

Estimating the Foreclosure Effect of Exclusive Dealing: Evidence from the Entry of Specialty Beer Producers*

Chia-Wen Chen[†]

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Abstract

This paper estimates an entry model to study the effect of exclusive dealing between Anheuser Busch and its distributors on rival brewers' entry decisions and consumer surplus. The entry model accounts for post-entry demand conditions and strategic spillover effects. I recover a brewer's fixed costs using a two-step estimator and find spillover effects on brewers' entry decisions. I find that a brewer has higher fixed costs at locations where Anheuser Busch employ exclusive distributors, but the effect is only statistically significant in certain local areas. The estimates also show that a brewer is less likely to enter a location that is farther from its brewery, has lower expected demand, or is smaller in store size. I implement counterfactual experiments to study the effect of banning exclusive contracts between Anheuser Busch and its distributors. The results show that the welfare improvement associated with banning such contracts is very small.

Keywords: Exclusive Dealing; Foreclosure; Entry; Beer industry.

JEL Classification Numbers: L42; L12; K21

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[†]Contact information: Department of Economics, National Taipei University, 151 University Road, San Shia District, New Taipei City, 23741 Taiwan. Email: cwwchen@mail.ntpu.edu.tw

1 Introduction

An exclusive dealing contract is a vertical agreement between a manufacturer and a distributor that forbids the distributor from promoting other manufacturers' products. Such a contract is controversial in competition policy, because of the potential foreclosure effects. For example, in 1997 Anheuser Busch launched an incentive program that provided discounts and other benefits to distributors that went exclusively with Anheuser Busch. At that time, many microbreweries complained they were being dropped by distributors due to this practice. The theory suggests that exclusive dealing can be efficiency-enhancing, because it encourages investment in manufacturer-distributor relationships, but it also suggests that exclusive dealing can be anticompetitive due to raising rivals' entry costs. In practice, the extent to which exclusive dealing enhances investments in a vertical relationship or dampens competition remains an empirical question to be explored.¹

This paper examines whether exclusive contracts between a dominant firm and its distributors have a foreclosure effect. More importantly, by quantifying the magnitude of diverted sales from a potential foreclosed firm to the dominant firm and the changes in consumer surplus, this paper looks at the motivations behind exclusive dealing and the welfare implications from banning such contracts. The empirical setting is the U.S. beer industry. Aside from mainstream mass producers (Anheuser Busch, Miller, and Coors), many entrepreneurs entered this industry during the microbrew movement that took off in the 1980s. Most microbreweries founded during this era were clustered on the West Coast along the "Interstate 5 corridor" from San Francisco to Seattle.² The boom ended with a shakeout in the late 1990s. One particular factor that may have contributed to the shakeout is Anheuser Busch's exclusive dealing program beginning in 1997, which eliminated one of the most dominant distribution vehicles from its rivals' choice set. Because there were other distributors available in the market, the extent of the foreclosure effect requires further examination. The main task of this paper is to model each specialty beer producer's entry decision for a location in a set-

¹The foreclosure argument led the courts to condemn exclusive dealing contracts between dominant firms and their distributors after the enactment of the Clayton Act in 1914. However, the Chicago school's defense of exclusive dealing started to prevail in the 1970s, and since then the courts have emphasized a rule of reason approach to such provisions. For earlier cases where the courts were against exclusive dealing, see *Standard Fashion Co. v. Magrane-Houston Co.*, 258 U.S. 346 (1922) and *Standard Oil Co. of California et al. v. United States*, 337 U.S. 293 (1949). For decisions favoring exclusive contracts, see *Tampa Electric Co. v. Nashville Coal Co.*, 365 U.S. 320 (1961) and *Beltone Electronics Corp.*, 100 F.T.C. 68 (1982). In Europe, a recent practice by Intel, which provided rebates and cash benefits to manufacturers and retailers in exchange for purchasing most of their products from Intel, was found to be anticompetitive by the European Commission and resulted in a €1.06 billion fine in 2009.

²Tremblay and Tremblay (2005) provide an excellent treatment on the history of the microbrewery movement. Most specialty beer producers remain microbreweries, but some of them (Boston Beer Company and Sierra Nevada Brewing Company) have grown successfully and are no longer microbreweries.

ting where their fixed entry costs may be affected by (1) exclusive dealing between Anheuser Busch and its distributors and (2) spillover effects resulting from other entrepreneurs' entry decisions. I then take the estimates from the analysis to perform counterfactual experiments.

This paper contributes to the literature and policy discussion of exclusive contracts in several ways. First, even though the theoretical literature on exclusive dealing has presented many fruitful insights, the effect of exclusive dealing is still ambiguous. Empirically, the data availability problem and the fact that a distributor's enrollment into an exclusive program and a brewer's entry decision are both endogenous to unobserved market conditions have resulted in few empirical studies in this area. For example, all things being equal, a distributor that serves an area with a higher demand for domestic products is more likely to enroll into such a program compared to another one that serves an area with a lower demand for domestic products. In addition, demand conditions directly affect domestic specialty beer producers' entry decisions into a market and result in an endogeneity problem. To this end, I collect entry data of specialty beer producers and address the endogeneity problem by controlling for consumers' demand for beer products in a setting of differentiated products, which is different from most previous empirical works in this area (Sass 2005; Rojas 2010).³ I show that without accounting for the endogeneity of the exclusivity decision, estimates of exclusive dealing on the probability of entry are biased upwards.⁴

Another major contribution of this paper is to take advantage of demand-side estimates to conduct counterfactual experiments. I study whether a foreclosure-based motivation alone can rationalize Anheuser Busch's continuing support for exclusive contracts, as well as to what extent the consumer surplus would increase if such contracts were banned. Compared to a previous work (Asker 2005) that tests the foreclosure hypothesis and focuses mainly on the supply side, this paper quantifies the potential benefits on consumer surplus from banning exclusive dealing by removing the foreclosure effect and expanding consumers' choice sets, which is not directly addressed in the previous literature (Sass 2005; Rojas 2010; Asker 2005; Chen 2013).⁵ From an antitrust policy's perspective, such an estimate of consumer surplus is

³Sass (2005) studies a cross-sectional survey of 381 beer distributors in 1997 and finds that exclusive dealers on average generate higher prices and larger sales for their suppliers, which is more consistent with the incentive-based theory. Rojas (2010) looks at a scanner dataset of 63 metropolitan areas from 1988 to 1992 and uses average exclusive dealing intensity that a brand has in other cities in the same region as an instrumental variable for the exclusive dealing decision. He finds that exclusive dealing increases consumers' willingness to pay and provides a cost advantage for firms.

⁴Another possible source of endogeneity is the extent to which a distributor can effectively increase local demand over its products due to legal restrictions. For example, Sass (2005) considers state laws banning outdoor advertising of malt beverages and argues that these laws influence participation in the exclusive program across states. In this paper, I do not address this kind of endogeneity because this paper's empirical setting is entirely in Northern California, and so the legal environment is more homogeneous than the one considered in Sass (2005).

⁵When products are differentiated, the introduction of new products with quality improvements can

crucial in evaluating vertical restraints in the marketplace. I show that even when efficiency gains from exclusive contracts are not acknowledged *and* even when exclusive contracts have raised rivals' entry costs in some local areas, if the antitrust agency adopts a consumer surplus standard (as it currently does) rather than a total welfare standard to evaluate vertical restraints, then policy intervention in banning such contracts may be ineffectual.⁶

Inferences about the foreclosure effect through direct comparisons of entry patterns can suffer from omitted variable bias, because post-entry market outcomes may differ across locations and firms. Thus, I estimate the demand for beer to construct counterfactual expected post-entry sales. With the panel structure of the dataset, I can control for invariant brand and location fixed effects. I estimate the demand system using a nested logit model. The model allows the substitution patterns to vary based on product segments (e.g., country origin or style of beer) and has more reasonable substitution patterns than a simple logit model.⁷

This paper also builds on empirical studies that estimate static entry games. Bresnahan and Reiss (1991) show how to estimate an equilibrium model of entry for symmetric firms with data on market characteristics and the number of firms. Similar to Bresnahan and Reiss (1991), I allow both total variable profits and fixed costs to depend on the number of brewers. Moreover, given that I observe a pool of global potential entrants, along with their actual sales and entry patterns, my model allows heterogeneous brewers to produce differentiated products with different fixed costs.⁸

Following recent developments in estimating strategic games (Seim 2006; Augereau, Greenstein, and Rysman 2006; Ellickson and Misra 2008; Sweeting 2009; Bajari, Hong, Krainer, and Nekipelov 2010), I model the entry behavior of specialty beer producers using an incomplete information framework that helps to incorporate a large number of players in the game. In this setup, a brewer's entry decision depends on the expected market profitability and private information. I estimate the model following a two-step estimation procedure, similar to that of Ellickson and Misra (2008) and Bajari, Hong, Krainer, and Nekipelov

improve consumer surplus significantly, and counterfactual analysis based solely on a single dimension (the average price or an aggregate sales measure) may underestimate the foreclosure effects on consumer welfare.

⁶I thank anonymous referees for directing me to a consumer surplus approach and for pointing out that if Anheuser Busch adopts an exclusive contract for efficiency reasons, then equilibrium prices are likely to be lower. If this is the case, one can interpret the result in this paper as that the collateral damage in blocking some craft breweries from operating is small.

⁷The nested logit model has wide applications in estimating transportation and energy demand and is also applied to other industries such as automobiles, movies, home videos, and banking (Goldberg 1995; Einav 2007; Chiou 2008; Dick 2008). In particular, Ho, Ho, and Mortimer (2012) estimate a nested logit model in the context of empirical analyses of vertical contracts.

⁸Berry (1992) first estimates a model of entry in the airline industry that allows for firm heterogeneity in fixed costs. This present paper exploits data on beer prices and sales and allows a firm's variable profits to also depend on rivals' identities.

(2010), and use the demand estimates to control for post-entry sales. The estimation is done in three steps. The first step estimates the equilibrium entry probabilities implied by the model. The second step estimates the demand for beer. Using the demand estimates and the beliefs about rivals' entry probabilities, I construct expected post-entry sales. The third step then plugs the above estimates into the likelihood function to recover a brewer's fixed costs.

Economic theories vary in their explanations of exclusive contracts. Traditionally, the Chicago school has argued that exclusive dealing cannot be used as a device for monopolization (Posner 1976; Bork 1978): if the sole purpose of exclusive contacts were to restrict competition, then downstream buyers would never sign them in the first place, because doing so would only lower the potential total surplus. Incentive theories show that exclusive dealing enhances incentives for investment when investments made by parties in a bilateral relationship have external effects on outside parties (Marvel 1982; Klein and Murphy 1988; Besanko and Perry 1993; Martimort 1996; Bernheim and Whinston 1998; Segal and Whinston 2000a).⁹

Anticompetitive arguments focus on the foreclosure effect of exclusive dealing. In this literature, manufacturers either sign exclusive contracts with lower-cost buyers, trying to raise their rivals' costs, or with a large number of buyers, trying to foreclose the market directly when facing minimum economies of scale.¹⁰ Segal and Whinston (2000b) point out that whether manufacturers can successfully carry out the above "naked exclusion" scheme depends on how well they are able to exploit the coordination problem faced by buyers.¹¹

Most previous studies of exclusive dealing in the U.S. beer industry find efficiency reasons more consistent with empirical evidence (Sass 2005; Rojas 2010; Chen 2013). Specifically, using variation generated from distribution contract changes, Chen (2013) finds that a brand's market share is higher when the brand's distributor has fewer external trading opportunities.¹² Nevertheless, most of the above papers assume products are homogeneous and do

⁹In fact, Segal and Whinston (2000a) show that restricting a distributor's external trading opportunities increases the level of investment when a distributor's investment has a substitutable effect, i.e., investment devoted to one brand hurts the value of other brands in the same distribution network; or when a manufacturer's investment has a complementary (positive spillover) effect.

¹⁰Salop and Scheffman (1983), Aghion and Bolton (1987), Rasmusen, Ramseyer, and Wiley (1991), and Bernheim and Whinston (1998) provide theoretical foreclosure arguments for exclusive dealing. For a recent theoretical treatment on vertical exclusion without an explicitly written exclusive contract, see Asker and Bar-Isaac (2014).

¹¹Simpson and Wickelgren (2007), Abito and Wright (2008), and Doganoglu and Wright (2010) also provide settings that allow exclusive dealing to achieve inefficient outcomes. Simpson and Wickelgren (2007) and Abito and Wright (2008) consider the case when buyers compete, and Doganoglu and Wright (2010) study exclusive contracts under the network effect.

¹²Chen (2013) exploits a distribution deal between Anheuser Busch and InBev in 2007 to study the effect of allowing more brands to have access to exclusive distribution networks on brand level outcomes in Northern

not speak to the effect of exclusivity on consumer surplus and its foreclosure effect when products are differentiated, which is the main focus of this paper.

