Earthquakes and Brand Loyalty: Beyond the short-term effects of product unavailability*

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Abstract

The marketing and economics literature has investigated the impact of product unavailability on consumer choices, primarily focusing on how a stockout episode influences consumer choices during the same or the next trip. This paper focuses instead on the long-term implications of product unavailability. We leverage a quasi-natural experiment that exogenously removed the top leading beer brands from retail stores for several weeks. We test whether these prolonged stockouts can erode market shares beyond the current or subsequent purchase occasions and study the potential mechanisms at play. Using panel data of consumer purchases before and after the product shortage, we observe that the top brands only partially recovered their pre-stockout market shares, especially among their most frequent buyers. We identify a sizable portion of consumers who tried small brands for the first time during the stockout period and remained to buy those products persistently. To control for prices, state dependence, and product availability, we estimate a choice model with heterogeneous preferences and find that exposure to stockouts has long-run effects on purchase behavior. We interpret our estimates as evidence that consumers facing a restricted choice set may learn or become aware of competing products with long-lasting consequences on preferences.

Keywords brand loyalty consideration sets natural experiment stockouts
JEL Codes: M31

1 Introduction

Brand switching has received substantial attention in the marketing literature investigating the role of prices, advertising, and sales promotions as drivers of consumer choices and brand loyalty (e.g., Bronnenberg et al. 2008; Grover and Srinivasan 1992; Yoo et al. 2000).

In addition to pricing and promotions, another critical driver of consumer purchases is the set of options available to consumers. The available products are given by long-term assortment decisions and the temporary fluctuations that arise when the inventory of a product is depleted (i.e., stockouts). In contrast with price and promotions, stockouts impose constraints on consumers by removing alternatives from their choice sets. Hence, consumers who do not find the product they intended to buy are forced to substitute the missing alternative with one of the available products (or an outside option), purchase the product from another vendor or postpone its purchase.

Most research about the impact of product availability on purchase behavior in retail stores focused on the effects of stockouts on consumers' choices during the same trip in which a given product is unavailable (contemporaneous effects) (Vulcano et al., 2012; Bruno and Vilcassim, 2008; Musalem et al., 2010; Conlon and Mortimer, 2013). A few articles have examined the impact of stockouts beyond the same visit by considering consumer choices in the *subsequent* store visit (Che et al., 2012; Campo et al., 2003).

This paper has four essential differences relative to previous research. First, instead of considering stockout effects in the same or subsequent visit to the retail store, we study whether prolonged stockouts lead to systematic changes in preferences beyond the short run.[1] Second, we consider stockout events that lasted several weeks, as opposed to the shorter events observed in prior work (e.g., Vulcano et al. 2012, Conlon and Mortimer 2013). Third, we provide evidence of a learning mechanism explaining the observed systematic changes in consumer preferences. Fourth, to identify causal effects, we rely on a quasi-natural experiment that led to the removal of the top brands of beer from the shelves to study consumer behavior. This unanticipated supply shock implies that the treatment is independent of demand shocks and ensures no planned stockpiling.

More specifically, an earthquake in 2010 caused a significant disruption in the main bottling factory of two of the leading beer brands in Chile. Given the nature of the scarcity and that it affected all retailers within Santiago, the stockout episodes were not informative to consumers about the quality of the affected products or the retailer's assortment. We use loyalty card data to observe consumer-specific exposures to product-specific stockouts at different stores. In effect, the shortage generates a considerable variation in the severity of the stockout-treatment across prod-

[1] Other papers have also considered the long-run effects of product unavailability but in different settings such as catalog purchases (Anderson et al., 2006) and online transactions (Jing and Lewis, 2011). Gijsenberg et al. (2015) study the impact of service crises on perceived quality. Using time-series analysis, they find that adverse shocks have more significant effects on quality perception and last many years after an exogenous disruption occurs in railway services.

ucts and consumers that allows us to study whether these prolonged stockouts changed purchase behavior beyond the short run.

Furthermore, the earthquake affected product availability but did not imply price changes. Cavallo et al. (2014) studied online prices and found compelling evidence that most prices remained unchanged in Chile after the earthquake in 2010. Among other reasons, the Chilean law considers price increase after a major catastrophe as illegal, and most retailers choose not to change prices. Moreover, national statistics indicate that employment and economic activity were only affected for a brief period and then showed a speedy recovery due to the significant fiscal expenditure to rebuild public infrastructure.

We focus on 5,668 frequent buyers of the top leading brands, covering 21 weeks before the earthquake, seven weeks of frequent stockouts, and 16 weeks when the top products gradually became available on shelves again. We find that six percent of the most frequent buyers of leading brands persistently stopped purchasing them after the shortage. Moreover, many consumers tried the less popular brands for the first time (in our data) when the top brands were unavailable, and a substantial fraction of these consumers did not switch back to the top leading products. Overall, this analysis indicates that, even several months after this severe shortage, the leading brands only partially recovered their pre-stockout market shares.

A priori, these findings could be explained perhaps by other reasons different from stockouts, such as price changes. To evaluate and quantify the relevance of alternative mechanisms, we estimate a discrete choice model that incorporates the effect of the stockout exposure on choices in the post-treatment period. In particular, we estimate a random coefficients logit model accounting for prices, state dependence, seasonality, availability, and unobserved heterogeneity in preferences (Heckman, 1981; Dubé et al., 2010). Thus, the discrete choice model allows the valuations of leading brands to be permanently affected by the degree of stockout exposure each consumer faced. We also include a state dependence term to distinguish between transitory and more permanent changes in purchasing behavior. We estimate the demand model using Bayesian methods accounting for unobserved heterogeneity in preferences (Rossi and Allenby, 2003).

Our key finding is that, after controlling for differences in prices, state dependence, seasonality, and product availability, the smaller brands systematically increase their valuations (and market shares) at the expense of the top brands among those consumers who experienced more significant exposure to stockouts. We find that the stockout treatments generally negatively affect the leading brand valuations, leading to decreased market shares in the post-treatment period. We use our structural estimates to compute the counterfactual long-run market shares after the stockout treatments and the price discount needed to offset the adverse stockout effects. We also quantify the market share losses of an additional week of shortage to shed light on the optimal resources to prevent stockouts. Finally, we characterize the first-time purchasers' preference parameters of small brands to shed light on potential mechanisms at play.

We interpret our estimates as evidence that removing top products from the stores forced consumers to become aware of or willing to learn about competing products that became their top choices for a significant share of these first-timers. The empirical study of consideration sets is remarkably challenging as endogenous consideration sets typically preclude researchers from disentangling whether consumers have a strong taste for the leading brands or have not explored enough for competing products (Roberts and Lattin, 1991). Ideally, the identification of consideration sets would rely on an exogenous change in product availability that is uncorrelated with taste shock and (perceived) product quality. Our setting is consistent with that ideal case since our stockouts are exogenous and unanticipated. Another typical difficulty in most settings, including ours, is that consideration sets are unobservable as researchers do not observe which products are being inspected by consumers during their shopping trips. Nevertheless, we can show that the weekly average of first-time consumers of non-top products grows substantially during the stockout period, suggesting that the quasi-experimental shortage enlarged their choice set. The excellent match value of the initially unknown products implied that, at least for a subset of consumers, the new choices remained preferred over the leading brands after the stockout episode.

We discuss whether our results could be explained by other brand preference mechanisms, such as gradual or instantaneous customer learning of new products, switching costs, advertising, habit formation, peer influence, or evolving quality beliefs (Bronnenberg et al., 2019). Our results imply that the observed market share changes are primarily driven by the first-time purchasers of small brands who tried those products only after being exposed to the leading brands' unavailability (Erdem and Keane, 1996; Ching et al., 2013; Shin et al., 2012). Since the first purchase reveals most of the uncertainty about beer's match value, we see trying a product for the first time equivalent to one-shot learning. In effect, we track these first-timers' purchases and verify that their new preferences persist even after the stockouts are over. In addition to one-shot learning, we see the gradual learning hypothesis as a complementary force. However, incremental learning requires a greater level of product quality variability that seems somewhat limited in the beer industry relative to other sectors like, for instance, restaurants.

Other alternative mechanisms seem less relevant in our setting. First, leading brands have substantial incentives to recapture the market through massive advertisements, so we do not believe that small brands' marketing campaigns could explain some consumers persistently remaining away from the leading brands. Second, time-invariant switching costs in the supermarket industry could not support our findings either.

Regarding the existing literature, our paper contributes to two main streams of research. First, our paper relates to the empirical research on the interplay between the origins of brand loyalty (Bronnenberg et al., 2019; Dubé et al., 2010; Horsky et al., 2006) and consideration sets (Nedungadi, 1990; Roberts and Lattin, 1991; Bronnenberg et al., 2016). Our paper analyzes a unique and novel quasi-natural experiment that provides an exogenous change in availability that allows us to identify various drivers of preferences while accounting for individual unobserved persistent heterogeneity and state dependence. Our evidence suggests that the prolonged stockouts change the consideration set for a substantial share of consumers, who became aware or learned about competing products with long-lasting consequences in equilibrium market shares. Thus, our evidence is consistent with Bronnenberg et al. (2021), who emphasize the importance of product availability for brand loyalty relative to other arguments in the US market of craft beers.

