508	0.0316	0.1508	0.01%	0.0316	0.0134	0.1508	0.00%	0.0316	173.7386
13	0.1535	0.0267	0.1543	0.53%	0.0267	1.0875	0.1534	-0.05%	0.0267	5.8248
14	0.1530	0.0318	0.1537	0.47%	0.0318	0.7983	0.1529	-0.09%	0.0318	7.5808
15	0.1468	0.0788	0.1453	-1.07%	0.1127	-0.5697	0.1539	4.82%	0.0688	6.5430

Note: Model 1 = No buyouts; Model 2 = Brewery A (Brand 2), Model 3 = Brewery B (Brand 9) buyout. Note also that %Δ is percentage change relative to the base case of no buyouts.

Table 9. Loyalty Impact on Pricing: With and Without Brand 2 and 9 Buyouts

	Model 1: Base		Model 2: Brand 2 Buyout				Model 3: Brand 9 Buyout			
Brand	Price	Se	Price	%Δ	Se	t-ratio	Price	%Δ	Se	t-ratio
1	0.1587	0.0389	0.1589	0.12%	0.0389	0.1690	0.1581	-0.39%	0.0389	-0.5569
2	0.1577	0.0338	0.1518	-3.73%	0.0338	-6.1555	0.1568	-0.55%	0.0338	-0.9088
3	0.1513	0.0701	0.1514	0.07%	0.0701	0.0555	0.1510	-0.20%	0.0701	-0.1504
4	0.1770	0.0297	0.1778	0.43%	0.0297	0.8979	0.1723	-2.67%	0.0297	-5.6230
5	0.1553	0.0497	0.1553	0.00%	0.0497	0.0014	0.1552	-0.01%	0.0497	-0.0135
6	0.1519	0.0316	0.1519	0.02%	0.0316	0.0358	0.1518	-0.07%	0.0316	-0.1120
7	0.1534	0.0752	0.1535	0.00%	0.0752	0.0024	0.1534	-0.02%	0.0752	-0.0160
8	0.1527	0.0337	0.1527	0.01%	0.0337	0.0115	0.1526	-0.04%	0.0337	-0.0608
9	0.1546	0.0433	0.1547	0.05%	0.0433	0.0645	0.1740	12.53%	0.0433	15.8061
10	0.1564	0.0257	0.1566	0.11%	0.0257	0.2321	0.1559	-0.34%	0.0257	-0.7335
11	0.1554	0.0437	0.1555	0.03%	0.0437	0.0429	0.1549	-0.33%	0.0437	-0.4195
12	0.1511	0.0316	0.1511	0.00%	0.0316	0.0022	0.1511	-0.01%	0.0316	-0.0101
13	0.1548	0.0267	0.1549	0.05%	0.0267	0.0967	0.1544	-0.28%	0.0267	-0.5643
14	0.1501	0.0318	0.1501	0.02%	0.0318	0.0345	0.1498	-0.20%	0.0318	-0.3407
15	0.1412	0.0477	0.1419	0.53%	0.0477	0.5518	0.1520	7.67%	0.0477	8.0323

Note: Model 1 = No buyouts; Model 2 = Brewery A (Brand 2), Model 3 = Brewery B (Brand 9) buyouts.