There is a growing empirical literature on estimating industry models with vertical restraints (in particular, Asker 2005; Ho, Ho, and Mortimer 2012; Crawford and Yurukoglu 2012; Lee 2013; Conlon and Mortimer 2013; Sinkinson 2014).¹³ More closely related to my paper is Asker (2005), who also studies exclusive contracts in the beer industry and takes a structural approach in a differentiated product framework to recover the costs incurred and the promotional efforts made of distributors in exclusive and less exclusive markets. Asker (2005) finds that distributors in less exclusive markets are not more efficient than distributors in exclusive markets and rejects the foreclosure hypothesis. Even though the main focus of Asker (2005) is on the supply side, the beer products in his analysis are mainly produced by domestic or foreign mass-producers, which are unlikely to be forced out of the market due to exclusive dealing in the first place. By contrast, the structural approach in this paper allows me to directly look at the entry patterns of firms that are more likely to be foreclosed, and more importantly, to estimate the effect of banning exclusive dealing on consumer surplus.

I find that the demand for beer is elastic and that the price of a specialty beer product is lower at locations closer to its producer's establishment. Controlling for prices, I also find that consumers enjoy a product more if it is locally brewed. These findings explain why most specialty beer producers are not present in every location. I then take the demand estimates to the model of entry. When strategic interactions are not allowed in the model, exclusive dealing shows no impact on a specialty beer producer's entry decision. Once strategic interactions are allowed, I find that in some local markets, a store with an Anheuser Busch exclusive distributor is associated with a reduction of 6 percentage points (21%) in a specialty beer producer's entry probability, suggesting a foreclosure effect due to exclusive dealing. I also show that a specialty beer producer has lower fixed costs at a location where the number of rivals is larger. The result implies that firms can benefit from clustering their strategic decisions, which is similar to the findings in previous studies that estimate strategic effects, such as Ellickson and Misra (2008), Sweeting (2009), Bajari, Hong, Krainer, and Nekipelov (2010), and Vitorino (2012).

Finally, I use demand estimates to carry out counterfactual experiments that remove exclusive dealing. The magnitude of the foreclosure effect is too small to claim that Anheuser

California. The result suggests InBev brands' market shares to be higher once they were allowed access to Anheuser Busch's exclusive distribution networks. In addition, other brands' market shares were lower when their distributor gained InBev products. The results are consistent with an incentive-based explanation for firms preferring exclusive contracts.

¹³For a thorough review of earlier empirical studies on vertical integration and vertical restraints, see Lafontaine and Slade (2007) and Lafontaine and Slade (2008).

Busch’s exclusive dealing program is entirely driven by a foreclosure motivation. Thus, the decrease in entry probabilities in some local markets is more likely to be a side-effect of exclusive contracts. I do not find much change in welfare due to banning exclusive dealing contracts between Anheuser Busch and its distributors. In fact, I show that adding more specialty brands does not provide much benefit to consumers: when exclusive dealing is removed in a market, the change in aggregate consumer welfare is only \$15 per store per quarter. This result, complemented by the findings from Sass (2005), Rojas (2010), and Chen (2013) supporting the efficiency motives behind exclusive dealing, reinforces that banning exclusive contracts in the current beer industry is hardly welfare improving.

This paper proceeds as follows. I begin by examining the industry and the data. I then describe the model of demand and entry behavior. Next, I discuss the corresponding estimating procedures and identification issues. Finally, I present the empirical results and discuss the implications and potential future research.

2 Industry Background

The U.S. beer industry has nearly 3,000 brewing establishments and accounts for approximately \$100 billion in annual sales.¹⁴ During the sample period of the data (2006-2008), Anheuser Busch, Miller, and Coors collectively held nearly 80% of the market, with Anheuser Busch being the most dominant firm in the industry (50% market share).¹⁵ Since the end of Prohibition, the industry has been heavily regulated by state laws, under which vertical integration between manufacturers, distributors, and retailers is not allowed. The vertically-separated “three-tier system” (manufacturing, distribution, and retailing) is one of the main features of the beer industry.¹⁶

Beer manufacturers rely on distributors to transport and rotate their products in local markets so as to guarantee product availability and freshness. Distributors are also responsible for point-of-sale promotional activities. Building and maintaining good relationships with distributors to receive adequate promotional support are thus vital to a brewer’s success, especially when it comes to entering a new market or launching a new advertising campaign. While a brewery would prefer its distributors to be exclusive and to devote as much promotion efforts to its products as possible, it may not be in the best interest of dis-

¹⁴Statistics are obtained from the Beer Institute website.

¹⁵The industry has become even more concentrated after two mergers in 2008. Miller and Coors formed a joint venture. Anheuser Busch then merged with InBev, the biggest brewer in Europe.

¹⁶The extent to which administrators regulate alcoholic beverages vary by state and in alcohol content. For beer, most states regulate private licensed retailers and distributors and adopt the three-tier system to restrict private ownership across different tiers. For wine and spirits, several so-called *control* states buy alcohol directly from manufacturers and act as monopolies in the wholesale and retail distribution tiers. For recent studies that examine possible welfare losses created by state regulations on alcoholic beverages, see Seim and Waldfogel (2013), Miravete et al. (2014), and Conlon and Rao (2014).

tributors to build a relationship with just one brewery. To maintain a stable cash stream and warehouse/route efficiency, a distributor is more likely to prefer having all the best-selling products in its brand portfolio. Conflicts of interest handling multiple brands from competing breweries at the same time often render lower promotional efforts than what would be considered optimal from a brewer’s perspective. One of the main efficiency arguments for exclusive dealing is to create a loyal vertical relationship and enhance a distributor’s promotional investments.¹⁷

The beer industry is divided into three segments: domestic macro brands, imported brands, and specialty brands. The top three domestic mass-producers (Anheuser Busch, Miller, and Coors) focus on “regular domestic beer,” which are mainstream, lower-priced, light lager products with large package size options. Imported brands include products (usually well-established ones) from foreign countries that are typically priced higher than domestic beer. The last category, domestic specialty brands, refers to domestic brands that emphasize flavor and taste. According to Tremblay and Tremblay (2005), specialty beer producers emulate the business model of wineries in Northern California by providing “boutique” products in small batches. They advocate the taste of “real beer” and encourage consumers to choose craft beer instead of beer that contains a high concentration of adjuncts and that lacks flavor. Sierra Nevada Brewing and Boston Beer Company are pioneers of the microbrewery movement during the 1980s and are the most successful and nationally known companies in this segment.

Most firms of specialty beer products enjoy a higher market share in geographic areas closer to their brewery, which is consistent with Bronnenberg et al. (2009).¹⁸ Taking Sierra Nevada Brewing as an example, while it has a 1% market share across all stores in the sample data, in Chico, California where its brewery is located, it has an average 8% market share, putting it very close to Anheuser Busch’s market share (9% in Chico, 10% overall). Because Sierra Nevada is so successful in Chico, one might presume that it would be difficult for other microbreweries to break into store shelves there. However, the store that carries

¹⁷Both manufacturers and distributors can make investments to enhance the value of their relationships. For example, a brewer can provide training programs on consumer behavior for distributors. Similarly, a distributor can make efforts to secure better shelf space for its brewers. These investments not only increase the value of vertical relationships, but also alter bargaining positions between the parties involved. In the former case, if training lessons are not specific to the relationship, then providing training lessons may hurt a brewer’s ex-post bargaining power. On the contrary, if promotional efforts are tailored to a brewer, then such investments can hurt a distributor’s ex-post bargaining power. Segal and Whinston (2000a) point out that when investments have external values and are not contractible, exclusivity can lead to a higher level of investments under some circumstances. Therefore, an important motivation for exclusive dealing is to address the incentive problems in vertical relationships.

¹⁸Bronnenberg et al. (2009) find an early entry advantage for several consumption goods, such as beer, coffee, and mayonnaise. The order of entry into a market is correlated with the rank of market share and perceived product quality.

the most number of California specialty beer brands is also in Chico (39 brands per store on average, compared to 24 brands per store on average). In this specific case, the entry of a rival microbrewery does not seem to create an entry barrier for other firms. In the empirical setting, a potential spillover effect is taken into account by allowing fixed costs to depend on the expected number of specialty beer producers. I also allow a “locally brewed” effect when I estimate consumers’ demand for beer and consider the possibility that the distance between a grocery store and a product’s brewery does affect the entry pattern of specialty beer producers.¹⁹

In response to consumers’ demand for specialty brands, top domestic mass-producers acquired several microbreweries and introduced their own brands of specialty beer in the late 1990s. Anheuser Busch launched an incentive program during the late 1990s, called “100 percent share of mind.” The program provided discounts and other benefits for distributors in exchange for exclusivity with Anheuser Busch. As a result, many brands of other breweries were dropped by their Anheuser Busch distributors. Figure 1 illustrates the impact of Anheuser Busch’s exclusive dealing program in the three-tier system. In panel (a), specialty and imported products are allowed to share distribution networks with Anheuser Busch. It presents that Microbrewery 1 chooses to hire an Anheuser Busch distributor while Microbrewery 2 chooses to work with a Miller distributor. In panel (b), because the Anheuser Busch’s distributor is exclusive, all of the specialty and imported products that are not affiliated with Anheuser Busch are squeezed out of Anheuser Busch’s distribution network and are crowded out to other distribution networks.

Given that the other two leading brewers (Miller and Coors) rarely share distribution networks with Anheuser Busch, exclusive dealing cannot completely foreclose all distribution channels. Nevertheless, Anheuser Busch’s exclusive dealing program may raise distribution costs for potential entrants by (1) enhancing rival distributors’ bargaining power and by (2) forcing rival brewers to use less efficient distributors, thus reducing the likelihood of entry events. When most of the specialty and imported brands from competing breweries are crowded out into one distribution network, it enhances the distributor’s bargaining power, which raises the entry barrier for a prospective microbrewery into a new market. The crowding-out effect also intensifies incentive conflicts within a distribution network and may drive a distributor’s promotional efforts of a brand further away from its optimal level. Finally, exclusive dealing may raise rivals’ costs by forcing them to team up with smaller or less efficient distributors, because Anheuser Busch is the biggest competitor in the industry and its distribution networks are often viewed as a superior promotional vehicle due to its

¹⁹The dummy variable “locally brewed” is set to be 1 when the brewery is located within a 10-mile radius of a store.

economies of scale in distribution.²⁰

3 Data

The scanner dataset is provided by Nielsen. The dataset contains weekly price and sales data of the malt beverage category for all stores of a major grocery chain in Northern California from April 2006 to April 2008. The original dataset comes at the Universal Product Code (UPC) level, which includes all sales records from all packaging options for all brands. I collapse the data to a quarterly brand level to take into account that some specialty brands may have very little (or even no) sales within a week or a month at the UPC level, and because the demand estimates from quarterly data are more likely to be suitable for policy analysis.²¹ I search a product’s website for information on the product’s country of origin (domestic or foreign) and product ownership. For domestic specialty beer producers, I calculate the distance from a store to the firm’s nearest establishment (brewery or brewpub) using Google’s map service. I also collect data on local contract rents at the zip code area level (“Gross Rent”) from Census 2000 as a further control for a location’s fixed costs.²²

The scanner dataset also includes a product category variable, made up of light, lager, ale, stout/porter, malt liquor, and non-alcoholic (alcohol by volume of less than 0.5%) beer, and three categories for alternative malt beverage. Due to product similarity, I assign all alternative malt beverages to one style (alternative) and generate a new style specifically for domestic mainstream lager products.²³ In this way, I end up with eight different product styles.

Data on Anheuser Busch exclusive distributors and their territories are from the California Beer and Beverage Distributors (CBBB) annual member directories. Each directory contains a list of each member distributor’s representative brewers and the counties it operates within California.²⁴ Table 1 lists some typical entries from the 2006 CBBB directory, with California specialty beer producers that are matched to the scanner dataset denoted by bold type. Most distributors represent at least one of the domestic macro brewers (Anheuser

²⁰Economies of scale are important in distribution. For example, Bump Williams, an IRS industry analyst, notes that “there’s nobody better than these three networks (Anheuser Busch, Coors, and Miller). They can get these beers on shelves overnight.” See Kesmodel (2007).

²¹I divide total revenue during a quarter by the number of six-packs sold during a quarter to calculate a product’s price at the quarterly level. When products are storable goods, using temporary price promotions in weekly data to identify price elasticities can lead to an overestimation of price sensitivity (Hendel and Nevo 2006).

²²In Census 2000, “Gross Rent” is defined to include “contract rent and estimated average monthly cost of utilities (electricity, gas, water, and sewer) and fuels (oil, coal, kerosene, wood, etc.) if these are paid by the renter.”

²³I define a product to be domestic mainstream lager if it is a lager product from one of the three biggest domestic competitors in the industry and has large package size options.

²⁴The 2006 and 2007 trade directories were provided by local distributors.

Busch, Miller, and Coors) and also carry other imported brands and domestic specialty brands. In addition, there are independent distributors that do not carry any brands from domestic macro firms, but collect a large number of specialty or imported brands.

3.1 Store Attributes

Table 2 provides the attributes of stores that carry the highest/lowest number of California specialty beer producers. The top 10 stores with the highest number of California specialty beer producers have on average 12.3 firms, of which the minimum quantity of six-packs sold per store during a quarter is 15.4 units. On the other hand, the bottom 10 stores with the lowest number of California specialty beer producers have on average 5.4 firms, of which the minimum quantity of six-packs sold per store during a quarter is 43.4 units. The minimum of six-packs sold per store can be interpreted as a rough index for a store's entry threshold, and it appears that stores with more firms have a lower entry threshold (as opposed to having a bigger market). Moreover, because it is unlikely that price-cost margins would increase with the intensity of retail competition, variation in entry thresholds is most likely driven by variation in fixed costs.