Second, our paper also relates to empirical studies on the effects of stockouts on purchase behavior at retail stores. Most of the literature focuses on the short-run effects on consumer choice (e.g., Vulcano et al., 2012; Bruno and Vilcassim, 2008; Musalem et al., 2010). The effects of stockouts are typically measured in the same or next shopping trip the stockout occurred. In contrast, we study systematic and persistent changes in consumer preferences driven by prolonged product unavailability months after the shortage.

The rest of this paper is organized as follows: Section 2 describes the data and the Chilean beer market; Section 3 provides statistical analysis of the leading brands' unavailability on consumer purchase behavior; Section 4 introduces our theoretical framework to study long-lasting effects of stockouts in choices; Section 5 presents our econometric model and results; and Section 6 concludes.

2 Empirical Setting

The beer market in Chile is highly concentrated, as it is often the case worldwide (Adams, 2006). CCU is the largest supplier accounting for over 70 percent of the beer market and produces the two leading brands in the market: Cristal and Escudo. We describe next the data used to measure customer behavior and characterize the shopping environment.

2.1 Description of the transactional data

We use loyalty card data from a big-box supermarket chain in Chile, covering 64 stores in Santiago's metropolitan area. The point-of-sale (POS) individual-level data include quantities and prices paid for each stock keeping unit (SKU) within each transaction involving the beer, water, and soft drink categories. These shopping baskets account for a large number of our relevant consumer trips. We have access to panel data since the retailer's loyalty program identi es transactions where the same loyalty identi cation number was provided. We note however that most customers belonging to the same household use a single number to accumulate loyalty points at a faster rate. Hence, we consider our panel data to be at the household instead of at the individual consumer level. According to the retailer, purchases of brand loyalty card members account for about 80 percent of its total revenues.

Within this market, Cristal and Escudoare the top two leading brands. We focus on their most popular formats and group their SKUs into six alternatives: Cristal one-liter bottles (1000cc), Cristal individual cans (350cc), Escudo one-liter bottles (1000cc), Escudo individual cans (350cc), other SKUs from Cristal, and other SKUs from Escudo. [2]

The recorded transactions took place between early October 2009 and late July 2010. This period includes 21 weeks before the earthquake on February 27th (labeled as the pre-treatment period), 7 weeks immediately after the earthquake where frequent stockouts were observed (treatment period), and 16 weeks when the availability of top brands was gradually restored (post-treatment period). Figure 1 illustrates the start and end dates and labels of the different periods that we use in our analysis. The full sample contains 28,005 households who purchased any beer products at least ten times during the pre-treatment period. The selected consumers made 586,989 beer transactions in the pre-treatment period and 244,622 transactions during the post-treatment period. The average consumer spent approximately 21 dollars and purchased 10.18 items per visit. [3] A store in our sample generated, on average, approximately 2,300 daily transactions including a product from one of the four categories in our data set. Variation in the total number of transactions and revenue across stores re ects differences in store size and location.

We focus on the sub-sample of consumers most loyal to the leading brands. Hence, we consider 5,674 households having at least ten purchase events of the top brand products in the pre-treatment period. This sub-sample made 169,986 beer transactions in the pre-treatment period and 71,845 transactions during the post-treatment period. This reduction in purchases is consistent with an expected seasonality as the Fall starts in mid-March in the Southern hemisphere.

Table 1 presents summary statistics for these frequent buyers of the leading brands. The table shows the average price, the percentage of trips purchasing each product combining the pre- and post-period data. It also presents the market shares before and after the treatment period. Panel A displays the gures for the leading brand in various formats, while Panel B shows the summary statistics for the small brands. The fractions of trips (or incidence rates) are similar to the market shares, indicating that consumers of different brands buy similar quantities. Finally, excluding bottles, there are small price differences among leading and small brands, since most price gaps are caused by one-liter bottles being considerably more expensive than individual cans.

Table 2 shows detailed summary statistics for prices (Panel A), value market shares (Panel B) and incidence rates (Panel C) for each product across the three periods. Panel A shows that prices did not suffer signi cant changes during the three episodes, consistent with the fact that the Chilean law forbids abusive price increases after catastrophes like earthquakes. Instead, Panel B and C show changes in market shares and incidence. We see how product shortage during the treatment period creates a substantial decrease in shares and incidence among Escudo's bottle and can products in that period, which as we will show later exhibited frequent stockouts. Then, the post-treatment market structure resembles their pre-earthquake con guration. However, we observe that leading brands did not quite reach their initial market shares. In relative terms, small

[2]We combine returnable and disposable bottles into the same alternative since their prices and content are identical.

[3]Amounts in US dollars, using the average exchange rate for that period.

brands gained a sizable increase in market shares.

Based on the summary statistics, we observe a 5.5 percentage point decline in the combined market share for the Cristal and Escudo brands after the stockout treatment period (see Table 1, Panel A). This noticeable decrease is mostly driven by households who are frequent buyers of the leading brands (Cristal and Escudo). In contrast, we find a smaller reduction of their market shares in the full sample.[4]

2.2 Identification of Stockouts

As mentioned above, CCU is the dominant beer producer in Chile and owns two major bottling plants. The closest plant to Santiago suffered severe damages after the February 27, 2010 earthquake. As a consequence of this disruption, there was a substantial shortage of CCU's leading beer brands in the forthcoming weeks.

Table 3 presents the number of stores that faced high and low frequencies of stockouts per week. We consider a product to be out-of-stock on a given day and store if no sales are observed. The suggested stockout measure could be misleading for products infrequently sold (slow-moving products). However, for leading brands in fast-moving product categories, as it is the case in our setting, our measure should provide a good approximation of product availability.

We observe substantial variance of stockouts across products and periods, with the treatment period (i.e., between February 26th, 2010, and April 15th, 2010) exhibiting stockout episodes more frequently. Escudo (1L bottle) was the most heavily affected by the factory disruption, while Cristal (350cc can) remained unaffected. Also, the data show that the production shortage impacted more severely the bottle format products. In addition, different products were more affected than others across different stores.

It may be argued that the retailer could have strategically and selectively managed the frequency of stockouts at different stores. For example, it may have prioritized certain stores with greater demand for the affected products. To investigate this possibility, we run a regression of the stockout indicator on store and time fixed effects. The idea is that the explaining power of the store fixed effects should capture the ability of the retailer to offset stockouts. Table 4 shows the marginal contribution of the store fixed effects to the total R-squared on the primary regression. We find that the store fixed effects only explain less than four percent of the variation in three of our main products. Cristal 1L bottle is the exception, with the marginal contribution of the store fixed effects being close to ten percent. Hence, we conclude that the retailers displayed limited efforts to selectively avoid stockouts at certain stores. This finding supports our approach of considering these stockout episodes as a quasi-natural experiment.

We also note that even if retailers had in fact strategically avoided more stockout events at

[4] Table B.1 and B.2 presents the summary statistics for the entire sample of 28,005 households, similar to Tables 1 and 2.

certain stores, our identi cation strategy will still be valid. This is because, we will also rely on within store variation, where customers visiting a particular store on different dates were exposed to different stockout frequencies. Our data allow us to complement this stockout exposure variation across stores with variation across consumers within a store. We construct an individual measure of stockout exposure for each of the six leading brand products considered. The speci c product-consumer measurement is the number of store visits where the consumer faced a leading brand being unavailable. Figure 2 shows the distribution of stockout treatment across individuals and products. From the gure, we can see that the variation across consumers is substantial. Table 5 summarizes the considerable heterogeneity of stockout exposure we observe in the data. Therefore, this quasi-natural experiment provided us with a signi cant exogenous variation in product availability, which will allow us to identify the causal effects of stockouts on future purchase behavior of the more affected individuals.

Our proposed metric of stockout treatment has signi cant advantages over previous papers on stockouts. First, our unanticipated supply shock implies that the treatment variable is independent of demand shocks, ensuring a necessary exogeneity of stockouts to identify their causal effect. Second, we obtain considerable variation in the severity of the stockout-treatment across products and consumers, ideal for econometric identi cation. And third, given the nature of the shortage, the stockout episodes were not informative to consumers about the quality of the products nor the quality of the retailer's assortment. Arguably, one should not expect that these massive stockouts lead to consumer migration between supermarket chains or between stores within a chain.

3 The Treatment Effect of Stockouts on Consumers

This section provides statistical analysis of the leading brands' unavailability on consumer purchase behavior. Thus, we consider the exposure to out-of-stock products as a (continuous) treatment on consumers and seek to estimate the average treatment effect (see details in Imbens and Rubin, 2015).

Our analysis examines whether the increase in market shares of the small brands after facing prolonged stockouts is driven by consumers who have no records of purchasing those products before, labeled as rst-timers. Moreover, we will consider the extent by which the probability of buying one one of the small brands for the rst time correlates with the severity of the stockouts faced by each consumer.

Table 6 describes the statistics of rst-time consumers of small brand products over time. Each panel reports the number of new and total buyers for a speci c small brand product, the ratio of these two quantities, the (potential) number of consumers who could become rst-time buyers in each period and the weekly average of rst-time buyers for each product. Column (1) shows the pre-treatment period, which is our baseline. Column (2) in Table 6 shows that for four out of these six small brands, the new buyers are about 30 percent of their consumers (see fraction of rst timers in this table). This impressive growth in a few weeks is not replicated in Column (3), ruling out a potential market trend in the post-treatment period. Furthermore, since the treatment period is only seven weeks long, the weekly average of new consumers is remarkably higher during the weeks after the shortage.[5]

At this point, we have shown that the market share increase observed in small brands occurs after the earthquake. However, the link with the earthquake can be strengthened in our analysis. Thus, we exploit the variation across consumers with different stockout treatments to shed light on this issue.