Table 10. Buyout Simulations: Margins with and Without Brand 2 and 9 Buyouts

	Model 1: Base		Model 2: Brand 2 Buyout				Model 3: Brand 9 Buyout			
Brand	PCM	Se	PCM	%Δ	Se	t-ratio	PCM	%Δ	Se	t-ratio
1	0.3452	0.0011	0.3488	1.04%	0.0007	134.2659	0.3455	0.10%	0.0012	10.2329
2	0.3467	0.0005	0.3392	-2.16%	0.0328	-11.4340	0.3465	-0.06%	0.0004	-17.4691
3	0.3865	0.0016	0.3584	-7.27%	0.0002	-860.0072	0.3821	-1.14%	0.0015	-101.0271
4	0.3351	0.0041	0.3310	-1.21%	0.0003	-49.8973	0.3352	0.04%	0.0037	1.0911
5	0.3381	0.0084	0.3319	-1.83%	0.0056	-30.7184	0.3380	-0.03%	0.0083	-0.4663
6	0.3175	0.1201	0.2974	-6.34%	0.0105	-8.3519	0.3171	-0.12%	0.1140	-0.1178
7	0.3605	0.0578	0.3542	-1.74%	0.0310	-4.7871	0.3604	-0.01%	0.0576	-0.0306
8	0.2993	0.0019	0.3098	3.50%	0.0013	226.1711	0.2993	0.00%	0.0019	0.1876
9	0.4122	0.0017	0.3936	-4.49%	0.0004	-518.7451	0.3801	-7.78%	0.0002	-919.4737
10	0.2952	0.0171	0.2884	-2.31%	0.0027	-19.6409	0.2948	-0.12%	0.0165	-0.7152
11	0.3114	0.0006	0.3157	1.37%	0.0003	331.0177	0.3110	-0.13%	0.0006	-26.5165
12	0.3701	0.9350	0.4052	9.48%	0.0650	1.8720	0.3707	0.17%	0.8947	0.0240
13	0.3122	0.0016	0.3259	4.40%	0.0008	382.6071	0.3125	0.09%	0.0016	5.8385
14	0.3380	0.0626	0.3438	1.73%	0.0114	4.5886	0.3381	0.04%	0.0604	0.0862
15	0.3468	0.0003	0.3405	-1.82%	0.0001	-914.9733	0.3431	-1.05%	0.0003	-409.2093

Note: Model 1 = No buyouts; Model 2 = Brewery B (Brand 2), Model 3 = Brewery B (Brand 9) buyout. PCM is the price-marginal cost margin, and Se is its standard error.

Table 11. Loyalty Impact on Margins: With and Without Brand 2 and 9 Buyouts

	Model 1: Base		Model 2: Brand 2 Buyout				Model 3: Brand 9 Buyout			
Brand	PCM	Se	PCM	%Δ	Se	t-ratio	PCM	%Δ	Se	t-ratio
1	0.3562	0.0507	0.3556	-0.17%	0.0311	-0.5215	0.3579	0.47%	0.0823	0.8644
2	0.3478	0.0006	0.3569	2.62%	0.0031	143.2926	0.3507	0.82%	0.0006	168.1539
3	0.3761	0.0005	0.3692	-1.85%	0.0004	-545.5948	0.3816	1.47%	0.0007	330.9010
4	0.3342	0.0025	0.3337	-0.13%	0.0021	-6.9790	0.3340	-0.05%	0.0037	-1.8095
5	0.3329	0.0163	0.3332	0.11%	0.0157	0.7731	0.3326	-0.09%	0.0171	-0.6147
6	0.2819	0.0202	0.2827	0.26%	0.0172	1.3784	0.2784	-1.26%	0.0220	-5.9403
7	0.4427	0.0732	0.4406	-0.46%	0.0707	-1.0023	0.4496	1.57%	0.0767	3.2776
8	0.3040	0.0014	0.3051	0.36%	0.0014	27.5238	0.3024	-0.54%	0.0015	-40.0821
9	0.4033	0.0006	0.4005	-0.69%	0.0006	-168.6268	0.3445	-14.58%	0.0002	-4,534.5916
10	0.2866	0.0018	0.2897	1.10%	0.0016	65.4559	0.2850	-0.54%	0.0019	-29.5112
11	0.3065	0.0040	0.3067	0.08%	0.0035	2.1655	0.3050	-0.47%	0.0060	-10.0039
12	0.4451	0.1542	0.4447	-0.11%	0.1301	-0.1165	0.4444	-0.17%	0.1558	-0.1688
13	0.3262	0.0007	0.3264	0.07%	0.0006	12.6996	0.3261	-0.04%	0.0008	-6.8000
14	0.3486	0.0097	0.3486	0.01%	0.0090	0.1133	0.3485	0.00%	0.0106	-0.0348
15	0.3305	0.0003	0.3275	-0.91%	0.0003	-376.5992	0.3364	1.80%	0.0004	581.8286

Note: Model 1 = No buyouts; Model 2 = Brewery A (Brand 2), Model 3 = Brewery B (Brand 9) buyouts.