Figure 2 shows geographic areas that include stores from the grocery chain studied in this paper and also presents Anheuser Busch distributors' exclusivity status. Table 3 shows the means and standard deviations for store attributes. I provide summary statistics for stores with Anheuser Busch non-exclusive distributors and stores with Anheuser Busch exclusive distributors. About 17% of the stores are located in counties in which Anheuser Busch has exclusive distributors. On average, these stores have more California specialty beer producers entering the markets and generate more sales. Therefore, it appears that exclusive dealing has no anticompetitive effect on a firm's entry decision. However, Table 3 also shows that store attributes and demographics differ across the two types of stores. Inferences about the foreclosure effect directly from Table 3 can thus suffer from omitted variable bias. For example, suppose Anheuser Busch is more likely to hire exclusive distributors where the demand for beer is higher. If higher demand also leads to more entrants, then our simple comparison will push the exclusive effect to be biased upward (less foreclosure).

To deal with the potential problem from omitted variable bias, the empirical strategy to identify the exclusive effect in this paper is to first control for firm specific post-entry sales by estimating the demand for beer. In addition, I control a firm's fixed entry costs at a location by using the size of the store's physical selling area, gross rents in the store's zip code area, the distance between a store and a product's brewery, and the expected number of rivals.

3.2 Entry Variation

There are 32 specialty beer producers in the data, and 26 of them are California-based firms. Many firms cluster their breweries around the San Francisco Bay Area and Sacramento. I tabulate their entry patterns in Table 4 to show variation in the data. From the table, firms vary by the number of stores they enter. Some firms enter all 229 locations, but then there are also firms that are more local and have sales at fewer than 10 stores. Moreover, breweries from other states are more likely to be well-established ones and on average enter more stores than local firms. As will become clearer in the empirical estimation, I use the distances from breweries to stores as exclusion restrictions to identify the strategic entry effect. Because the distances from stores to the main breweries of non-California firms are extremely far, I only consider the entry decisions of California specialty beer producers in the empirical section.

4 Model

4.1 Demand Side

A consumer's decision problem for purchasing a beer product is modeled using a discrete choice model. Each consumer is presented with different types of beer with various quality levels and is assumed to decide whether or not to purchase one unit of beer.²⁵ Consumers are differentiated by the markets where they live, and their preferences for different types of beer. In particular, consumer c purchasing product j in market t receives a mean utility term δ_{jt} and an idiosyncratic term ν_{cjt} . The utility from consuming beer is:

$$u_{cjt} = \delta_{jt} + \nu_{cjt}.$$

When ν_{cjt} is independently distributed with Type 1 extreme value distribution, the model is a logit model that offers easy tractability. Nevertheless, the logit specification is well-known to produce unrealistic substitution patterns driven by market shares instead of product similarities.

To allow for more plausible substitution patterns, the independence assumption for ν_{cjt} can be relaxed by introducing random coefficients on product attributes. In particular, a nested logit model allows ν_{cjt} to include correlated shocks from different market segments, and so a consumer who purchases a certain type of beer will be more likely to substitute it for products with similar attributes. Similar to Chiou (2008), I use a four-level nested structure, which is shown in Figure 3. The nesting is consistent with the data that have a category variable (beer style) and the industry practice that uses products' country of origin (domestic/imported) for market segmentation. I allow the correlated shocks for consumer

²⁵A unit is defined as a six-pack of beer (72 ounces in total).

c to come from three possible sources: a shock, ζ_b , for all beer products; a shock, ζ_d , for all products in domestic group d ; and a shock, ζ_g , for all products under a specific domestic/foreign beer style g . Following Cardell (1997), the error structure of a nested logit model can be decomposed as:

$$\nu_{cjt} = \zeta_{cb} + \lambda_3 \zeta_{cd} + \lambda_2 \lambda_3 \zeta_{cg} + \lambda_1 \lambda_2 \lambda_3 \omega_{cjt},$$

where ω is independent and identically distributed with Type 1 extreme value, and the correlated shocks ζ are from a distribution, such that if ω is distributed with Type 1 extreme value, then $\zeta + \lambda\omega$ is also distributed with Type 1 extreme value when $0 < \lambda \leq 1$.

The λ terms measure how products in the same category are independent of each other: when all λ s approach to 1, all shocks are independent and the model reduces to a simple logit model. The nested logit model is basically a random coefficients model with coefficients on group dummy variables, which allows the correlation to be higher within a group and still preserves the closed-form tractability similar to a logit model.

The mean utility of product j in market t is specified to be:

$$\delta_{jt} = x_j \beta - \alpha p_{jt} + \gamma A_{jt} + \xi_{jt},$$

where x_j includes observed fixed product attributes such as alcohol by volume and calories, p_{jt} is the price, and ξ_{jt} is the unobserved (by an econometrician) advantage for brand j in market t . To allow preferences for local products, I include a dummy variable A_{jt} , which is equal to one if the product is locally brewed (the distance between a store and a brand's brewery is less than 10 miles). In the estimation, I include brand, store, and quarter dummies to absorb invariant product and market attributes. Consumers are allowed to not purchase any product presented in the model. The mean utility from purchasing an outside good is normalized to zero.

The mean utility can be recovered using Berry (1994)'s inversion technique:

$$(1) \quad \ln(s_{jt}) - \ln(s_{0t}) = x_j \beta - \alpha p_{jt} + \gamma A_{jt} + (1 - \lambda_1 \lambda_2 \lambda_3) \ln(s_{j|g}) + (1 - \lambda_2 \lambda_3) \ln(s_{g|d}) \\ + (1 - \lambda_3) \ln(s_{d|b}) + \xi_{jt},$$

where s_{jt} and s_{0t} are the respective market shares for product j and the outside good, $s_{j|g}$ is the market share for brand j as a fraction of the market share of group g , $s_{g|d}$ is the market share for group g as a fraction of the market share of the domestic/foreign product group, and $s_{d|b}$ is the market share for the domestic/foreign product group as a fraction of the market share of all beer products.

The market share of product j is the probability that product j is chosen by consumers. In a nested logit model, there is a closed-form solution for the choice probability. First, I decompose the choice probabilities (market shares) into conditional probabilities (omitting subscript t):

$$(2) \quad s_j = s_{j|g} \times s_{g|d} \times s_{d|b} \times s_b,$$

where s_b is the probability of choosing the inside good. Following McFadden (1978), the inclusive values for each nest are defined as

$$I_{1g} \equiv \log \left(\sum_{j \in G_g} \exp((x_j \beta - \alpha p_{jt} + \gamma A_{jt}) / \lambda_1 \lambda_2 \lambda_3) \right)$$

$$I_{2d} \equiv \log \left(\sum_{g \in D_d} \exp(\lambda_1 I_{1g}) \right)$$

$$I_3 \equiv \log \left(\sum_{d \in B} \exp(\lambda_2 I_{2d}) \right).$$

I then express the conditional probabilities as:

$$(3) \quad \begin{aligned} s_{j|g} &= \frac{\exp((x_j \beta - \alpha p_{jt} + \gamma A_{jt}) / \lambda_1 \lambda_2 \lambda_3)}{\sum_{k \in G_g} \exp((x_k \beta - \alpha p_{kt} + \gamma A_{kt}) / \lambda_1 \lambda_2 \lambda_3)} \\ s_{g|d} &= \frac{\exp(\lambda_1 I_{1g})}{\sum_{l \in D_d} \exp(\lambda_1 I_{1l})} \\ s_{d|b} &= \frac{\exp(\lambda_2 I_{2d})}{\sum_{m \in B} \exp(\lambda_2 I_{2m})} \\ s_b &= \frac{\exp(d_q z_q + d_s z_s + \lambda_3 I_3)}{1 + \exp(d_q z_q + d_s z_s + \lambda_3 I_3)}, \end{aligned}$$

where z_q and z_s are the respective dummy variables for quarters and stores, and d_q and d_s are the corresponding coefficients that do not vary for all inside goods. Moreover, G_g , D_d , and B are the sets of all products in domestic/foreign beer style group g , in domestic/foreign group d , and in the inside good group B , respectively. Combining (2) and (3) gives the choice probability of product j as a function of model parameters.

4.2 Entry Game

Following the setup in Bajari, Hong, Krainer, and Nekipelov (2010), I model a specialty beer producer's entry decision using a static discrete choice model with private information. In

each period, N potential entrants make entry decisions to different locations simultaneously.²⁶ Let a_i denote firm i 's entry decision, where a_i is equal to one if it enters, and a_i is equal to zero if it does not enter. Let a_{-i} denote rivals' action profile $(a_1, \dots, a_{i-1}, a_{i+1}, \dots, a_N)$. Let s denote public state variables, commonly known by all firms and econometricians, and let ϵ_i denote firm i 's private information. Following the literature, I assume private information shocks are independent and identically distributed from a known distribution.

Firm i 's period utility function is a function of its own action, a_i ; rival firms' action profile, a_{-i} ; state variables, s ; its private information, ϵ_i ; and model parameters, θ . The period utility function can be expressed as:

$$u_i(a_i, a_{-i}, s; \theta) = \pi_i(a_i, a_{-i}, s; \theta) + \epsilon_i(a_i),$$

where

$$\pi_i(a_i, a_{-i}, s; \theta) = \begin{cases} V_i(a_{-i}, s; \theta) - F_i(a_{-i}, s; \theta) & \text{if } a_i = 1 \\ 0 & \text{if } a_i = 0, \end{cases}$$

and $V_i(a_{-i}, s; \theta)$ and $F_i(a_{-i}, s; \theta)$ are firm i 's variable profits and fixed costs, respectively. In the specification, both variable profits and fixed costs depend on rivals' actions.²⁷ I assume demand shocks are realized after a firm's entry decisions, which is a standard approach used in the literature.²⁸ Under this assumption, firms receive demand shocks for each brand after they have committed to their product choices. Still, when product entry is endogenous, the obtained price elasticities are likely to be biased and misleading (Musalem and Shin 2013). I return to the discussion of endogenous product entry in the appendix.

Since firm i does not observe its rivals' private shocks, firm i 's decision rule is a function of state variables and its own private information. Therefore, the entry probability of firm i conditional on state variables is an integral of the decision rule over all possible values of ϵ_i

²⁶It is worth noting that in reality, an entry decision is never determined solely by brewers, but rather is an outcome jointly determined by the actions of brewers, distributors, and retailers. In fact, when interested in a market, a brewer needs to contact distributors in that area to see whether a distribution contract can be reached. Even though a brewer assigns a distributor in an area, this does not guarantee its products' penetration to all of the distributor's retail accounts. A brewer still needs to constantly work with the distributor and different retailers to make sure its products are properly promoted. Because a full-fledged model of the search and negotiation process between manufacturers, distributors, and retailers is out of the scope of this paper, I assume that manufacturers know the demand conditions and fixed costs involved in entering a market prior to their entry decision and make decisions accordingly.

²⁷In the current static setup, I cannot distinguish between sunk entry costs and fixed costs that are not sunk. The estimated fixed costs are a combination of both types of costs.

²⁸For instance, in Eizenberg (2014)'s study of the home personal computer market, even though product line configurations are allowed to be endogenous, firms are assumed to only observe the realization of demand shocks after they make product line configuration decisions. As discussed in Eizenberg (2014), this assumption can be further relaxed to allow firms to forecast systematic demand effects, as long as these effects are controlled for in the demand estimation (using store or brand fixed effects).

weighted by the density of ϵ_i .

Let $\sigma_i(a_i = 1|s)$ denote firm i 's entry probability conditional on state variables, and let $\sigma_{-i}(a_{-i}|s) = \prod_{j \neq i} \sigma_j(a_j|s)$ denote the probability of an action profile from rivals. Firm i chooses to enter a location if:

$$\sum_{a_{-i}} \pi_i(a_i = 1, a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s) + \epsilon_i(a_i = 1) > \epsilon_i(a_i = 0).$$

If we assume private information shocks are distributed with Type 1 extreme value distribution, then equilibrium entry probabilities from a Bayesian Nash Equilibrium are:

$$(4) \quad \sigma_i(a_i = 1|s) = \frac{\exp(\sum_{a_{-i}} \pi_i(a_i = 1, a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s))}{1 + \exp(\sum_{a_{-i}} \pi_i(a_i = 1, a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s))}, \text{ for } i = 1, \dots, N.$$

Equation (4) implies that given any set of parameters, the optimal entry probabilities need to satisfy a fixed point condition. In his work studying a dynamic programming model, Rust (1987) shows one can estimate an equation similar to equation (4) with a nested fixed point algorithm (NFXP). Specifically, for any set of parameters, a NFXP algorithm searches for the implied fixed point (conditional choice probabilities) in (4) to construct the likelihood. Thus, it requires solving a fixed point for many values of parameters. Moreover, constructing the likelihood under the case of multiple equilibria requires specifying an equilibrium selection mechanism.