We focus on the sub-sample of 1,225 potential rst-time consumers, i.e., those customers who have not purchased any of the small brands during the initial 21 weeks in our data. We estimate probability models where the dependent variable is whether the consumer becomes a rst-timer of any of the small brands in a given week. The explanatory variable of interest is the stockout treatment (number of visits with unavailable leading brands). We also include store xed effects and the number of pre-treatment visits, although different speci cations yield the same conclusions.[6]

Table 7 shows the estimated average treatment effect on the probability of being a rst-time purchaser of small brands. Panel A and B considers a linear probability model and logit model, respectively. Columns (1)-(2) in both panels of Table 7 show that consumers facing more stockouts of leading brands' during the treatment period are more likely to be a rst-timer of small brands, even when controlling for store- xed effects and the number of store visits during the pre-treatment period. Regarding the size of the stockout effect, we nd that the rst-purchase probability is about 7 or 8 percent higher for the average stockout exposure relative to the full availability baseline of 29 and 35 percent in Columns (1) and (2) of Panel A, respectively. Hence, the observed purchasing behavior is consistent with stockouts changing the set of products that consumers typically consider to purchase making households more likely to try new products during the treatment period. We also observe in Columns (3)-(4) of Table 7 that the impact of stockouts during the treatment period on being a rst-timer in the post-treatment period is not signi cant in both panels. Hence, during the post-treatment period, new buyers are not signi cantly driven by the stockout treatment. [7]

To account for heterogeneity across stores, we estimate the logit model above considering store-speci c stockout effects (i.e., including the interaction of stockouts and store xed effect).

[5] As shown in Section 2 above, the smaller formats were less affected by stockouts, which can justify the switching from large bottles to the can format. However, the format cannot explain the brand switching taking place away from Cristal and Escudo towards smaller brands.

[6] In this analysis, we normalize the maximum treatment per product to be one (the average normalized treatment is 0.122 after dividing by the maximum exposure observed in the data).

[7] We validate the quality of our stockout treatment by replicating the estimates using a stockout measure using pre-treatment stockouts. Table C.1 in Appendix C shows that measures of pre-treatment stockouts do not explain consumer behaviour of rst-timers.

Figure 3 shows the histogram of the estimated stockout coef cients during both periods. The histograms con rm that, despite some heterogeneity across locations, the estimates are positive for most stores during the treatment period. In contrast, the estimated effects in the post-treatment data are noisy, with most estimates around zero.

We now turn to investigate whether consumers who became rst-timers of small brands during the treatment period stopped buying them in the subsequent weeks (post-treatment period). Consider the case where rst-timers during the treatment period correspond to consumers loyal to the leading brands being forced by heavy stockouts to try new products. In that case, we should expect no (or at least very limited) repurchase of those small brands by these consumers in the post-treatment period. Figure 4 shows the purchase behavior of rst-timers for each speci c small brand product. The fraction of rst-timers repurchasing the particular product they tried for the rst time during the treatment period ranges between 16.5 percent (Heineken) and 27.7 percent (Becker). Therefore, at least a fraction of households kept buying the new product, thus their purchase behavior is not reversed in the post-treatment period, suggesting a persistent effect. Nevertheless, we also note that a majority of rst-timers stopped buying that speci c product in the post-treatment period. They split between buying leading brands only or mixing leading brands with other small brands or not buying any beer products (probably due to seasonality reasons).

We now replicate this analysis focusing on consumers who purchased one of the small brands during the pre-treatment period. Figure 5 shows their distribution of choices in the pre- and post-treatment periods.

We observe that the fraction of consumers repurchasing each speci c small brand remains virtually unchanged between treatment and post-treatment periods. Hence, we conclude that the leading brands' unavailability did not boost small brand purchases among consumers who have already tried them in the past. This nding supports the idea that the effect of stockouts on choices is driven by consumers who learned about new products during the treatment period. We formalize this argument in the theoretical model in Section 4.

In summary, we nd suggestive evidence that the frequent and prolonged stockouts change purchase behavior for a sizable fraction of consumers. However, a thorough analysis needs to weigh alternative explanations like a change in relative prices, potential state-dependence in consumer choices, and product availability (as some top products were slowly becoming available in the post-treatment period). We use a structural demand model, described in the next section, to account for these different factors and quantify the long-run costs of stockouts.

4 Model of Consumer Choice under Product Unavailability

Based on the ndings above, we consider rationalizing the persistent effects of stockouts on purchase behavior through long-lasting changes in the consideration set of consumers. As in Gensch (1987), we model consumer choice as a two-stage process in which brands are rst screened and then evaluated for the actual purchase. In the first stage, consumers reduce the relevant information by eliminating alternatives (among those they are aware of) until consumers can deal comprehensively with a smaller set of options. In the second stage, consumers thoroughly compare the subset of alternatives for selection (Shugan, 1980).

The literature on two-stage choice models distinguishes between *brand awareness* (i.e., recalling a brand during a purchase or consumption occasion) and *brand consideration*, which is related to the consumer's endogenous deliberation process before making a brand choice (Keller, 1993). Consistent with this approach, the consumer is only aware of a subset of all products and their expected match valuations. Importantly, the consumer has no information on the products outside her awareness set. In terms of the available options in the awareness set, denoted by S^h_{at}, the consumer will decide ex-ante in the first stage, how much product information to acquire. Thus, the first stage optimization determines the subset of options to be inspected in the second stage (Roberts, 1989; Roberts and Lattin, 1991; Bronnenberg et al., 2019). The optimal consideration set, denoted by S^h_{ct}, then solves the following expected utility maximization problem:

$$S^h_{ct} = \arg\max_{s^h_{ct} \subseteq S^h_{at}} \left\{ E\left(\max_{j \in s^h_{ct}} (u^h_{jt})\right) - C\,(s^h_{ct}) \right\} \tag{1}$$

where $C(s^h_{ct})$ is the cost of product evaluation associated with assessing the consideration set s^h_{ct}; and u^h_{jt} is the standard utility of alternative j in period t for household h.

We argue that the extended unavailability of leading brands may change consumers' awareness set, S^h_{at}. In effect, when facing the empty shelves of the most popular products, the competing products previously ignored are now among the only available alternatives. Thus, some previously unaware consumers may then be induced to start learning about the attributes of less popular brands.

Thus, we conjecture that the extended stockouts may have substantially changed consumer awareness of beer brands. The inclusion of new products in S^h_{at} might have temporary effects if the entrant products were perceived as worse than the unavailable top brands. If so, once the shortage episode is over, the leading brands could recapture their pre-stockout market shares. If, however, the new products in the awareness set compare favorably relative to the initially unavailable leading brand products, then the change in purchase behavior can be long-lasting, and in the limit, permanent.

Estimating a model of choice and consideration is challenging, particularly when consideration sets are unobserved. For tractability, we will then formulate a discrete choice model focusing on the products of the two leading brands, but allowing the other alternatives and the outside good to become more attractive in the post-treatment period. These changes in brand valuations will be modeled as a function of a consumer's exposure to the leading brands' stockouts.

We assume that each household h makes discrete choices among the J available products and the outside option (0) in each visit to the supermarket. The close relationship between purchase incidence and market shares shown in the data section (see Table 2) suggests that modeling purchase incidence should yield similar insights compared to the analysis of quantity choices. We capture inertia (or variety-seeking behavior) by including the previous product choice in current utilities (Guadagni and Little, 1983). Thus, the utility of alternative j for consumer h in week t of the pre-treatment period is given by:

$$u_{jt}^h \quad = \quad a_j^h + h^h \ln(p_{jt}) + g^h I f s_t^h = j g + d^h X_t + \#_{jt}^h \tag{2}$$

where p_{jt} is product j's price in period t, $I f s_t^h = j g$ equals one if product j is the last product that was purchased by the consumer, where s_t^h 2 f 1, ..., J g is the index of the previous alternative purchased by the consumer; X_t is a control variable to parsimoniously account for seasonality calculated as the mean temperature registered in Santiago for each week in our data set; and $\#_{jt}^h$ is a random utility shock i.i.d. according to a Type I extreme value distribution. [8] Consequently, the parameter h^h is the price sensitivity coef cient, while g^h is the state dependence coef cient for household h.[9]

The product-speci c intercepts a_j^h represent the household's persistent brand valuation for product j relative to the outside option. In our estimation, we consider $J = 12$ alternatives in addition to the no purchase option. The rst six products correspond to the top leading brands: Cristal 1 liter bottle, Cristal can, Escudo 1 liter bottle, Escudo can, Other Cristal products, Other Escudo products. Alternatives 7-11 correspond to products from smaller brands: Baltica, Becker, Stella Artois, Heineken, Royal Guard, while the 12th alternative considers all other beer products.

If frequent stockouts of the leading brands enlarged consumers' awareness set with better products than the initial inside goods, then we should observe a reduction in the relative valuations of leading brands. Furthermore, we expect that the more stockouts the consumer faced, the greater the product valuation reduction should be for that speci c unavailable product.