To reduce the computation burden from a NFXP algorithm, Aguirregabiria and Mira (2002) propose a two-step approach. Instead of assuming the equilibrium is unique or employing a specific equilibrium selection mechanism, the two-step approach only requires that the equilibrium played in the data does not switch.²⁹ In the first step, a researcher estimates the consistent choice probabilities conditional on observed states. In the second step, the researcher then recovers the parameters of the utility function conditional on these choice probabilities.³⁰

I now turn to the specifications of the variable profits and the fixed costs in order to estimate the model. For each rival action profile, there is a corresponding variable profit

²⁹This assumption is less restrictive when more data on specific markets are available. For example, with detailed cross-sectional data, Ellickson and Misra (2008) adopt a two-step estimator and estimate each firm's beliefs by pooling observations with similar characteristics across markets. In contrast, I employ a panel dataset that allows me to estimate the entry probabilities of rivals market-by-market, and so the assumption made in this paper is even weaker than Ellickson and Misra (2008).

³⁰The two-step approach leads to many applications in dynamic games such as those in Bajari, Benkard, and Levin (2007) and Pakes, Ostrovsky, and Berry (2007).

$V_i(a_{-i}, s; \theta)$ for firm i when it enters a market. I specify $V_i(a_{-i}, s; \theta)$ as:

$$V_i(a_{-i}, s; \theta) = m_i S_i(a_{-i}, s; \theta),$$

where $S_i(a_{-i}, s; \theta)$ is the total units of sales for firm i (in terms of the number of six-packs), and m_i is firm i 's variable profits per unit of sales. Total units of sales of firm i are:

$$S_i(a_{-i}, s; \theta) = \sum_{j \in \mathcal{F}_i} M_s s_j(a_{-i}, s; \theta),$$

where \mathcal{F}_i is the set containing all products from firm i , s_j is the market share for product j , and M_s is the potential market size of store s . Note that in this specification a firm's average variable profit does not vary according to the identity of rivals or locations. The underlying assumptions are that the number of specialty beer producers does not have immediate effects on the equilibrium prices upon entry and a firm's average variable profit is constant across stores. Given that specialty beer producers are fringe firms in each market, it is not unreasonable to assume that the presence of rivals in this segment does not have much effect on other firms' pricing strategy and that these firms have relatively the same margins across stores.

Similar to Bresnahan and Reiss (1991), I allow later entrants to have different fixed costs than incumbents have and use the following specification for the fixed costs:

$$(5) \quad F_i(a_{-i}, s; \theta) = d_i + s' \eta + \tau \sum_{j \neq i} 1\{a_j = 1\}.$$

As Bresnahan and Reiss (1991) discuss in their paper, τ is positive when later entrants are less efficient or face entry barriers, and they impose τ to be positive in their estimation. However, since the industry context in this present paper is very different from theirs, I do not restrict τ to be positive.³¹ The state variables s entering into equation (5) include factors that affect access to distributors and to shelf space after controlling for post-entry variable profits. In the estimation, the above state variables s include each firm's distance from a store to its brewery, the size of a store's selling area, and the presence of an Anheuser Busch exclusive distributor. Firm fixed effects, d_i , are also included to allow for firm heterogeneity.³²

³¹Bresnahan and Reiss (1991) look at the entry behaviors of doctors, dentists, druggists, plumbers, and tire dealers.

³²Here, the distance variable is used to capture fixed costs associated with entering into a new market. Factors that affect a firm's variable profits in a distant market are controlled for by using "predicted price" and "locally brewed" variables obtained from the demand estimation.

Using the specifications for the variable profits and the fixed costs, equation (4) becomes:

$$\sigma_i(a_i = 1|s) = \frac{\exp\left(m_i \sum_{a_{-i}} S_i(a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s) - (d_i + s' \eta + \tau \sum_{j \neq i} \sigma_j(a_j = 1|s))\right)}{1 + \exp\left(m_i \sum_{a_{-i}} S_i(a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s) - (d_i + s' \eta + \tau \sum_{j \neq i} \sigma_j(a_j = 1|s))\right)},$$

(6) for $i = 1, \dots, N$.

For each location, the final state variables s in equation (6) are the store's potential market size, each product's attributes, each firm's distance from the store to its brewery, the size of the store's physical selling area, and whether Anheuser Busch has an exclusive distributor. Parameters θ include the demand-side parameters and the supply-side parameters. Demand-side parameters are marginal utility of income, α ; marginal utility of fixed product attributes, β_j ; marginal utility of the locally brewed product, γ ; and the inclusive values from the nested logit model, λ_1 , λ_2 , and λ_3 . Supply-side parameters are each firm's variable profit per unit (m_i), and the fixed cost parameters (d_i , η , and τ) are firm fixed effects, store size, distance from stores to breweries, the presence of an Anheuser Busch exclusive distributor, and the strategic effect on fixed costs.

Ellickson and Misra (2008) and Bajari, Hong, Krainer, and Nekipelov (2010) both estimate a static game using a two-step approach. They first estimate firms' beliefs about the choice probabilities and then maximize the pseudo likelihood function. Following the same approach, I first estimate the equilibrium entry probabilities $\sigma_i(a_i = 1|s)$. Moreover, I exploit the data on price and quantity to estimate the predicted total units of sales, $\hat{S}_i(a_{-i}, s; \theta)$. Finally, I plug the above estimates into (6) to maximize the pseudo likelihood. The estimation is done in three steps as follows.

1. Estimate the consistent choice probabilities conditional on the state variables. This produces $\hat{\sigma}_i(a_i = 1|s)$ for $i = 1, \dots, N$.
2. Estimate the demand system. Given the estimates of the demand system, predict units of sales conditional on each rivals' action profile and construct $\sum_{a_{-i}} \hat{S}_i(a_{-i}, s) \hat{\sigma}_{-i}(a_{-i}|s)$.
3. Plug the estimated $\sum_{a_{-i}} \hat{S}_i(a_{-i}, s) \hat{\sigma}_{-i}(a_{-i}|s)$ and $\hat{\sigma}_j(a_j = 1|s)$ into equation (6) and estimate the supply parameters by maximizing the pseudo likelihood.

The final estimating equations are:

$$\sigma_i(a_i = 1|s) = \frac{\exp\left(m_i \sum_{a_{-i}} \hat{S}_i(a_{-i}, s; \theta) \hat{\sigma}_{-i}(a_{-i}|s) - (d_i + s' \eta + \tau \sum_{j \neq i} \hat{\sigma}_j(a_j = 1|s))\right)}{1 + \exp\left(m_i \sum_{a_{-i}} \hat{S}_i(a_{-i}, s; \theta) \hat{\sigma}_{-i}(a_{-i}|s) - (d_i + s' \eta + \tau \sum_{j \neq i} \hat{\sigma}_j(a_j = 1|s))\right)},$$

(7) for $i = 1, \dots, N$.

The section below discusses the estimation procedure and the identification assumptions in detail.

5 Empirical Implementation

5.1 Market Definition

An entry is made when a firm has access to a store's shelf space. I study the entry decisions of specialty beer producers at the store-quarter level. Because the scanner data only include sales data that actually occur, the entry variable is defined to be one when a firm has positive sales in a store during a quarter. Since there are 229 stores and 8 quarters in the data, store s is from 1 to 229, quarter q is from 1 to 8, and market t is from 1 to 1832.

I calculate the market share for brand j using the total quantities sold (adjusted for different package sizes) divided by the potential market size. The challenge is to find a variable that the potential market size is proportional to and to allow for a positive share of the outside good (Nevo 2000). One way to accomplish this is to define the potential market as beer consumption through the supermarket channel and use per capita consumption and the legal drinking age population in the zip code area to construct the market size (Hellerstein 2008). However, directly applying this approach to the dataset in this paper produces unreasonable market shares for the inside good for some markets.³³ Instead, I define the potential market as alcoholic beverages (beer, wine, and spirits) consumed during a quarter in a retail grocery store. Because aggregate alcohol consumption is likely proportional to beer consumption, I multiply a store's maximum total sales of beer by a potential market factor (which is 2) to construct the potential market and then check the sensitivity of the results to this market definition.³⁴

³³Since beer consumption per capita per year in California is 25 gallons and the volume of beer sold through the supermarket channel is around 16%, the per capita beer consumption through the supermarket channel per quarter is $25 * 0.16/4 \approx 1$ gallon, which is around 1.78 six-pack units per capita per quarter. The potential market size is thus the legal drinking age population in the zip code area multiplied by 1.78. However, there are 80 stores in which the sales of the inside good exceed the potential market size defined above. Therefore, I need to either adjust the per capita beer consumption or drop some stores to eliminate erroneous shares of the inside good. The above adjustments provide estimates that are very close to the ones presented in the empirical section and are thus not reported.

³⁴I do not have sales data for wine and spirits, however, in the alcohol industry, the combined retail dollar

5.2 Pricing

I predict California specialty beer producers' post-entry retail prices using a reduced-form approach.³⁵ Table 5 presents the results from pricing regressions for brands of California specialty beer producers. As previewed in Table 3, stores with exclusive distributors are more likely to be located in rural areas and have a lower average price. This is supported by the results in column (1): on average, a brand is priced 10 cents lower per six-pack in stores with an Anheuser Busch exclusive distributor. Columns (2) to (7) provide results that control for brand, store, and quarter fixed effects. The coefficient of distance is positive and statistically significant across all specifications, suggesting that a brand has higher prices at stores that are farther away from the firm's brewery. Neither the number of California firms nor the number of total firms in a market has a statistically significant (at the 5% level) impact on a specialty beer product's price. One potential explanation for these results is that many specialty beer producers are fringe firms that carry only an average of two products.

Given that the presence of additional rivals has no impact on a specialty beer product's price, I use the baseline results in column (2) of Table 5 to construct predicted post-entry retail prices of California specialty beer producers. The predicted retail prices are then used to construct expected post-entry sales given the current market conditions. Moreover, because equilibrium prices differ with respect to exclusivity, in estimating specialty beer producers' entry probabilities, I allow for a firm's variable profit per unit to differ with regard to an Anheuser Busch distributor's exclusivity.

5.3 Estimation

Entry Probability

The equilibrium entry probability of firm i at store s can be estimated using its empirical sales of wine and spirits are roughly equal to the dollar sales of beer. In the empirical setting, the price coefficients are robust to this definition of an outside good, because store fixed effects are included in all specifications. I also apply the same price coefficients to different definitions of outside good to calculate the price elasticities. For example, I double/triple the market size, and the elasticity estimates are robust to different definitions of potential market.

³⁵Equilibrium prices can also be recovered by modeling the vertical relationships between retailers, distributors, and manufacturers and through solving the pricing game backward in the spirit of Villas-Boas (2007) (see Miravete, Seim, and Thurk 2014 for an application in the liquor industry). However, this approach relies on correctly backing out retail margins in the first place. Because I do not observe the wholesale prices for the retailer chain or the prices set by other grocery chains, and given that the retailer chain is clearly not a monopolist at the retail level, I am not able to use demand estimates to pin down retail margins without making further assumptions. Therefore, I do not pursue this approach and instead use a reduced-form approach to construct predicted prices.

counterpart. Given the panel structure of the data, a simple frequency estimator is:

$$\hat{\sigma}_{is}(a_{is} = 1) = \frac{\sum_{q=1}^Q a_{iqs}}{Q},$$

where a_{iqs} is equal to one if firm i chooses to enter store s in quarter q . The expected number of rivals of firm i at store s is the sum of all firms' entry probabilities subtracted by firm i 's own entry probability.³⁶

Demand-Side Parameters

Recall that the estimating equation for the demand system in (1) is:

$$\begin{aligned} \ln(s_{jt}) - \ln(s_{0t}) &= x_j\beta - \alpha p_{jt} + \gamma A_{jt} + (1 - \lambda_1\lambda_2\lambda_3) \ln(s_{j|g}) + (1 - \lambda_2\lambda_3) \ln(s_{g|d}) \\ &+ (1 - \lambda_3) \ln(s_{d|b}) + \xi_{jt}. \end{aligned}$$

There is a potential endogeneity problem in estimating the coefficients on p_{jt} , $\ln(s_{j|g})$, $\ln(s_{g|d})$, and $\ln(s_{d|b})$, because these variables may be correlated with unobserved product quality in a specific market, ξ_{jt} . For example, if a firm has a higher unobserved quality level in market t and is able to price higher and earn a large market share, then the price and the λ coefficients will be biased. To deal with this endogeneity problem, I decompose $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$, in which ξ_j is the unobserved brand fixed effect, ξ_t is the unobserved market fixed effect, and $\Delta\xi_{jt}$ is the unobserved deviation from brand and market fixed effects. Given this, I include brand, store, and quarter dummies in the estimation to control for ξ_j and ξ_t .

Because beer tastes better when it is fresh, and consumers usually value a product more if it is made locally, I construct a dummy variable “locally brewed” when the brewery is located within a 10-mile radius of a store. This helps to explain some variation in $\Delta\xi_{jt}$. However, unobserved promotional activities at the brand level are still a concern. Therefore, I pursue an instrumental variable approach that requires finding instrumental variables that are correlated with the explanatory variables, but are uncorrelated with $\Delta\xi_{jt}$. To this end, I instrument for p_{jt} and $\ln(s_{j|g})$ using the number of brands a firm carries and the number of rival brands in group g . The maintained identification assumption in the demand estimation is that local demand shocks are realized after firms make their entry decisions.

For a domestic (foreign) product, I similarly use the number of rival domestic (foreign) brands with different styles and the number of total foreign (domestic) brands in the market

³⁶I can also estimate the entry probabilities by fitting a linear probability model. I run a regression of entry decisions on store, quarter, and firm fixed effects. I also include firm by store interactions in the regression. The predicted entry probabilities are basically the same as the ones calculated using the simple frequency estimator described above. However, there are predictions outside of the $[0, 1]$ interval, and thus I do not use results from the linear probability model.

to instrument for $\ln(s_{gd})$ and $\ln(s_{dlb})$, respectively. The estimation is done using the two-stage least squares method with standard errors clustered at the store level.

Using the demand estimates and the predicted prices, I can predict sales for each firm at each location under any rivals' action profile using the nested logit probability formula. Ideally, I calculate the predicted demand conditional on each potential rivals' action profile and use the corresponding probabilities of rivals' action profile to construct the expected sales. However, given that I have 26 players in the entry game, to calculate the exact expected sales for any firm in any market I will need 2^{25} permutations of rivals' action profiles. To reduce the number of permutations, the expected sales are calculated two different ways: first by a "naive" approach and second by simulation. The naive approach uses the exact identity of rival firms observed in the market to calculate the expected sales. The advantage of this approach is that it only takes one evaluation for each firm in each market. I also conduct a simulation to approximate expected sales. Using the first-stage entry probabilities, for each store I form draws of rivals' action profiles, calculate the sum of predicted sales from these draws, and divide the predicted sales by the number of draws. For each location, I use the base quarter (January to March) to form the predicted sales for the store.

Supply-Side Parameters

As discussed in previous sections, the identification strategy of the effect of exclusive dealing on a firm's entry decision is to control for post-entry sales and the number of expected rivals. It is important to note that a foreclosure effect is present when exclusive dealing raises a firm's fixed entry cost. However, exclusive dealing may reduce a firm's entry probability not only by raising its fixed entry cost, but also by lowering its average variable profit. Regarding this, I also provide several robustness checks that allow for interaction terms between an area's exclusivity, expected sales, and the number of rivals.

I now discuss the assumptions used to identify the strategic effect. Let $\Pi_i(a_i, s, \theta) = \sum_{a_{-i}} \pi_i(a_i, a_{-i}, s; \theta) \sigma_{-i}(a_{-i}|s)$ be the deterministic part of the expected profit. It has been shown that one is not able to identify $\Pi_i(a_i, s, \theta)$ without imposing distribution assumptions on the stochastic shocks ϵ . Following the standard treatment for this problem, I assume ϵ is identically and independently distributed with a Type 1 extreme value distribution. Furthermore, I am only able to identify the deterministic part of the expected profit up to the difference between $\Pi_i(a = 1, s, \theta) - \Pi_i(a = 0, s, \theta)$, and so I normalize $\Pi_i(a = 0, s, \theta)$ to zero in order to identify $\Pi_i(a = 1, s, \theta)$. Therefore, I assume that a firm's payoff from staying out of the market is zero in the model, which is similar to the outside good assumption made in standard discrete choice models. In addition, there can be multiple equilibria in the game. Following the literature on two-step estimation methods, the estimates are herein obtained under the assumption that in each location, firms play the same strategy and do not switch

to others.

The estimating equations are a system of simultaneous equations. Bajari, Hong, Krainer, and Nekipelov (2010) discuss that one needs exclusion restrictions to non-parametrically identify a static game. Even though nonparametric identification is not the main purpose of this paper, having variables that satisfy exclusion restriction conditions better explains where the identification comes from.³⁷ Basically, the exclusion restriction condition says one needs to have state variables that affect rival firms' entry probabilities, but do not enter into a firm's payoff directly. In this paper I use the distances between rival breweries to a store to satisfy the exclusion restriction condition. If a firm is more likely to enter stores closer to its brewery, which is the case in the beer industry, and the locations of rival firms' breweries do not enter into the firm's profit function directly, then the distances of rival firms' breweries to a store can serve as exclusion restrictions.

One concern of using distances to satisfy the exclusion restriction is that the proximity to rivals' breweries may affect a firm's profitability through demand. If consumers prefer to purchase locally-brewed products, then a firm's market share can be lower when it enters a store closer to a rival's brewery. To deal with this problem, I include a "locally brewed" variable in the demand estimation to capture these effects, and the maintained assumption will be that after controlling for demand, the distance variables of rival firms do not enter into a firm's profit function.

Another concern is that a firm's choice of brewery location may not be exogenous. Out of 26 specialty beer producers in the data, 13 of them set up their breweries around San Francisco (i.e., located within the Bay Area counties) and Sacramento.³⁸ Because the Bay Area counties and Sacramento County are the two major urban areas in Northern California, the observed clusters of breweries raise a concern about whether the exclusion restrictions are valid.³⁹ If firms choose their breweries' locations based on unobserved common factors in these areas, then the estimated strategic effect will be biased upward. I address this concern by conducting robustness checks. I provide results that include and exclude all the stores in the counties of the Bay Area and Sacramento County.

Standard Errors

³⁷In the main estimating equation, each firm's entry probability into a grocery store depends both on its distance from the brewery to the grocery store and its rivals' entry probabilities. Stacking all the firms' entry decisions, I arrive at a model with a system of equations. One is unable to identify the strategic effect variable if exclusion restrictions are not imposed.

³⁸The Bay Area counties are: Alameda County, Contra Costa County, Marin County, Napa County, San Francisco County, San Mateo County, Santa Clara County, Solano County, and Sonoma County.

³⁹The average annual median household income and the monthly gross rent in the Bay Area counties and Sacramento County are \$62,066 and \$957, respectively, while the average annual median household income and the monthly gross rent in the other 20 counties are \$44,704 and \$703, respectively.

Since the estimation is done in two steps, I bootstrap the standard errors across stores by resampling. The assumption is that after controlling for brand, quarter, and store dummies, the error terms across stores are independent. Moreover, given that I estimate a static model with eight quarters of data, I cluster the standard errors at the store level to control for the likely positive correlation over time.

6 Results

I first estimate an entry model without controlling for demand or strategic effects. Table 6 shows the estimation results. Column (1) provides the baseline regression results. Column (2) further controls for gross rent, and columns (3) and (4) provide results with squared distances as robustness checks. All coefficients on store size, distance, and gross rent have the expected signs: a location that has a larger selling area, is closer to a firm’s brewery, or has lower gross rent is associated with higher entry probability. All coefficients on the Anheuser Busch exclusive distributor indicator variable are positive, though only the coefficient in (3) is statistically significant at the 5% level. As discussed in the previous section, the coefficient of the exclusive variable is likely to be biased upward. In fact, column (2) presents that the coefficient of the exclusive variable goes down once I control for gross rent. To explore more rigorously the effect of exclusive dealing on a firm’s entry decision, I proceed by estimating the demand for beer and the entry game with strategic interactions.

6.1 Demand Estimates

The demand system is estimated to achieve two goals. First, it provides predictions for counterfactual post-entry sales. Second, it enables welfare analysis.

Table 7 provides demand estimation results using a logit model. Column (1) gives the OLS regression results, and column (2) provides the results from the instrumented regression. All specifications include brand, store, and quarter fixed effects. As can be seen in column (2), the magnitude of the negative coefficient on price increases when prices are instrumented. In both specifications, a consumer enjoys a product more if it is brewed locally. The implied mean price elasticity is -7.82, suggesting that the demand is quite price elastic.⁴⁰

Table 8 presents the demand estimation results using a nested logit model, with prices instrumented in column (2). Columns (3) to (6) show the first-stage results, where the various instruments are presented in section 5.3. In column (3), the instrument for $\ln s_{j|g}$, the number of rival brands in group g , is negatively correlated to $\ln s_{j|g}$ and is significant.

⁴⁰Hellerstein (2008) estimates a model of beer demand using a random-coefficients model with data from 1991 to 1994. The estimated demand for beer is also very elastic. The own elasticities of her selected beer products are between -5.71 to -6.37. The data used by her are monthly data and contain no specialty beer products.

The results in columns (4) and (5) are similar to those in column (3) and have the expected signs for the instruments: as the number of the brands in other rival groups increases, the market share of a product's own group will decrease. In column (6), the number of brands a firm carries in group g is associated with lower prices for its brands in group g . This association is probably due to the fact that big domestic firms are more likely to enjoy economies of scale and are more capable of providing products at very low prices. The first-stage F-statistics, with standard errors clustered at the store level, are 125.16, 44.27, 25.64, and 121.09, suggesting that the instruments are not weak.

A comparison of the first two columns in Table 8 shows that demand becomes more elastic once prices are instrumented. As in the logit model, consumers also prefer to have local products in both specifications. The mean own price elasticity of the nested logit model is -8.41. Table 9 provides the percentiles of price elasticities based on the logit and the nested logit models using the estimates in columns (2) in Table 7 and Table 8. The nested logit model provides less elastic demand estimates across percentiles. To give a sense of the price elasticities using the nested logit model, the average own price elasticities of Budweiser (domestic mainstream lager) and Lost Coast Downtown Brown Ale (domestic ale) are -5.48 and -7.91, respectively. When the price of Lost Coast Downtown Brown Ale increases, the cross price elasticity between Budweiser and Lost Coast Downtown Brown Ale is 0.039, and the cross price elasticity between Newcastle Brown Ale (foreign ale) and Lost Coast Downtown Brown Ale is 0.015. The substitution pattern suggests that consumers view domestic ale and foreign ale products as more distinct products than they view domestic ale and domestic mainstream lager products.⁴¹

The coefficients on $\ln(s_{j|g})$, $\ln(s_{g|d})$, and $\ln(s_{d|b})$ represent the similarities within nests. As McFadden (1981) shows, a nested logit model is consistent with a utility maximization model for any values if all of the inclusive value coefficients are within the $[0, 1]$ interval. A negative estimate of an inclusive value indicates a violation of utility maximization. The implied inclusive value coefficients (λ_1 , λ_2 , and λ_3) in the nested logit model are 1.59, 0.53, and 0.35, respectively.⁴² Given that the similarity coefficients are not jointly zero, I can reject a simple logit model, and so I use the nested logit model as my preferred setting to predict post-entry sales.

Table 10 presents the results that control for demand, but not strategic entry decisions.

⁴¹The average price elasticities in this example are calculated using data from stores with positive sales of the above three products.

⁴²The coefficient λ_1 being greater than one means consumers substitute more often across different beer styles than within the same style. However, I cannot reject the hypothesis that λ_1 is equal to one at the 5% level. I also estimate equation (1) with the constraint that λ_1 is equal to one, and the results are similar to those reported above.

The first two columns restrict the average variable profits of sales across firms to be the same. Column (3) allows average variable profits of sales to differ across firms, and columns (4), (5), and (6) add the squared distance as robustness checks. The coefficients on expected sales have the expected positive signs and are significant. Compared to the results in Table 6, the exclusive coefficients are smaller and are no longer statistically significant in all specifications.

6.2 Strategic Entry

To allow for strategic interactions between firms, I estimate the fixed costs using equation (7), along with the demand estimates and the beliefs about entry probabilities constructed before. Tables 11 and 12 provide the results from the naive approach and from simulation (with 50 draws), respectively. The two methods provide similar estimation results. The coefficients for store size, distance, and expected sales are all statistically significant and have the expected signs.

Compared to the results in Table 10, the magnitudes of the coefficients for store size and gross rent are smaller in Tables 11 and 12. Controlling for expected sales and expected number of rivals, the AB exclusive distributor coefficients are negative in most of the specifications, but cannot be precisely estimated. The coefficients for the expected number of rivals are also positive and significant: the presence of an additional specialty beer producer raises a firm's entry probability by 3.6 to 5 percentage points.

The above results suggest spillover effects for specialty beer producers on the cost side. One potential reason for this spillover effect is that a store needs many brands to create a specialty beer category. When a store prefers to build a specialty beer segment to attract certain types of consumers (while currently carrying many specialty brands), it is easier for a firm or a distributor to persuade the store to add additional specialty brands, compared to persuading another store that has no interest in building a specialty beer category (while currently carrying very few specialty brands) to have more brands.

As discussed in the previous section, the identification strategy for the strategic effect relies on using the distances from a store to rival firms' breweries as exclusion restrictions. However, as previously discussed, there are many breweries clustered around the San Francisco Bay Area and Sacramento. The observed clusters of breweries raise a concern about whether the exclusion restrictions are valid. If there are common factors that affect a brewer's location decision for its brewery and the distribution decisions of its retail outlets, and these common factors are uncontrolled for, then the strategic effect estimated in this paper will be biased. To ease this concern, I provide results that exclude all stores in the counties within the Bay Area and Sacramento County in Table 13. The strategic coefficients remain positive and significant in all specifications. Moreover, the coefficients of the exclusive variable re-

main negative, but are now statistically significant in all specifications, suggesting that there is a foreclosure effect due to Anheuser Busch’s exclusive dealing program in areas where microbreweries are not clustered. The coefficients of “store size” are greatly reduced in all specifications and are not precisely estimated, probably because the stores in the subsample are more likely to be located in rural areas where the size of the physical selling area is less likely to play a major role in affecting a product’s shelf availability.