Therefore, we incorporate the potential effects of stockout treatments in the utility function for the post-treatment periods. Thus, the utility for small brand products (7-12) follows Equation (2), whereas the utility of the top leading brand products (1-6), is modelled as follows:

$$u_{jt}^h \quad = \quad a_j^h + r_j ST_j^h + h^h \ln(p_{jt}) + g^h I f s_t^h = j g + d^h X_t + \#_{jt}^h, \qquad j = 1, .., 6 \tag{3}$$

where the stockout treatment, ST_j^h, is the number of stockout episodes of product j that consumer h was exposed to during the treatment period. If the stockouts for product j led to lower prefer-

[8] A typical concern when estimating demand is the potential endogeneity of prices. In our setting, prices are identical across consumers as the retailer follows a national pricing policy eliminating a possible correlation with the individual demand shocks. See a more comprehensive discussion in Chintagunta et al. (2005).

[9] The model allows for inertia in brand choices if $g^h > 0$. Conversely, $g^h < 0$ predicts variety-seeking behavior.

ence for this product, then the changes in product j valuation should be captured by a negative parameter r_j. There is experimental evidence of consumers' response to stockouts being positive in some cases (Fitzsimons, 2000; Moore and Fitzsimons, 2014). Hence, we do not restrict the valence of these changes in the relative valuations of the brands due to the stockout treatment and let the data inform us about the sign of this effect.

Note that Equations (2) and (3) include consumer-specific coefficients. We allow for unobserved heterogeneity among consumers with a random coefficients specification. We use Bayesian estimation via Markov chain Monte Carlo simulation. Letting $q^h \quad (a^h_1, .., a^h_{12}, h^h, g^h, d^h)^0$, we specify the following prior distribution: $q^h \quad N(\bar{q}, L)$. We also specify the following weak prior and hyper-prior distributions: $r \quad N(0, 100^2)$, $\bar{q} \quad N(0, 100^2)$, $L \quad \text{InverseWishart}(17, 17I_{15})$, where I_{15} denotes an identity matrix with 15 rows and columns.

Finally, we account for changes in product availability in our estimation since stockouts were observed not only during the treatment period, as shown in Table 3. Thus, we adjust the choice set appropriately for each transaction during the pre- and post-treatment periods. Note that the stockout treatments are not affected by this inclusion, as we do not use the seven weeks of the treatment period in our estimation. [10]

5 Structural Demand Estimates

We estimate several specifications and perform model selection given the marginal log-likelihood of each model. Estimation results of our preferred specification are presented in Tables 8 and 9. [11]

Consistent with the evidence in Section 3, we confirm that stockouts explain purchase behavior in the post-treatment period. In effect, the best model in terms of marginal likelihood includes the interaction between the product-level stockout treatment with their correspondent product-dummies for all the six alternatives manufactured by CCU. The log Bayes Factor for the comparison of this model against the same specification but without treatment variables is 99.9, suggesting very strong evidence in favor of the inclusion of the stockout treatment variables.

The effects of stockouts are significant and negative for four of the leading brand alternatives (Cristal bottle, Cristal can, Escudo bottle and Escudo can) and negative and marginally significant for Cristal Other. Thus, our estimates imply that stockouts have long-lasting effects on consumer preferences, decreasing brand-specific valuations. These estimates are consistent with more fre-

[10] To estimate the discrete choice model, we use the subsample of 5,674 households corresponding to the most frequent buyers of the two leading brands. We discard transactions with more than one beer product to ensure mutually exclusive options consistent with the discrete choice model, dropping six customers that only have multiple beer transactions. Thus, the final estimation sample contains 5,668 households. We provide further details about the data used in the structural estimation in Appendix Section A.

[11] For computational convenience and ease of interpretation, the treatments were normalized by the overall average stockout exposure across consumers (6.34).

quent stockouts making consumers more likely to try different products that may eventually yield higher match values. The model captures this effect by reducing the brand valuation in the post-treatment period for those consumers who faced more stockouts during the treatment period. We also nd positive and signi cant effects for Escudo Other formats, which might be consistent with the experimental ndings of Moore and Fitzsimons (2014), which suggest that certain individuals increase their valuation of out-of-stock products after their availability is restored. Furthermore, there is some evidence that the purchases of Escudo Other resemble those of small brand products regarding the existence of rst-time purchasers during the treatment period. In particular, consumers not nding the 1 liter bottle and the 350cc can products from this brand may have switched to other formats during the treatment period (see Appendix D).

Note that the model does allow for a degree of transitory inertia in addition to the long-run effects. We estimate a positive state dependence coef cient for the average consumer implying that consumers are on average prone to repurchase their previous choice. However, unlike the decrease in product valuations, this inertia can be reversed by adverse changes in relative prices or shocks. Thus, the model allows for stockouts to alter the last purchase and induce the consumer to repeat that purchase away from the leading brand product temporarily. However, the fact that our treatments are signi cant after controlling for state dependence in our speci cation are consistent with a lasting instead of a transitory impact of stockouts on preferences.

The other parameters are in the expected range. Weekly temperature signi cantly captured seasonality in the beer demand as the post-treatment period covers a typically colder (autumn) low-season for the beer market. As expected, the price estimates are negative for almost all consumers.

We now use the estimates of our structural demand model to assess the impact of product unavailability on consumer behavior.

5.1 Quantifying the Effects of Stockouts in Market Shares

We quantify the effects of stockouts on purchase behavior under different counterfactual scenarios. Unlike our descriptive analysis, the structural assessment accounts for observed prices, availability, state dependence, seasonality, and the average stockout-treatment.

First, we compare the steady-state market shares under full availability relative to the scenario with the average stockout level we observe. Hence, as our baseline, we evaluate our estimated demand function at average levels of price, temperature and state dependence and assuming no consumers had been exposed to stockouts during the treatment period. Next, we compute market shares, using the same average prices and state-dependence, but under the stockout exposure observed in the treatment period.

Table 10 shows the posterior mean of the market shares in the long-run and their changes due to the observed stockout exposure. Column (1) shows the baseline market shares assuming no exposure to stockouts during the treatment period, while Column (2) shows the same calculations but under the stockout exposure observed for each consumer in the treatment period. Column (3) shows the difference, and Columns (4)-(5) provide the 95 percent posterior probability intervals for this difference. Finally, Column (6) shows the relative change in the long-run market shares due to the stockouts observed in the treatment period.

We see that, in general, the combined market share of the leading brands exhibits a significant reduction. This is driven by the market shares of Cristal bottle, Escudo bottle, and Escudo can which have substantial decreases. Cristal bottle market share decreases from 6.2 to 5.4 percent, which is a 14 percent reduction. Both the bottle and can formats of Escudo are impacted by the stockouts: bottles decrease its preference from 7.0 to 5.5 percent (-21%), while cans decrease from 15.6 to 15.2 (-2%). No significant changes are observed for Cristal cans and Cristal Other, which is consistent with these products being less affected by stockouts, as shown in Figure 2. At the same time, the long run market share of "Escudo Other" increases. We conjecture that this increase may be associated with a segment of consumers that try this option for the first time (in our data) during the treatment period. [12]

Regarding the impact on small brands, we observe an increase in total market shares, which is somewhat small when expressed in percentage points (column 3), but non-negligible when considered in relative terms (column 6). The magnitudes of the market share increases are significant and in the order of 0.1 percent for all small brands. However, their relative increases are substantial for all small brands and range between 3.8 percent for Heineken and 6.2 percent for "Other brands". We stress that these sizable increases did not disappear, at least, several months after the stockout episodes.

Our results in Table 10 also imply that the outside good increased substantially after the stockout period. The corresponding share increased from 41 percent to 42.9 percent. Therefore, we see that the top brands' unavailability also led to a shrinking in category sales. Notice that seasonality is controlled for in this exercise (as measured by the average temperature).[13] Hence, we interpret this finding as being consistent with substitution of beer consumption through purchases in other categories, probably wine and soft drinks.

Second, to assess the economic magnitude of this effect, we compute the price discount that would offset the negative impact of stockouts on consumer utility for the average consumer. The required price discount for product j, denoted by d_j, should satisfy the following condition: $\bar{\beta}\ln((1-d_j)\bar{p}_j) = \bar{\beta}\ln(\bar{p}_j) - \gamma_j\overline{ST}_j$, where $\bar{p}_j$ is the average price for product j over time; $\bar{\beta}$ and $\overline{ST}_j$ are the average price coefficient and the average stockout treatment across consumers, respectively. Table 11 presents the discounts needed for each leading brand product to offset the adverse effects of the average stockouts. The estimated discounts are 20 and 30 percent for the

[12] See Appendix D for further details.

[13] To test whether our measure of seasonality is driving the results, we perform a robustness check which conditions on buying beer in subsection 5.3.

bottle format products for Cristal and Escudo, respectively. These sizable discounts result from large values of both r_j and $\overline{ST}_j$ (especially for Escudo bottle). The remaining products require a single-digit discount to offset the observed stockout effect.

Finally, we also compute the marginal impact of additional stockout episodes during the treatment period for every consumer. These estimates provide a useful benchmark regarding the nancial consequences of stockouts and give insights on the resources that may be allocated towards avoiding them. Table 12 shows the post-treatment market shares for each alternative when adding one week of stockouts to the average treatment for different products. The rst column shows the baseline market share. The next columns contain the counterfactual market shares under one additional week of stockout exposure to all consumers in each speci c top brand product. The numbers in bold (diagonal of upper sub-matrix) show the effect of the own-product unavailability. The largest market share loss is -3.9 percent for Cristal can (i.e., 13.11-9.24%) and -1.5 percent for Cristal bottle (i.e., 5.35-3.82%), which are the products with the largest estimated stockout coef cients.