To interpret the magnitude of the foreclosure effect in potentially foreclosed areas, I use the estimates from column (2) in Table 13 to calculate the marginal effects. I find that a store with an Anheuser Busch exclusive distributor reduces a firm’s entry probability by approximately 6 percentage points. The effect does not appear large at first glance, but given that the mean entry probability of the 23 specialty beer producers in the subsample is only 28 percentage points (excluding the three California firms that enter all 229 stores), the exclusive effect plays an important role in a firm’s entry decisions. The results also show that a decrease in sales of 100 six-packs a quarter reduces a firm’s entry probability by 6 percentage points, a reduction in 10,000 square feet of store size reduces a firm’s entry probability by 1 percentage point, and a 10-mile increase in the distance between a firm’s brewery and a store reduces the firm’s entry probability by 3.4 percentage points.

I finally conduct counterfactual experiments to study the effect of banning exclusive dealing through relaxing the foreclosure effect on consumer welfare and Anheuser Busch’s sales. Holding equilibrium prices constant, in areas where exclusive dealing is banned, the entry probabilities of specialty beer producers increase. In such situations, consumers are able to select beer products from a presumed more diverse mix, and the magnitude of the increase in consumer welfare would depend on the product attributes of the newly included products. The monetary measure that is used here is equivalent variation, which measures the income changes required to make consumers just as well off as they are once their choice sets are expanded.

I simulate demand using the predicted entry probabilities with and without exclusive dealing. Following Small and Rosen (1981), the changes in consumer welfare per consumer per quarter can be found by:

$$\Delta EV_t = \frac{1}{\alpha} \left[\ln \left(\sum_{j \in J^1} e^{\delta_j} \right) - \ln \left(\sum_{j \in J^0} e^{\delta_j} \right) \right],$$

where J^0 and J^1 are the respective choice sets before and after removing exclusive dealing.⁴³

Table 14 provides the results of counterfactual experiments based on 100 draws from

⁴³I find $\sum_{j \in J} e^{\delta_j}$ by using the $(1 + \exp(d_q z_q + d_t z_t + \lambda_3 I_3))$ term in equation (3).

the predicted entry probabilities. Removing exclusive dealing does not have much impact on entry behavior: at most only one additional firm will enter a market, and the impact on consumer welfare is almost zero. The average quarterly sales per store in an exclusive dealing area are less than 30,000 six-packs, and with an average welfare increase of \$0.0005 per quarter per six-pack, changes in consumer welfare per store per quarter are less than \$15. In fact, given the demand structure, even if we allow all the California specialty beer producers to enter a store with an Anheuser Busch exclusive distributor, the implied increase in an average consumer's welfare is around \$0.017 per market (a store in a quarter).

There are several reasons for getting such small estimates. First, as shown in Table 5, adding specialty brands does not impact pricing very much. Second, most of the specialty brands that do not have a presence in many markets have very little market shares even in stores where they do have a presence. It is also important to note that the welfare improvement from adding more products may be even less than the above estimates. This is because in the demand model employed in this paper, each new product enters by adding independent and identically distributed logit errors, which allows consumers' willingness to pay for new products to increase without bound as the number of products increases. Therefore, though exclusive dealing increases the fixed costs for some specialty beer producers, the welfare improvement from banning exclusive dealing is very limited. Moreover, as discussed throughout the paper, exclusive contracts may lead to efficiency gains that eventually enhance consumer welfare, and thus banning such contracts may involve a decrease in consumer welfare. Consequently, the estimate from removing exclusive dealing reported above reflects an upper bound on the net benefits associated with banning exclusive dealing.

The results in Table 14 also imply that foreclosure alone is not the motivation behind Anheuser Busch's continuous support for its exclusive program. Enforcing exclusive dealing may decrease the entry probability of specialty beer producers, yet the market shares of these potentially foreclosed firms are extremely low to begin with. The demand substitution pattern of beer products also restricts the gains of Anheuser Busch from profiting through foreclosure: the increase in diverted sales from foreclosing one additional specialty beer producer is at most 31 six-packs per store per quarter. Therefore, while the empirical evidence suggests that in some rural markets exclusive dealing may lower rivals' entry probability, the effect is more likely a side-effect of Anheuser Busch's exclusive dealing program.

6.3 Robustness Checks

One potential concern about the preferred specification is that even if exclusive dealing reduces the entry probability of specialty beer producers, it may not be driven by higher fixed distribution costs. There are two ways to interpret the correlation between the reduction of

entry and the presence of an AB exclusive distributor. First, exclusive dealing intensifies local competition, which lowers retail margins for specialty brands. In this case, exclusive dealing is not anticompetitive. Second, exclusive dealing raises distribution costs, either by increasing the marginal or the fixed distribution costs, and the latter represent the interpretation of this paper. Regarding this concern, I include an interaction term that interacts a firm’s expected sales in a market with the market’s exclusivity status.

Another concern is that because controlling for the number of rival firms affects the coefficients of the exclusive effect, the estimated exclusive effect may be picking up non-linearity in the effect of the number of rivals. I address this issue by including a squared term for the number of rivals and allow the number of rivals to interact with the “expected sales” term. Doing so captures non-linearity in the effect of the number of rivals on margins.

Table 15 provides the results of the above robustness checks by using the subsample that excludes Bay Area counties and Sacramento County. Allowing stores with Anheuser Busch distributors to have a different variable profit per unit does not affect the point estimate of the AB exclusive coefficient, but does reduce the statistical significance to the 10% level. Columns (2) to (4) present the results by adding interaction terms of expected sales and a store’s AB exclusive status, as well as a squared term of the expected number of rival firms. Including the additional controls does not affect the magnitude of the exclusive effect.

I lastly note the maintained assumption in demand estimation is that demand shocks are realized after a firm makes its entry decision. It is important to stress that when product entry is endogenous, the obtained price elasticities are likely to be biased. In the appendix, I provide additional results from demand estimation that address this issue. I show that estimates from weekly data as well as estimates that exploit new products launched from the mainstream producers in the third quarter of 2007 confirm the conclusion that banning exclusive dealing has limited impact on consumer surplus.

7 Conclusion

Why does a dominant firm such as Anheuser Busch incentivize its distributors to be exclusive? Efficiency arguments suggest that promoting and protecting investments in brewer-distributor relationships are the main motivations for such programs. However, recent theoretical studies have explored several settings in which exclusive dealing is driven by anticompetitive motives. The results in this paper do not support the hypothesis that foreclosure is the main motivation behind Anheuser Busch’s exclusive dealing program: even though exclusive dealing has raised entry costs for some rivals, the magnitude of the foreclosure effect itself is unable to justify Anheuser Busch’s adoption and continuation of the program. The estimated foreclosure effect is thus interpreted as a side-effect of Anheuser Busch’s exclusive

dealing program. In addition, the estimated change in consumer welfare when exclusive dealing is removed is very limited. The results, along with recent studies from Sass (2005), Rojas (2010), and Chen (2013), suggest that exclusive dealing in the beer industry is unlikely a device used by Anheuser Busch solely to foreclose new entrants or to dampen market competition, but is more likely a mechanism to compete with other brewers more efficiently.

It should be noted that the results of this paper refer to data used from one major grocery chain in Northern California. On the one hand, because grocery stores are only one of many retail channels for beer products, if the entry of specialty beer products is not depressed in other retail formats, then the overall foreclosure effect might not even harm specialty beer producers as much. On the other hand, because all results are based on data of Northern California, in which consumers historically have more appeal to specialty beer products, the foreclosure effect may be larger in other states.

One limitation of this paper is that the welfare analysis herein focuses only on consumer surplus from direct beer consumption and does not include potential (negative) externalities caused by beer consumption. The negative externalities from alcohol consumption are some of the reasons for regulations in the beer industry. However, a comprehensive welfare analysis for the societal effects of beer consumption is beyond the scope of this paper.

Entry decisions of firms are jointly determined by many factors. In this paper I find that a dominant incumbent's vertical arrangements with its existing distributors have raised the fixed costs of specialty beer producers significantly in some areas. The presence of other specialty beer producers, to the contrary, results in a spillover effect and lowers the fixed costs of specialty beer producers. Given the static setting in this paper, it is difficult to disentangle whether the above effects come from changes in sunk costs or in fixed costs in every period. Future research on questions regarding entry and market structure in a dynamic setting will be highly valuable.

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Table 1: Some Typical Entries From the CBBB Annual Directory

Distribution Status	Brand Portfolio
Exclusive AB distributor	180 Energy Drink, Anheuser-Busch, Redhook Ale Brewery, Rolling Rock, Widmer Brothers Brewing
Non-exclusive AB distributor	Anheuser Busch, Arizona Beverage, Gambrinus , Gordon Biersch Brewing , Heineken USA, InBev USA, Redhook Ale Brewery, Scottish & Newcastle Importers, Sierra Nevada Brewing , Spaten North America, Widmer Brothers Brewing
Non-AB distributor 1	Anchor Brewing , Asahi Breweries, Boston Beer, Diageo-Guinness USA, Gambrinus , Heineken, Hornell Brewing, InBev USA, Mark Anthony Brands, McKenzie River , Miller Brewing, Pabst Brewing, Pyramid Breweries , Sapporo USA, Scottish & Newcastle Importers, Sierra Nevada Brewing , Sierra Springs Water, US Beverage
Non-AB distributor 2	Alaskan Brewing, Barton Beers, Boston Beer, Diageo-Guinness USA, InBev USA, Lake Tahoe Brewing , Mark Anthony Brands, Miller Brewing, Molson Coors Brewing, New Belgium Brewing, Pyramid Breweries , Redhook Ale Brewery, Sapporo USA, Sierra Nevada Brewing
Independent distributor	Alaskan Brewing, Allagash Brewing, Anderson Valley Brewing , Arizona Beverage, Asahi Breweries USA, Bear Republic , Binding International, Bison Brewing, California Cider, Constanca Brewery, Firestone-Walker Brewing , Friedlin Imports Full Sail Brewing Co., Humboldt Brewing , InBev USA, Mad River Brewing , Mendocino Brewing , Marin Brewing , Moylan's Brewery , Nestle Beverage, Ommegang Brewery, Pabst Brewing, Panorama Brewing , Sapporo USA, Scottish & Newcastle Importers, Sierra Nevada Brewing , Spaten North America, Speakeasy , Stone Brewing, Sudwerk Privatbrauerei , Thames America Trading, US Beverage, Wyder's Beverage

Notes: AB (Anheuser Busch). 180 Energy Drink, Redhook, Rolling Rock, and Widmer Brothers are all affiliated Anheuser Busch products listed on the Anheuser Busch company website. California specialty beer producers that can be matched to the scanner dataset are denoted by bold type.

Table 2: Number of Entrants and the Minimum Six-Packs Sold During a Quarter per Store

	Top 10 stores with the most number of CA specialty beer producers	Bottom 10 stores with the least number of CA specialty beer producers
Number of CA firms	12.3	5.4
Minimum six-packs sold per quarter	15.4	43.4
Average price	7.16	7.31

Note: Average price (in \$) is the price of products from California specialty beer producers.

Table 3: Summary Statistics

	Anheuser Busch Non-exclusive Stores	Anheuser Busch Exclusive Stores
Number of stores	189	40
Number of CA specialty beer producers	9.29 (1.61)	10.06 (1.19)
Store total sales	24362 (9025.83)	29148 (8835.98)
Store size	2.87 (1.09)	3.07 (0.90)
Population	33255 (16740)	26236 (12966)
Household income	64964 (22403)	48375 (18137)
Gross rent	992 (278)	794 (254)

Notes: All entries reported are means with standard deviations shown in parentheses. “Store total sales” are the number of volume-adjusted six-packs (in quantity) sold per quarter. “Store size” is measured in 10,000 square feet.

Table 4: Number of Stores a Firm Entered

Firm	2006q2	2006q3	2006q4	2007q1	2007q2	2007q3	2007q4	2008q1	mean
Non-CA Firm 1	204	204	203	204	203	209	211	210	206
Non-CA Firm 2	229	229	229	229	229	229	229	229	229
Non-CA Firm 3	188	193	192	197	197	210	209	205	199
Non-CA Firm 4	193	193	191	193	194	200	197	197	195
Non-CA Firm 5	215	217	214	213	209	216	152	143	197
Non-CA Firm 6	229	229	229	229	229	229	229	229	229
CA Firm 1	229	229	229	229	229	229	229	229	229
CA Firm 2	174	172	168	166	164	177	165	161	168
CA Firm 3	126	114	111	110	109	150	152	149	128
CA Firm 4	6	6	6	7	7	7	5	8	7
CA Firm 5	3	97	177	20	6	4	1	0	39
CA Firm 6	3	3	3	3	3	3	2	2	3
CA Firm 7	4	4	4	4	4	4	4	4	4
CA Firm 8	2	2	2	2	2	2	2	2	2
CA Firm 9	11	3	1	0	1	0	0	0	2
CA Firm 10	193	196	198	200	198	207	202	200	199
CA Firm 11	229	229	229	229	229	229	229	229	229
CA Firm 12	3	3	3	3	3	4	5	4	4
CA Firm 13	220	221	221	222	223	229	229	229	224
CA Firm 14	3	3	3	3	3	3	3	2	3
CA Firm 15	181	175	172	173	172	177	199	203	182
CA Firm 16	9	8	8	8	9	8	8	8	8
CA Firm 17	1	1	1	1	1	1	1	1	1
CA Firm 18	209	212	216	220	219	221	215	215	216
CA Firm 19	3	2	2	2	2	2	0	0	2
CA Firm 20	47	42	36	38	38	32	16	12	33
CA Firm 21	1	1	1	1	1	0	0	0	1
CA Firm 22	227	225	225	225	225	229	229	229	227
CA Firm 23	6	7	8	7	8	17	6	2	8
CA Firm 24	229	229	229	229	229	229	229	229	229
CA Firm 25	9	9	9	9	8	8	7	7	8
CA Firm 26	7	7	7	6	6	6	1	1	5
Total	106	108	110	106	105	108	105	104	107

Notes: All entries reported are the counts of the variable “enter” for a firm across stores during a quarter. The variable “enter” is equal to one if a firm has positive sales in a store during a quarter.