The lower panel and the last row shows the corresponding market shares for the small brands and the outside good, respectively, summarizing the estimated substitution from leading brands towards speci c small brand products and the no purchase option.

In summary, Table 12 shows winners and losers from an additional episode of stockouts for each product of the leading brands. These exercises provide useful information to decision-makers regarding the resources that could be economically justi ed to prevent stockouts and their resulting losses or gains in market shares beyond the short-run.

5.2 Characterizing First-time consumers of Small brands

As we obtain estimates at the individual level, we can characterize the segment of consumers that tried the small brands during the treatment period. This exercise can help managers identify which consumer segment is more sensitive to stockouts and hence consider measures to gain them back.

We re-estimate the model using only pre-treatment data, and compare the structural parameter estimates of those who tried a small brand product for the rst time during the stockout period and those who did not. Using only the pre-treatment data allows us to obtain utility coef cients for each consumer that do not rely on the post-treatment behavior. These coef cients are then used to compare rst-timers to all other consumers.

Table 13 presents the posterior mean of the 15 estimated coef cients for both sub-samples. Column (1) shows estimates for the subsample of consumers who tried at least one small brand for the rst time during the treatment period, while Column (2) considers all other consumers. The third column provides the signi cance of the difference of mean coef cients across the two samples.

Based on Table 13, we find that the first-timers are less price-sensitive than Non first-timers, although the mean difference is relatively small. There are no significant differences between the two sub-samples in terms of the coefficients associated with state dependence or seasonality.

Regarding brand valuations, we observe that first-timers have greater intrinsic preference for Escudo products than non first-timers and are also relatively less prone to prefer Cristal products. In addition, there are some statistical differences in their preferences towards some of the small brands, particularly for Becker and the last alternative which combines all other small brands.

Therefore, from the pre-treatment behavior, we observe that first-timers are more likely to be frequent purchasers of Escudo. When facing Escudo stockout episodes, they are less prone to switch to Cristal and hence are more likely to explore small brands despite being slightly more expensive. This characterization of first timers may be useful to identify and potentially target different groups that might be at risk to switch to other brands when facing prolonged stockouts.

5.3 Robustness Check

We perform several robustness checks in this section. First, we focus on those consumers who faced a minimum exposure to stockouts during the treatment period. These consumers are suitable for a placebo test, and we can check whether their purchase behavior was affected after the earthquake. We define the low-treatment sample as those facing a sum of stockouts at the bottom five percentile of the aggregate exposure to stockouts. Thus, the placebo exercise is conducted using consumers who experienced at most three episodes of leading brand unavailability across all products and visits during the treatment period.

Table 14 focuses on the placebo sample and shows that the fractions of first-timers within this sample is much smaller relative to those in Table 6. Therefore, this evidence suggests that consumers with minimum exposure to stockouts did not change their purchasing behavior by trying small brand products.

Second, another potential concern is that the treatment period coincides with last weeks of the summer, thus, our findings could potentially be explained by seasonality not entirely captured by our average temperature measure, as the beer sales are higher during the summer than the rest of the year.

To address this concern, we re-estimated our counterfactual analysis by conditioning on buying beer. The corresponding counterfactual demand estimates show the redistribution of market shares within buyers, regardless of size of the market in the post-treatment period.

Tables 15 replicates the counterfactual calculations for the long-run market shares, conditional on buying. [14] Our conclusions are qualitatively very similar: the stockouts decrease the leading

[14]Notice that market shares are greater than those in Table 1 since these calculations do not consider the outside option.

brand market shares from 79.3 to 77.5 (a relative decrease of -2.2 percent). Small brand products gain a significant market share from 20.7 to 22.5 (a relative increase of 8.8 percent) after the treatment period. Notice that some of the less treated products, namely, can products, increase their market shares when conditioning on buying, consistent with substitution to the closest product. Nevertheless, this substitution does not eliminate our main finding that small brands increase their market shares (by a sizable 8.7 percent after conditioning on buying). Table 16 then shows the marginal stockout effect, conditional on buying. Naturally, the estimated changes are larger, but most findings are qualitatively similar to those in Table 12.

In sum, our results seem robust to capturing seasonality by including average temperature or conditioning on buying beer. However, we acknowledge that if different beers are especially appealing in certain seasons, we may have a confounding factor not included in our analysis. To the best of our knowledge, there is no evidence that this is the case in the Chilean beer market.

5.4 Discussion on Mechanisms and Brand Loyalty

Given our findings, we further discuss the connection between product unavailability and alternative sources of brand loyalty. We follow closely Bronnenberg et al. (2019), who point out that the capital stock of a brand can be explained by evolving quality beliefs through learning, switching costs, advertising, habit formation, and peer influence.

Our most plausible explanation is given by stockouts causing brand loyal consumers to try small brands for their first-time. Erdem and Keane (1996), Ching et al. (2013) and Shin et al. (2012) argue that quality beliefs about products evolve through gradual learning. Our results seem consistent with full learning after the first purchase, equivalent to one-shot learning, where the initial consumption removes most uncertainty about the product match value. Thus, we see the potential gradual learning hypothesis as a complementary force to our preferred explanation. We think that this explanation requires a certain level of volatility on product quality that seems limited in the beer industry relative to other sectors like, for instance, restaurants or airlines.

Other alternative mechanisms seem less relevant in our setting. First, although we have no data on advertising expenditure, we believe that the leading brands had all the incentives to recapture their original market shares through massive advertising. However, our evidence seems that for a subset of consumers, any marketing campaigns were ineffective, so we do not believe that a specific marketing campaign from leading or small brands could explain the persistence of altered market shares. Second, we argue that switching costs in the supermarket industry remained constant across periods and cannot explain the diverse consumer behavior we observe in the post-treatment period. Third, given the shortage's random nature, we believe consumers did not update their beliefs about the leading brands or the retailer's quality.

6 Conclusion

A quasi-natural experiment changes the availability of the leading brands in the Chilean beer market and allows us to study whether prolonged stockouts have persistent consequences in equilibrium market shares. After controlling for prices, heterogeneous preferences, state dependence, seasonality, and product availability, we find that the small brands increase their valuations (and market shares) beyond the short run at the expense of the leading brands among the consumers who were exposed to more extensive stockouts.

We find evidence that suggests that the frequent stockouts change the consideration set for a substantial share of consumers, who might have become aware of competing products with long-lasting purchase behavior. Our evidence stresses the importance of product availability for brand loyalty relative to other arguments as in Bronnenberg et al. (2021). Despite the advantages of our identification strategy, we acknowledge that our data comes from a specific retailer and category, limiting the generalization of our findings. However, we provide an empirical approach that could be replicated in the future when similar supply-side shocks generate exogenous stockouts.

Future research should follow the pool of first-time consumers several years after the incident to study more permanent consequences. Also, we believe that the purchase behavior of the first-time consumers could be useful to test competing theories of learning (Shin et al., 2012) and the origins of brand loyalty (Bronnenberg and Dubé, 2017).

We hope that our findings might be useful to researchers interested in understanding how product availability affects consumer choices and brand loyalty beyond the short run. We also believe that our findings should be helpful for scholars and practitioners concerned with improving inventory and assortment decision making.

References

Adams, W. J. (2006). Markets: beer in Germany and the United States. Journal of Economic Perspectives, 20(1):189–205.

Anderson, E. T., Fitzsimons, G. J., and Simester, D. (2006). Measuring and mitigating the costs of stockouts. Management Science, 52(11):1751–1763.

Bronnenberg, B. J. and Dubé, J.-P. (2017). The formation of consumer brand preferences. Annual Review of Economics, 9:353–382.

Bronnenberg, B. J., Dubé, J.-P., and Moorthy, S. (2019). The economics of brands and branding. In Handbook of the Economics of Marketing, volume 1, pages 291–358. Elsevier.

Bronnenberg, B. J., Dubé, J. P., Mela, C. F., Albuquerque, P., Erdem, T., Gordon, B., Hanssens, D., Hitsch, G., Hong, H., and Sun, B. (2008). Measuring long-run marketing effects and their implications for long-run marketing decisions. Marketing Letters, 19(3/4):367–382.

Bronnenberg, B. J., Dubé, J.-P. H., and Joo, J. (2021). Millennials and the take-off of craft brands: Preference formation in the U.S. beer industry. NBER Working Paper 28618, National Bureau of Economic Research.

Bronnenberg, B. J., Kim, J. B., and Mela, C. F. (2016). Zooming in on choice: How do consumers search for cameras online? Marketing Science, 35(5):693–712.

Bruno, H. A. and Vilcassim, N. J. (2008). Research note—structural demand estimation with varying product availability. Marketing Science, 27(6):1126–1131.

Campo, K., Gijsbrechts, E., and Nisol, P. (2003). The impact of retailer stockouts on whether, how much, and what to buy. International Journal of Research in Marketing, 20(3):273–286.

Cavallo, A., Cavallo, E., and Rigobon, R. (2014). Prices and supply disruptions during natural disasters. Review of Income and Wealth, 2(60):S449–S471.

Che, H., Chen, X., and Chen, Y. (2012). Investigating effects of out-of-stock on consumer stock-keeping unit choice. Journal of Marketing Research, 49(4):502–513.

Ching, A. T., Erdem, T., and Keane, M. P. (2013). Learning models: An assessment of progress, challenges, and new developments. Marketing Science, 32(6):913–938.

Chintagunta, P., Dubé, J.-P., and Goh, K. Y. (2005). Beyond the endogeneity bias: The effect of unmeasured brand characteristics on household-level brand choice models. Management Science, 51(5):832–849.

Conlon, C. T. and Mortimer, J. H. (2013). Demand estimation under incomplete product availability. American Economic Journal: Microeconomics, 5(4):1–30.

Dubé, J.-P., Hitsch, G. J., and Rossi, P. E. (2010). State dependence and alternative explanations for consumer inertia. The RAND Journal of Economics, 41(3):417–445.

Erdem, T. and Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. Marketing Science, 15(1):1–20.

Fitzsimons, G. J. (2000). Consumer response to stockouts. Journal of Consumer Research, 27(2):249–266.

Gensch, D. H. (1987). A two-stage disaggregate attribute choice model. Marketing Science, 6(3):223–239.

Gijsenberg, M. J., Van Heerde, H. J., and Verhoef, P. C. (2015). Losses loom longer than gains: Modeling the impact of service crises on perceived service quality over time. Journal of Marketing Research, 52(5):642–656.

Grover, R. and Srinivasan, V. (1992). Evaluating the multiple effects of retail promotions on brand loyal and brand switching segments. Journal of Marketing Research, 29(1):76–89.

Guadagni, P. M. and Little, J. D. (1983). A logit model of brand choice calibrated on scanner data. Marketing Science, 2(3):203–238.

Heckman, J. J. (1981). Heterogeneity and state dependence. In Studies in Labor Markets, pages 91–140. University of Chicago Press.

Horsky, D., Misra, S., and Nelson, P. (2006). Observed and unobserved preference heterogeneity in brand-choice models. Marketing Science, 25(4):322–335.

Imbens, G. W. and Rubin, D. B. (2015). Causal inference in Statistics, Social, and Biomedical Sciences. Cambridge University Press.

Jing, X. and Lewis, M. (2011). Stockouts in online retailing. Journal of Marketing Research, 48(2):342–354.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. Journal of Marketing, 57(1):1–22.

Moore, S. G. and Fitzsimons, G. J. (2014). Yes, we have no bananas: Consumer responses to restoration of freedom. Journal of Consumer Psychology, 24(4):541–548.

Musalem, A., Olivares, M., Bradlow, E. T., Terwiesch, C., and Corsten, D. (2010). Structural estimation of the effect of out-of-stocks. Management Science, 56(7):1180–1197.

Nedungadi, P. (1990). Recall and consumer consideration sets: In uencing choice without altering brand evaluations. Journal of Consumer Research, 17(3):263–276.

Roberts, J. (1989). A grounded model of consideration set size and composition. ACR North American Advances.

Roberts, J. H. and Lattin, J. M. (1991). Development and testing of a model of consideration set composition. Journal of Marketing Research, 28(4):429–440.

Rossi, P. E. and Allenby, G. M. (2003). Bayesian statistics and marketing. Marketing Science, 22(3):304–328.

Shin, S., Misra, S., and Horsky, D. (2012). Disentangling preferences and learning in brand choice models. Marketing Science, 31(1):115–137.

Shugan, S. M. (1980). The cost of thinking. Journal of Consumer Research, 7(2):99–111.

Vulcano, G., Van Ryzin, G., and Ratliff, R. (2012). Estimating primary demand for substitutable products from sales transaction data. Operations Research, 60(2):313–334.

Yoo, B., Donthu, N., and Lee, S. (2000). An examination of selected marketing mix elements and brand equity. Journal of the Academy of Marketing Science, 28(2):195–211.

Figures

Figure 1: Timeline

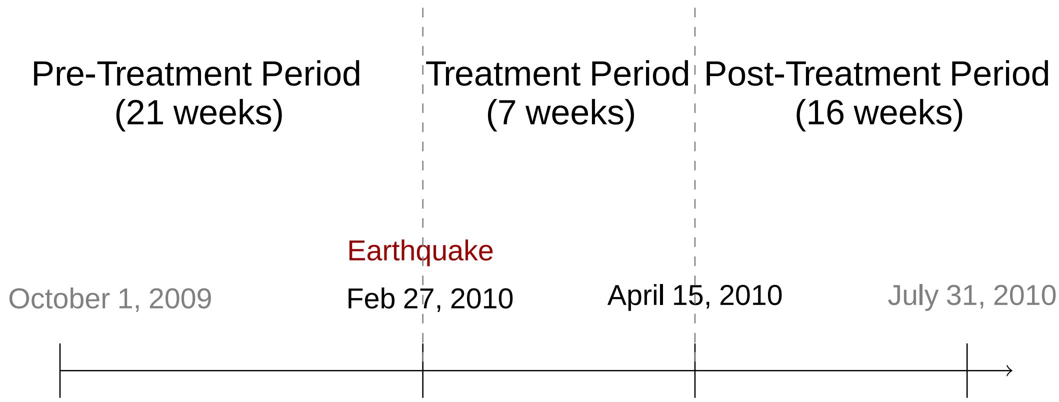


Figure 2: Histogram of Stockout Treatment across Products and Individuals

Notes:Each histogram shows the distribution of the days with stockouts that each consumer faced during the 7 weeks of the Treatment period. An stockout is de ned as a day with no sales of a given product in a given store. A consumer visiting more than one store in the same day may face more than one stockout episode per day.

Figure 3: Store-specific Stockout effects on First-time Purchase of Small Brands

(a) Treatment Period

(b) Post-Treatment Period

Notes: The histogram shows store-specific estimates of the effect of stockouts on the probability of a first-time purchase of small brand, conditional on having no records of previous small brand purchases.

Figure 4: Purchase behavior of Treatment First-timers of Small Brands in the Post-Treatment Period

Notes: The gure shows the purchase behavior in the post-treatment period of the subset of consumers who purchased small brands for the rst time during the treatment period. The gure shows that about one quarter of these rst timers purchased the same small brand during the post-treatment period. Y-axis is in percentage terms relative to total purchase in post-treatment period.

Figure 5: Purchase behavior of Pre-Treatment First-timers of Small Brands

Notes: The figure shows the purchase behavior over time of the subset of consumers who purchased small brands for the first time during the pre-treatment period. The figure is consistent with stockouts (during the treatment period) not altering the distribution of choices for this segment during the post-treatment period. Y-axis is in percentage terms relative to total purchase in the corresponding period.

Tables

Table 1: Summary Statistics for Frequent Buyers of Leading Brands

Panel A: Leading Brands	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Cristal (1L bottle)	1.26	9.5%	10.99%	6.98%
Cristal (350cc can)	0.47	19.1%	18.03%	17.67%
Escudo (1L bottle)	1.25	11.3%	11.82%	8.24%
Escudo (350cc can)	0.47	23.4%	23.64%	25.20%
Other Cristal	0.60	4.6%	5.50%	5.23%
Other Escudo	0.63	5.0%	7.04%	8.20%
All Escudo and Cristal			77.02%	71.52%

Panel B: Small Brands	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Baltica (350cc can)	0.39	3.0%	1.61%	2.81%
Becker (350cc can)	0.41	2.7%	1.83%	3.10%
Stella Artois (354cc can)	0.65	0.8%	0.83%	1.39%
Heineken (350cc can)	0.70	2.9%	3.66%	3.96%
Royal Guard (350cc can)	0.62	1.3%	1.62%	2.12%
Other Beers	0.87	16.3%	13.46%	15.09%
All Small Brands			22.98%	28.48%

No. of households	5,674	Av Trips per household	33.9
No. of Stores	64	Av Top Brand per household	25.9

Notes: Column (1) shows the average price for each product, Column (2) shows the percentage of purchases for each product, conditional on a beer purchase combining data from the pre- and post-treatment periods. Column (3) and (4) are the sales market shares before the Treatment period and after the Treatment period respectively. We only consider the 5,674 households that have at least ten beer transactions of the Leading Brand beers within the initial 21 weeks of data.

Table 2: Summary Statistics of Prices and Market Shares

Panel A: Prices	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cristal (1L bottle)	1.29	1.15	1.62	1.23	1.16	1.55	1.29	1.15	1.53
Cristal (350cc can)	0.50	0.44	0.59	0.48	0.44	0.56	0.47	0.43	0.55
Escudo (1L bottle)	1.31	1.14	1.71	1.31	1.17	1.62	1.25	1.13	1.59
Escudo (350cc can)	0.50	0.44	0.59	0.50	0.44	0.59	0.49	0.43	0.58
Other Cristal	0.65	0.51	0.77	0.66	0.53	0.73	0.67	0.52	0.75
Other Escudo	0.75	0.53	1.00	0.71	0.53	0.96	0.74	0.52	0.95
Baltica (350cc can)	0.43	0.37	0.50	0.41	0.37	0.48	0.41	0.35	0.47
Becker (350cc can)	0.46	0.40	0.56	0.47	0.41	0.54	0.42	0.37	0.53
Stella Artois (340cc can)	0.75	0.63	0.94	0.76	0.68	0.90	0.65	0.54	0.88
Heineken (350cc can)	0.72	0.67	0.79	0.74	0.68	0.81	0.72	0.66	0.80
Royal Guard (350cc can)	0.68	0.57	0.82	0.66	0.60	0.78	0.66	0.58	0.77
Other Brands/Formats	1.02	0.42	2.06	1.05	0.41	2.17	0.99	0.40	1.94