Table 5: Pricing for California Specialty Beer Products

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Distance	0.062*	0.081*	0.082*	0.082*	0.295**	0.295**	0.295**
	(0.024)	(0.035)	(0.035)	(0.035)	(0.102)	(0.102)	(0.102)
AB exclusive distributor	-0.104**						
	(0.028)						
Number of CA micro firms			-0.004			-0.004	
			(0.004)			(0.004)	
Number of firms				-0.003			-0.003
				(0.002)			(0.002)
Distance ²					-0.097**	-0.097**	-0.097**
					(0.033)	(0.033)	(0.033)
Constant	7.871**	7.888**	7.913**	7.967**	7.822**	7.846**	7.900**
	(0.040)	(0.065)	(0.073)	(0.086)	(0.048)	(0.058)	(0.073)
Store fixed effects?	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41027	41027	41027	41027	41027	41027	41027
Adjusted R^2	0.874	0.880	0.880	0.880	0.881	0.881	0.881

Notes: "Distance" is measured in hundreds of miles. All prices are volume adjusted six-pack prices. Data are collapsed to quarter/store/brand level. All regressions control for brand and quarter fixed effects. Standard errors, clustered at the store level, are shown in parentheses.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 6: Entry Probability without Controlling for Demand

	(1)	(2)	(3)	(4)
AB exclusive distributor	0.263 (0.168)	0.197 (0.181)	0.369* (0.172)	0.299+ (0.181)
Store size	0.455** (0.101)	0.448** (0.100)	0.460** (0.101)	0.453** (0.101)
Distance	-1.850** (0.163)	-1.866** (0.161)	-3.185** (0.356)	-3.218** (0.358)
Gross rent		-0.035 (0.028)		-0.038 (0.028)
Distance ²			0.540** (0.135)	0.549** (0.138)
Constant	-4.167** (0.529)	-3.802** (0.628)	-3.703** (0.555)	-3.312** (0.654)
Observations	42136	42136	42136	42136
Log likelihood	-7473.200	-7463.841	-7413.057	-7401.972

Notes: Data are collapsed to quarter/store/firm level. Results are Logit regression estimates where the dependent variable is California specialty beer producers' actual entry decision. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). "Distance" is measured in hundreds of miles. "Store size" is measured in 10,000 square feet. "Gross rent" is measured in hundreds of dollars.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 7: Demand Estimation Results from the Logit Model

	(1) OLS	(2) 2SLS
Locally brewed	0.643** (0.056)	0.527** (0.053)
Price	-0.319** (0.009)	-1.538** (0.177)
Constant	-4.192** (0.200)	7.148** (1.644)
Observations	205467	205467
Adjusted R^2	0.805	0.687

Notes: Data are collapsed to quarter/store/brand level. All regressions control for brand, quarter, and store fixed effects. Standard errors, clustered at the store level, are shown in parentheses. "Locally brewed" is equal to one when a store is located within a 10-mile radius of a firm's brewery.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 8: Demand Estimation Results from the Nested Logit Model

	First-stage results					
	OLS	2SLS	$\ln(s_{j g})$	$\ln(s_{g d})$	$\ln(s_{d b})$	Price
	(1)	(2)	(3)	(4)	(5)	(6)
Locally brewed	0.002* (0.001)	0.141+ (0.083)	0.503** (0.061)	0.196** (0.024)	-0.040** (0.009)	-0.087 (0.054)
Price	0.000 (0.001)	-0.353 (0.238)				
$\ln(s_{j g})$	0.998** (0.000)	0.704** (0.173)				
$\ln(s_{g d})$	0.996** (0.001)	0.814** (0.118)				
$\ln(s_{d b})$	1.000** (0.001)	0.649** (0.241)				
Instrumental variables for:						
Price			0.034** (0.008)	0.027** (0.006)	0.006** (0.002)	-0.048** (0.004)
$\ln(s_{j g})$			-0.022** (0.002)	0.024** (0.004)	0.004** (0.001)	-0.002** (0.001)
$\ln(s_{g d})$			-0.002** (0.001)	-0.004** (0.001)	0.003** (0.001)	-0.002** (0.000)
$\ln(s_{d b})$			-0.003** (0.001)	-0.003** (0.001)	-0.005** (0.001)	0.005** (0.000)
Constant	-0.779** (0.014)	1.001 (1.343)	-2.293** (0.199)	-3.443** (0.030)	-0.376** (0.024)	9.392** (0.121)
Observations	205467	205467	205467	205467	205467	205467
First-stage F-statistics			125.16	44.27	25.64	121.09
Adjusted R^2	0.996	0.975	0.852	0.937	0.914	0.936

Notes: Data are collapsed to quarter/store/brand level. All regressions control for brand, quarter, and store fixed effects. Standard errors, clustered at the store level, are shown in parentheses. “Locally brewed” is equal to one when a store is located within a 10-mile radius of a firm’s brewery.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 9: Price Elasticity Percentiles

	10%	25%	median	75%	90%
Logit	-12.27	-11.31	-9.75	-7.07	-5.95
Nested logit	-10.64	-9.45	-7.81	-6.05	-4.69

Notes: Price elasticities are calculated using columns (2) in Table 7 and Table 8.

Table 10: Entry Probability with Expected Demand: No Strategic Interactions

	(1)	(2)	(3)	(4)	(5)	(6)
AB exclusive distributor	0.084 (0.163)	0.036 (0.180)	-0.018 (0.179)	0.197 (0.165)	0.144 (0.179)	0.075 (0.177)
Store size	0.383** (0.092)	0.378** (0.092)	0.332** (0.091)	0.386** (0.093)	0.381** (0.092)	0.333** (0.091)
Distance	-1.743** (0.162)	-1.756** (0.160)	-1.717** (0.158)	-3.135** (0.357)	-3.158** (0.358)	-2.808** (0.353)
Expected sales	0.007** (0.001)	0.007** (0.001)		0.007** (0.001)	0.007** (0.001)	
Gross rent		-0.026 (0.027)	-0.015 (0.028)		-0.029 (0.027)	-0.018 (0.028)
Distance ²				0.563** (0.131)	0.568** (0.132)	0.440** (0.133)
Constant	-4.133** (0.505)	-3.859** (0.608)	-6.243** (0.750)	-3.644** (0.531)	-3.347** (0.632)	-5.797** (0.788)
Margins vary by firm?	No	No	Yes	No	No	Yes
Observations	42136	42136	42136	42136	42136	42136
Log likelihood	-7328.432	-7323.275	-6945.453	-7265.361	-7259.052	-6908.656

Notes: Data are collapsed to quarter/store/firm level. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). “Distance” is measured in hundreds of miles. “Store size” is measured in 10,000 square feet. “Gross rent” is measured in hundreds of dollars.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 11: Strategic Entry: the Naive Approach

	(1)	(2)	(3)	(4)	(5)	(6)
AB exclusive distributor	-0.092 (0.087)	-0.130 (0.096)	-0.163 (0.111)	0.038 (0.091)	-0.005 (0.096)	-0.045 (0.108)
Store size	0.187** (0.052)	0.183** (0.051)	0.153** (0.055)	0.187** (0.050)	0.183** (0.050)	0.149** (0.052)
Distance	-1.792** (0.148)	-1.802** (0.147)	-1.748** (0.143)	-3.325** (0.349)	-3.339** (0.344)	-3.071** (0.362)
Expected sales	0.004** (0.001)	0.004** (0.001)		0.004** (0.001)	0.004** (0.001)	
Expected number of rivals	0.623** (0.059)	0.621** (0.058)	0.591** (0.061)	0.631** (0.057)	0.630** (0.056)	0.602** (0.059)
Gross rent		-0.021 (0.015)	-0.010 (0.017)		-0.024 ⁺ (0.015)	-0.015 (0.016)
Distance ²				0.619** (0.108)	0.621** (0.106)	0.535** (0.117)
Constant	-7.664** (0.612)	-7.433** (0.621)	-9.709** (0.847)	-7.164** (0.618)	-6.902** (0.626)	-9.227** (0.855)
Margins vary by firm?	No	No	Yes	No	No	Yes
Observations	42136	42136	42136	42136	42136	42136
Log likelihood	-6799.318	-6796.272	-6487.496	-6724.039	-6719.892	-6436.687

Notes: Data are collapsed to quarter/store/firm level. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). "Distance" is measured in hundreds of miles. "Store size" is measured in 10,000 square feet. "Gross rent" is measured in hundreds of dollars.

⁺ significant at 10%, * significant at 5%, ** significant at 1%.

Table 12: Strategic Entry with Simulated Expected Demand

	(1)	(2)	(3)	(4)	(5)	(6)
AB exclusive distributor	-0.088 (0.088)	-0.127 (0.097)	-0.132 (0.110)	0.043 (0.092)	-0.001 (0.096)	-0.018 (0.107)
Store size	0.187** (0.052)	0.182** (0.051)	0.150** (0.054)	0.187** (0.050)	0.182** (0.050)	0.146** (0.052)
Distance	-1.787** (0.148)	-1.798** (0.147)	-1.713** (0.142)	-3.313** (0.350)	-3.328** (0.345)	-2.998** (0.363)
Expected sales	0.004** (0.001)	0.004** (0.001)		0.004** (0.001)	0.004** (0.001)	
Expected number of rivals	0.619** (0.059)	0.618** (0.058)	0.586** (0.061)	0.629** (0.057)	0.627** (0.056)	0.597** (0.059)
Gross rent		-0.021 (0.015)	-0.011 (0.017)		-0.025 ⁺ (0.015)	-0.015 (0.016)
Distance ²				0.616** (0.108)	0.618** (0.107)	0.519** (0.118)
Constant	-7.637** (0.612)	-7.404** (0.622)	-10.002** (0.879)	-7.143** (0.618)	-6.879** (0.627)	-9.537** (0.887)
Margins vary by firm?	No	No	Yes	No	No	Yes
Observations	42136	42136	42136	42136	42136	42136
Log likelihood	-6799.428	-6796.319	-6481.154	-6725.016	-6720.792	-6433.763

Notes: Expected sales are calculated by taking 50 draws of rivals' action profile in a given market. Data are collapsed to quarter/store/firm level. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). "Distance" is measured in hundreds of miles. "Store size" is measured in 10,000 square feet. "Gross rent" is measured in hundreds of dollars.

⁺ significant at 10%, * significant at 5%, ** significant at 1%.

Table 13: Strategic Entry: Regression without the Bay Area Counties and Sacramento County

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AB exclusive distributor	-0.297 (0.281)	-0.388* (0.151)	-0.458* (0.185)	-0.479* (0.203)	-0.262+ (0.152)	-0.323+ (0.183)	-0.337+ (0.197)
Store size	0.236+ (0.122)	0.066 (0.074)	0.067 (0.074)	0.059 (0.081)	0.069 (0.073)	0.071 (0.073)	0.049 (0.081)
Distance	-1.949** (0.220)	-1.867** (0.213)	-1.873** (0.214)	-1.770** (0.207)	-3.545** (0.501)	-3.544** (0.499)	-3.294** (0.569)
Expected sales		0.003+ (0.002)	0.003+ (0.002)		0.004* (0.002)	0.004* (0.002)	
Expected number of rivals		0.487** (0.078)	0.485** (0.077)	0.453** (0.089)	0.491** (0.076)	0.490** (0.075)	0.454** (0.086)
Gross rent			-0.039 (0.053)	-0.041 (0.050)		-0.033 (0.053)	-0.038 (0.047)
Distance ²					0.611** (0.158)	0.609** (0.157)	0.555** (0.189)
Constant	-2.503** (0.723)	-5.315** (0.846)	-4.993** (0.968)	-7.282** (1.186)	-4.762** (0.837)	-4.492** (0.965)	-6.837** (1.198)
Margins vary by firm?	No	No	No	Yes	No	No	Yes
Observations	8928	8928	8928	8928	8928	8928	8928
Log likelihood	-2173.945	-2023.394	-2022.301	-1889.399	-1989.193	-1988.405	-1866.253

Notes: Data are collapsed to quarter/store/firm level. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). “Distance” is measured in hundreds of miles. “Store size” is measured in 10,000 square feet. “Gross rent” is measured in hundreds of dollars. The Bay Area counties are Alameda County, Contra Costa County, Marin County, Napa County, San Francisco County, San Mateo County, Santa Clara County, Solano County, and Sonoma County.

+ significant at 10%, * significant at 5%, ** significant at 1%.