Panel B: Market Shares	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
Cristal (1L bottle)	12.66	6.84	20.47	11.33	5.07	18.17	8.77	2.70	17.99
Cristal (350cc can)	18.84	13.48	25.46	27.69	18.49	38.90	18.87	11.40	31.77
Escudo (1L bottle)	13.98	5.59	27.12	3.82	1.44	7.49	9.78	3.28	16.70
Escudo (350cc can)	25.23	13.99	32.94	16.70	10.22	26.14	26.08	17.04	37.82
Other Cristal	6.61	1.69	11.98	4.71	1.53	11.47	6.48	1.48	11.49
Other Escudo	7.73	1.38	17.76	7.67	3.50	15.56	9.22	2.92	18.82
Baltica (350cc can)	2.35	0.68	6.78	2.82	1.26	4.56	3.95	1.16	11.56
Becker (350cc can)	2.31	0.68	4.83	3.70	1.02	7.40	4.01	1.39	13.00
Stella Artois (354cc can)	1.12	0.33	2.06	2.10	0.53	3.68	1.79	0.42	3.44
Heineken (350cc can)	4.17	1.68	8.42	4.46	1.87	9.24	4.48	1.32	9.60
Royal Guard (350cc can)	1.83	0.44	4.08	4.09	1.14	7.26	2.43	0.45	4.93
Other Brands/Formats	14.40	8.82	22.74	18.72	9.54	26.66	16.03	7.81	28.31

Panel C: Incidence	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
Cristal (1L bottle)	12.42	5.83	24.90	11.69	5.34	19.87	8.52	3.87	15.82
Cristal (350cc can)	20.07	12.96	25.56	29.19	19.07	39.39	19.71	13.86	31.20
Escudo (1L bottle)	14.15	7.53	24.60	4.08	2.10	7.08	10.07	5.47	17.56
Escudo (350cc can)	24.61	13.74	33.57	16.28	11.54	24.52	25.23	17.47	36.32
Other Cristal	5.99	1.78	10.00	4.52	1.68	8.52	6.02	1.35	12.75
Other Escudo	5.72	1.45	11.09	6.00	3.26	8.91	7.65	2.48	13.17
Baltica (350cc can)	3.56	0.95	9.53	4.05	1.56	6.34	5.39	1.87	13.17
Becker (350cc can)	2.80	0.77	5.08	4.43	1.25	8.10	4.44	1.82	8.53
Stella Artois (354cc can)	0.92	0.21	1.50	1.85	0.52	3.11	1.47	0.32	2.47
Heineken (350cc can)	3.31	1.40	5.48	3.60	1.87	8.63	3.65	1.14	7.94
Royal Guard (350cc can)	1.45	0.52	2.51	3.17	1.17	5.50	1.94	0.51	4.49
Other Brands/Formats	16.77	11.02	24.36	19.29	12.35	26.79	18.29	9.96	29.25

Notes: The table shows the mean prices across transactions (top Panel A), the average value market shares calculated across stores (middle Panel B), and the incidence rate calculated as the average presence in consumer's trip across stores (bottom Panel C). For each period described in Figure 1, we report the mean and the percentiles 5 and 95 of the corresponding distribution. The statistics consider the sample of frequent beer purchasers that comprises 5,674 households.

Table 3: Number of Stores under Different Level of Stockouts

	Pre-Treatment (1)	Treatment (2)	Post-Treatment (3)
Panel A: Cristal (1L bottle)			
Less than 2 Stockouts per week	58	38	41
More than 2 Stockouts per week	6	26	23
Total	64	64	64
Panel B: Cristal (350cc can)			
Less than 2 Stockouts per week	63	63	63
More than 2 Stockouts per week	1	1	1
Total	64	64	64
Panel C: Escudo (1L bottle)			
Less than 2 Stockouts per week	60	0	45
More than 2 Stockouts per week	4	64	19
Total	64	64	64
Panel D: Escudo (350cc can)			
Less than 2 Stockouts per week	63	11	63
More than 2 Stockouts per week	1	53	1
Total	64	64	64
Panel E: Others Cristal			
Less than 2 Stockouts per week	61	17	49
More than 2 Stockouts per week	3	47	15
Total	64	64	64
Panel F: Others Escudo			
Less than 2 Stockouts per week	54	6	52
More than 2 Stockouts per week	10	58	12
Total	64	64	64

Notes: The table shows the number of stores under different levels of stockouts. We compute level of stockouts as the weekly average number of days with out-of-stock episodes for each product, across all 64 stores. Column (1), (2) and (3) reports those statistics for the pre-treatment, Treatment and Post-Treatment period, respectively.

Table 4: Stockout Regressions

	(1)	(2)	(3)
Panel A: Cristal (1L bottle)			
Adjusted R-squared	0.0935	0.2097	0.3033
Number of observations	3,136	3,136	3,136
Panel B: Cristal (350cc can)			
Adjusted R-squared	0.0927	0.2443	0.2875
Number of observations	1,760	1,760	1,760
Panel C: Escudo (1L bottle)			
Adjusted R-squared	0.4140	0.5141	0.5515
Number of observations	2,752	2,752	2,752
Panel D: Escudo (350cc can)			
Adjusted R-squared	0.2102	0.4361	0.4686
Number of observations	3,008	3,008	3,008
Week FE	Y	N	N
Date FE	N	Y	Y
Store FE	N	N	Y

Notes: The table shows the results of OLS regressions of the stockout indicator on store and time xed effects. Each panel is one of the four main products in the paper, and each column is a different speci cation. Column (1) adds only week FE. Column (2) adds date FE. Finally, column (3) adds both date and store FE. For each product the table reports the number of observations and the adjusted R-squared.

Table 5: Summary Statistics of Stockouts across Consumers

	Mean (1)	p5 (2)	p50 (3)	p95 (4)
Cristal (1L bottle)	3.47	0	2	11
Cristal (350cc can)	0.59	0	0	3
Escudo (1L bottle)	12.76	1	10	31
Escudo (350cc can)	7.33	0	6	19
Other Cristal	6.15	0	4	18
Other Escudo	7.75	0	6	20
Total Stockout Exposure	38.03	4	30	97

Notes:The table shows the statistics of the stockout episodes for each given product across consumers during the treatment period. Column (1) shows the mean, Column (2)-(4) presents the 5th, 50th, and 95th percentile of the distribution, respectively. Total stockout exposure is the sum of stockout episodes across products for a given consumer.

Table 6: Summary Statistics of First-Time Consumers of Small Brands Products

	Pre-Treatment (21 weeks) (1)	Treatment (7 weeks) (2)	Post-Treatment (16 weeks) (3)
Panel A: Baltica (350cc can)			
# First timers	-	325	139
# Total buyers	697	1,022	1,161
Fraction of rst timers	-	0.32	0.12
# Potential rst timers	5,674	4,977	4,652
# First timers per week	-	46.43	8.69
Panel B: Becker (350cc can)			
# First timers	-	354	237
# Total buyers	983	1,337	1,574
Fraction of rst timers	-	0.27	0.15
# Potential rst timers	5,674	4,691	4,337
# First timers per week	-	50.57	14.81
Panel C: Stella Artois (354cc can)			
# First timers	-	273	191
# Total buyers	559	832	1,023
Fraction of rst timers	-	0.33	0.19
# Potential rst timers	5,674	5,115	4,842
# First timers per week	-	39.00	11.94
Panel D: Heineken (350cc can)			
# First timers	-	284	266
# Total buyers	1,545	1,829	2,095
Fraction of rst timers	-	0.16	0.13
# Potential rst timers	5,674	4,129	3,845
# First timers per week	-	40.57	16.63
Panel E: Royal Guard (350cc can)			
# First timers	-	374	181
# Total buyers	845	1,219	1,400
Fraction of rst timers	-	0.31	0.13
# Potential rst timers	5,674	4,829	4,455
# First timers per Week	-	53.43	11.31
Panel F: Other Brands/Formats			
# First timers	-	516	249
# Total buyers	3,859	4,375	4,624
Fraction of rst timers	-	0.12	0.05
# Potential rst timers	5,674	1,299	783
# First timers per week	-	73.71	15.56

Notes: The table describes the number of new buyers of small brand products (panels) in each period (columns). We de ne new buyers (rst timers) as those who have not purchased the corresponding SKU in our data. Thus, the pre-treatment period is our baseline, with the potential of new buyers being all of the 5,674 households. Column (1) shows the records for the 21 weeks of Pre-treatment period; Column (2) for the 7 weeks of the treatment period; and Column (3) for the 16 weeks of the Post-treatment period. The gures highlight the remarkable peak of new consumers of the small brands during the treatment period as compared to the post-treatment period.