Table 14: The Effects of Banning Exclusive Dealing

Variable	Mean	Min	Max
Predicted number of CA specialty beer producers			
With exclusive dealing	9.89	6.19	13.64
Without exclusive dealing	10.36	6.67	14.4
Changes in Anheuser Busch’s sales (number of six-packs)			
Remove exclusive dealing	-11.88	-30.77	3.03
Changes in consumer welfare (dollars per six-pack)			
Remove exclusive dealing	0.0005	-0.0001	0.0016
Include all CA specialty brands	0.0169	0.0072	0.0413

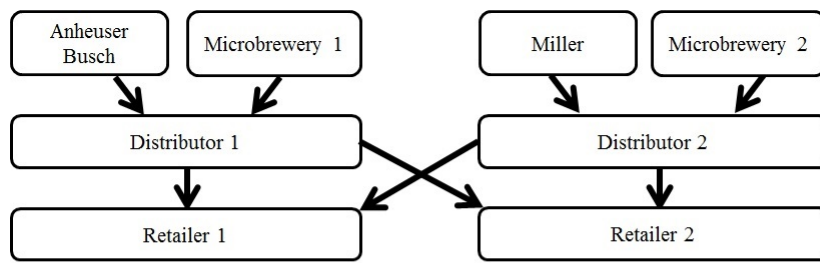
Notes: Based on estimation results of column (2) in Table 13. Welfare changes are evaluated at locations with Anheuser Busch exclusive distributors.

Table 15: Strategic Entry: Robustness Checks

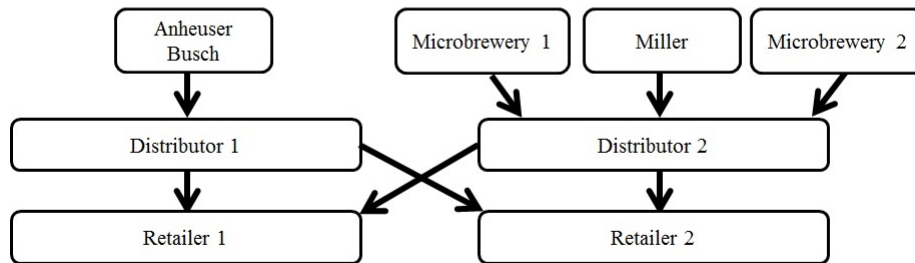
	(1)	(2)	(3)	(4)
AB exclusive distributor	-0.476 ⁺ (0.255)	-0.454* (0.184)	-0.453* (0.187)	-0.493 ⁺ (0.259)
Store size	0.068 (0.074)	0.065 (0.075)	0.058 (0.075)	0.055 (0.076)
Distance	-1.871** (0.217)	-1.878** (0.215)	-1.861** (0.213)	-1.859** (0.217)
Expected sales	0.003 ⁺ (0.002)	0.008 (0.006)	0.003 ⁺ (0.002)	0.008 (0.006)
Expected number of rivals	0.486** (0.077)	0.528** (0.082)	0.661* (0.336)	0.718* (0.352)
Gross rent	-0.039 (0.053)	-0.038 (0.053)	-0.041 (0.051)	-0.040 (0.051)
Expected sales×exclusive	0.000 (0.003)			0.001 (0.003)
Expected sales×number of rivals		-0.001 (0.001)		-0.001 (0.001)
Expected number of rivals ²			-0.014 (0.027)	-0.015 (0.027)
Constant	-4.992** (0.969)	-5.283** (1.031)	-5.469** (1.317)	-5.811** (1.431)
Observations	8928	8928	8928	8928
Log likelihood	-2022.277	-2021.268	-2021.683	-2020.472

Notes: All regressions exclude Bay Area counties and Sacramento County. Data are collapsed to quarter/store/firm level. All regressions control for firm fixed effects. Standard errors, clustered at the store level, are shown in parentheses. AB (Anheuser Busch). “Distance” is measured in hundreds of miles. “Store size” is measured in 10,000 square feet. “Gross rent” is measured in hundreds of dollars. The Bay Area counties are Alameda County, Contra Costa County, Marin County, Napa County, San Francisco County, San Mateo County, Santa Clara County, Solano County, and Sonoma County.

⁺ significant at 10%, * significant at 5%, ** significant at 1%.



(a)



(b)

Figure 1: Three-tier System: (a) Without Exclusive Dealing, (b) With Exclusive Dealing

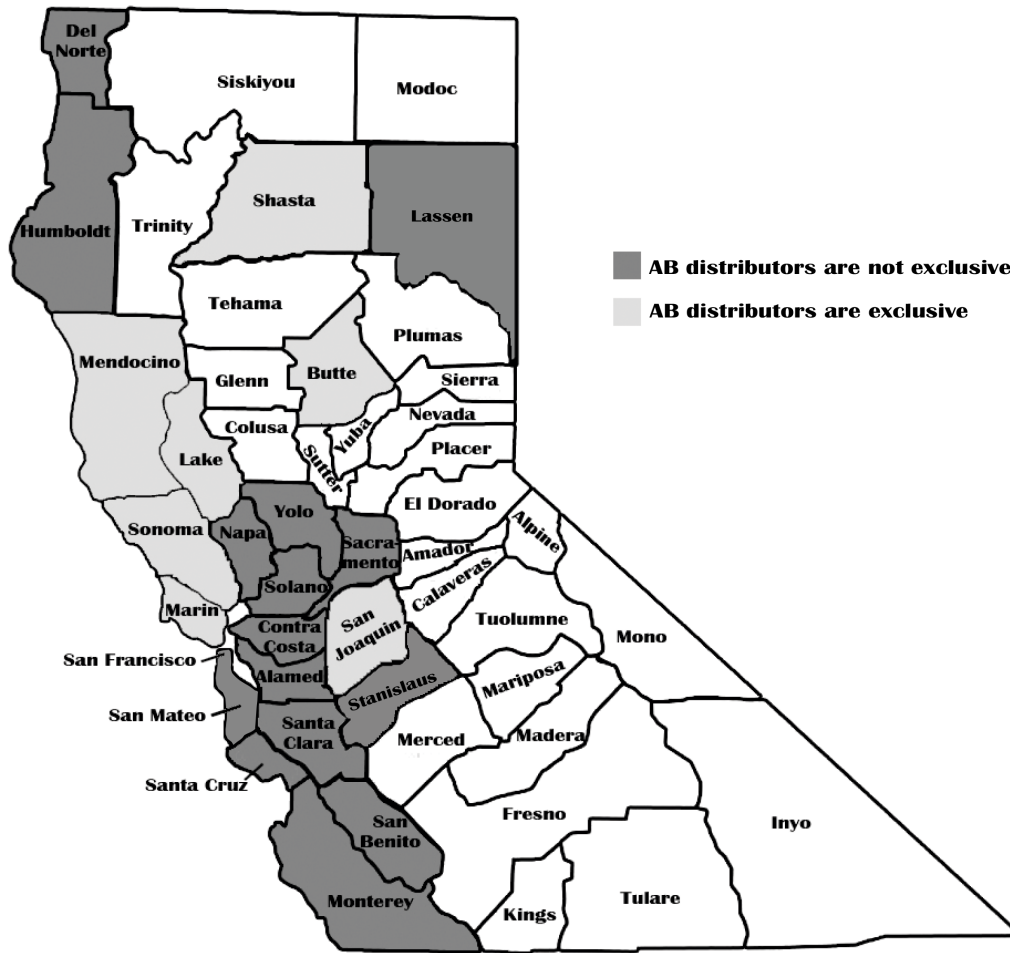


Figure 2: Anheuser Busch Distributors' Exclusivity Status

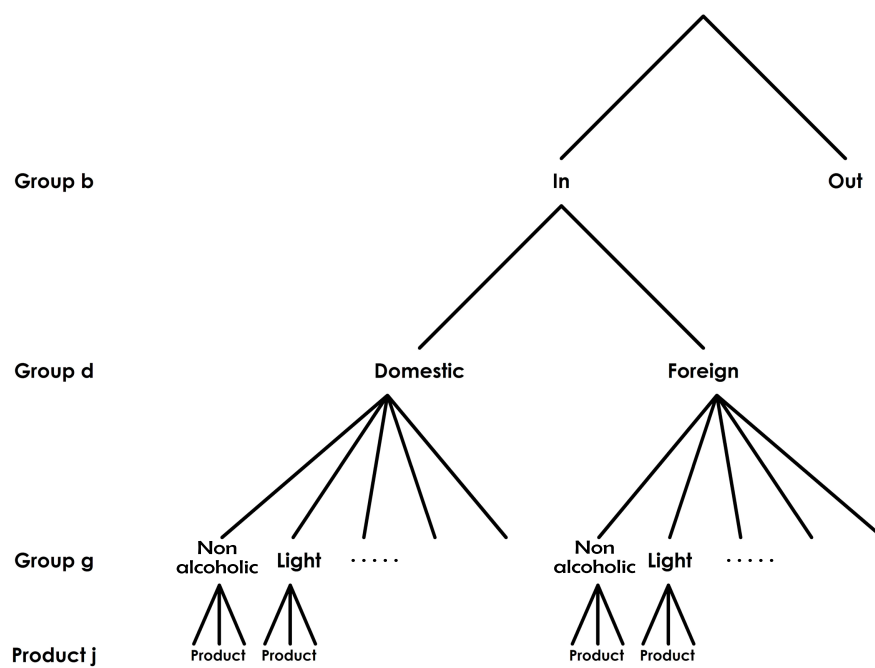


Figure 3: Tree Diagram for the Nested Logit Model

Appendices

A Demand Estimation: Additional Results

In this paper the maintained assumption in demand estimation is that local demand shocks are realized after a firm makes its entry decision. Even though the results from the demand estimation in the main text are obtained from controlling for brand, store, and quarter fixed effects, unobserved promotional activities at the brand level in a local market might still be correlated with product prices. In the main text I use measures of product isolation in the product space as instrumental variables to address this issue. The validity of the instrumental variables approach hinges on the exogeneity of product characteristics. For example, if several firms respond to a positive local demand shock by entering the market simultaneously, then the product space will be crowded, and competition will put downward pressure on prices. In this case, the estimated price sensitivity will be upward biased. Because specialty products are priced significantly higher than mainstream products, a higher price sensitivity would suggest that consumers are less likely to value specialty beer products, which would favor the welfare results in this paper. In this appendix, I provide regression results that are less likely to suffer from endogenous product entry concerns.

The results in the main text are based on quarterly data, because the substitution patterns generated from temporary weekly price promotions are not suitable for many policy applications. However, one way to generate exogenous variation from product entry is to use weekly data, in which product availability may be generated from temporary stocking changes. Another way to have exogenous variation from product entry is to focus on changes in product availability that are more likely to happen at the grocery chain level. For example, new products launched by mainstream producers are more likely to be available in multiple stores at the same time, and so variation in product entry generated from such events are less likely to be correlated with store level demand shocks in a given time period.

The time period that the mainstream brewers launched the most new products into the grocery chain studied in this paper is the third quarter (summer) of 2007. Products such as Busch (domestic mainstream lager) and Sparks Plus (domestic alternative malt beverage) were not carried in any of the stores before the third quarter of 2007. However, the two products were immediately available respectively in 196 and 198 stores (out of 216 stores) in the third quarter of 2007. Other products such as King Cobra (domestic alternative malt beverage) and Foster's Special Bitter Ale (foreign ale) were also available for the first time in the same time period and were immediately available in more than 50 stores. As a robustness check, I focus on this sharp change in the product mix between the second and

fourth quarters of 2007 to take advantage that changes in product isolation were more likely to be driven by a seasonal factor or by fixed store attributes, rather than by unobserved local demand shocks during these three time periods.

Columns (1) and (2) in Table A1 present demand estimation results from weekly data, while columns (3) and (4) provide the results that restrict the sample to the three quarters mentioned before. All the estimated coefficients on the price variable are negative. The estimated mean price elasticities are -13.25, -12.12, -13.02, and -12.28, respectively for the four columns. The price sensitivities from these estimates are all greater than the ones reported in the main text, and therefore using these estimates would only strengthen the results that the changes in consumer surplus from banning exclusive contracts and allowing for more specialty beer products to enter a market are extremely limited.

B Additional Table

Table A1: Demand Estimation: Additional Results

	(1) Logit	(2) Nested Logit	(3) Logit	(4) Nested Logit
Locally brewed	0.392** (0.0768)	0.702** (0.1707)	0.485** (0.0687)	0.188+ (0.0983)
Price	-1.997** (0.1255)	-3.836** (0.6201)	-1.945** (0.2513)	-0.758+ (0.4204)
$\ln(s_{j g})$		-1.266** (0.2750)		0.578** (0.2059)
$\ln(s_{g d})$		-0.402+ (0.2124)		0.663** (0.1829)
$\ln(s_{d b})$		-3.197** (0.9965)		0.454 (0.3030)
Constant	11.085** (1.1764)	22.890** (4.6465)	10.172** (2.2948)	3.539 (2.6187)
Data time interval	weekly	weekly	quarterly	quarterly
Observations	2250306	2250306	78614	78614

Notes: Columns (1) and (2) present two-stage least squares results using data from 104 weeks. Columns (3) and (4) present two-stage least squares results using data from three quarters (Q2, Q3, and Q4 in 2007). All regressions control for brand, week/quarter, and store fixed effects. Standard errors, clustered at the store level, are shown in parentheses. “Locally brewed” is equal to one when a store is located within a 10-mile radius of a firm’s brewery.

+ significant at 10%, * significant at 5%, ** significant at 1%.