Table 7: Effects of Stockouts on the First-Time Purchase Probability of Small Brands

	Treatment Period (7 weeks)		Post-Treatment Period (16 weeks)	
Panel A: OLS Linear Probability Model	(1)	(2)	(3)	(4)
Stockouts	0.606***	0.678***	0.066	0.063
	(0.160)	(0.174)	(0.127)	(0.125)
Constant	0.253***	0.314***	0.151***	0.139***
	(0.027)	(0.023)	(0.022)	(0.017)
R-squared	0.03	0.08	0.00	0.07
Panel B: Logit	(1)	(2)	(3)	(4)
Stockouts	2.594***	3.065***	0.539	0.606
	(0.709)	(0.809)	(0.997)	(1.079)
Constant	-1.049***	-0.819***	-1.702***	-1.803***
	(0.133)	(0.122)	(0.212)	(0.174)
Log-Likelihood	-793.36	-758.18	-494.22	-447.00
Store FE	N	Y	N	Y
Number of Observations	1,225	1,221	1,225	1,091

Notes: The table shows the average treatment effect of stockouts on the probability of a first-time purchase in small brand products (any brand different from Cristal and Escudo). Panel A uses a linear probability model and Panel B uses a logit model. The stockout variable is the consumer-specific sum of visits with unavailable leading brands during the six weeks of the treatment period, as described in Subsection 2.2. As a normalization, we divide the stockout variable by the maximum value. All specifications include the number of pre-treatment visits. Columns (2) and (4) add store fixed effects. Two stores have no variation in stockouts, and we must drop four observations when including store fixed effects (for the same reason we have less observations in Column (4)). Cluster-robust standard errors (at the store level) in parenthesis. P-values notation: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Empirical Results: Estimated posterior mean, standard deviation, 2.5% and 97.5% quantiles for $\bar{q}$, the square root of the diagonal elements of L and the treatment effects (r).

		Mean (1)	Std Dev (2)	pc 2.5% (3)	pc 97.5% (4)
Mean Preferences	Cristal Bottle	1.76	0.27	1.62	1.90
$\bar{q}_j$	Cristal Can	2.17	0.25	2.04	2.28
	Escudo Bottle	2.05	0.28	1.90	2.20
	Escudo Can	2.44	0.24	2.33	2.55
	Cristal Other	0.30	0.30	0.12	0.47
	Escudo Other	0.54	0.25	0.42	0.66
	Baltica	-2.34	0.28	-2.49	-2.19
	Becker	-0.95	0.31	-1.11	-0.75
	Stella Artois	-1.04	0.37	-1.28	-0.77
	Heineken	0.42	0.25	0.30	0.53
	Royal Guard	-0.81	0.27	-0.94	-0.64
	Other Brands	2.80	0.24	2.69	2.91
	Temperature	1.23	0.16	1.18	1.28
	State Dependence	0.56	0.11	0.53	0.58
	ln(Price)	-1.05	0.10	-1.07	-1.03
Preference	Cristal Bottle	4.57	0.05	4.47	4.68
Heterogeneity	Cristal Can	3.70	0.04	3.62	3.78
(diagonal elements)	Escudo Bottle	3.96	0.05	3.88	4.05
$\sqrt{L_{jj}}$	Escudo Can	3.55	0.04	3.47	3.63
	Cristal Other	3.56	0.05	3.47	3.65
	Escudo Other	3.45	0.04	3.37	3.54
	Baltica	4.29	0.06	4.17	4.40
	Becker	4.07	0.06	3.96	4.18
	Stella Artois	4.40	0.07	4.26	4.54
	Heineken	3.58	0.05	3.49	3.67
	Royal Guard	3.40	0.05	3.30	3.51
	Other Brands	3.58	0.04	3.51	3.66
	Temperature	1.24	0.02	1.19	1.28
	State Dependence	0.52	0.01	0.49	0.54
	ln(Price)	0.65	0.01	0.64	0.66
Treatment Effects	Cristal Bottle	-0.44	0.03	-0.50	-0.37
r_j	Cristal Can	-0.48	0.08	-0.65	-0.32
	Escudo Bottle	-0.19	0.01	-0.21	-0.17
	Escudo Can	-0.06	0.01	-0.09	-0.04
	Cristal Other	-0.04	0.02	-0.08	0.00
	Escudo Other	0.04	0.02	0.00	0.08

Table 9: Empirical Results: Estimated posterior mean, standard deviation, 2.5% and 97.5% quantiles for the variance covariance-matrix of the random coef cients L .

Table 10: Long-run market share estimates

	Baseline	Post Treatment	Absolute Change (2)-(1)	2.5%	97.5%	% Change 100*(3)/(1)
	(1)	(2)	(3)	(4)	(5)	(6)
Cristal Bottle	6.23	5.35	-0.88	-1.02	-0.74	-14.07
Cristal Can	13.19	13.11	-0.07	-0.18	0.04	-0.56
Escudo Bottle	7.01	5.52	-1.49	-1.65	-1.33	-21.31
Escudo Can	15.54	15.19	-0.35	-0.58	-0.11	-2.24
Cristal Other	2.30	2.32	0.02	-0.07	0.11	0.77
Escudo Other	2.54	2.80	0.27	0.16	0.38	10.54
Leading Brands	46.81	44.30	-2.51	-2.82	-2.21	-5.36
Baltica	1.30	1.35	0.06	0.05	0.07	4.58
Becker	1.56	1.63	0.06	0.05	0.08	4.14
Stella Artois	0.52	0.54	0.02	0.02	0.03	4.13
Heineken	1.46	1.52	0.06	0.05	0.07	3.82
Royal Guard	0.73	0.76	0.03	0.03	0.04	4.31
Other Brands	6.64	7.05	0.41	0.36	0.46	6.22
Small Brands	12.21	12.85	0.65	0.56	0.73	5.29
No purchase	40.99	42.85	1.86	1.65	2.09	4.55

Notes: Long-run market shares are calculated using demand estimates and average explanatory variables observed in the data. Column (1) shows the posterior mean of the market shares evaluating the estimated demand function at the average price, state dependence and temperature observed in the Pre-treatment period, imposing full availability. Column (2) shows the same calculation of Column (1) but assuming that all consumers faced the average stockout exposure observed during the Post-Treatment period. Column (3) shows the difference of posterior mean market shares due to stockouts, while Columns (4)-(5) provide the posterior probability intervals for this difference (95% of con dence). Column (6) shows the relative change in the long-run market shares caused by the presence of stockouts.

Table 11: Discounts that offset the Average Stockout Effect

	Av. Log(price) $\log(p_j)$	Stockout Eff. r_j	Av. Stockout $\overline{ST}_j$	Discount [%] d_j
	(1)	(2)	(3)	(4)
Cristal (1L bottle)	6.51	-0.44	0.55	20.46
Cristal (350cc can)	5.49	-0.48	0.09	4.13
Escudo (1L bottle)	6.49	-0.19	2.01	30.49
Escudo (350cc can)	5.51	-0.06	1.16	6.39
Cristal Other	5.73	-0.04	0.97	3.62

Notes: The price discount d_j that offsets the stockout effect, is such that $\hbar \ln((1 \quad d_j) p_j) = \hbar \ln(p_j) \quad r_j \overline{ST}_j$, where p_j is the average price over time for product j; the estimates of the stockout effects, r_j and the average price coef cient, $\hbar = \quad 1.05$ are taken from Table 8; and $\overline{ST}_j$ is the observed average stockout treatment across consumers. The treatments were normalized by the overall average stockout treatment (6.34). We do not include "Escudo Other" products that displayed a positive treatment effect.

Table 12: Marginal Changes in Market shares due to an Extra Week of Stockouts

	Baseline	Additional Stockout for Cristal Bottle	Cristal Can	Escudo Bottle	Escudo Can	Cristal Other	Escudo Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cristal Bottle	5.35	3.82	5.60	5.39	5.36	5.36	5.35
Cristal Can	13.11	13.33	9.24	13.14	13.16	13.13	13.11
Escudo Bottle	5.52	5.60	5.57	4.77	5.55	5.52	5.51
Escudo Can	15.19	15.24	15.51	15.31	14.58	15.20	15.17
Cristal Other	2.32	2.39	2.58	2.33	2.33	2.24	2.32
Escudo Other	2.80	2.82	2.86	2.84	2.85	2.81	2.89
Baltica	1.36	1.37	1.40	1.37	1.37	1.36	1.35
Becker	1.63	1.65	1.73	1.64	1.64	1.63	1.63
Stella Artois	0.54	0.55	0.57	0.55	0.55	0.54	0.54
Heineken	1.52	1.53	1.61	1.52	1.53	1.52	1.51
Royal Guard	0.76	0.77	0.81	0.76	0.77	0.76	0.76
Other Small Brands	7.05	7.19	7.34	7.14	7.11	7.06	7.05
Outside Good	42.85	43.77	45.18	43.26	43.20	42.88	42.82

Notes: The matrix shows the market shares for each product resulting in the demand function when using baseline parameters plus the post-treatment estimates at the average observed price and state dependence, but adding an additional week of stockout to the observed average stockout treatment. The difference between the baseline market share (in the rst row) is the marginal effect in market shares of an extra week of stockout. The expected effect is a reduction in the same product market share and a weekly increasing in competitor and outside good, that includes not buying beer.

Table 13: Demand Estimates of First-Timers and Non First Timers

Pre-Treatment Average Coef cients	First Timers Mean (1)	 Std Dev (2)	Non First-Timers Mean (3)	 Std Dev (4)	Comparison signi cance (5)
Price	-0.81	0.01	-0.84	0.01	<0.01***
State Dependence	0.46	0.02	0.46	0.01	0.46
Temperature	0.60	0.08	0.60	0.06	0.50
Cristal Bottle	0.94	0.07	1.65	0.04	<0.01***
Cristal Can	1.71	0.05	2.27	0.03	<0.01***
Escudo Bottle	1.81	0.05	1.63	0.05	<0.01***
Escudo Can	2.65	0.04	2.18	0.03	<0.01***
Cristal Other	-0.33	0.07	0.19	0.05	<0.01***
Escudo Other	0.57	0.06	0.11	0.07	<0.01***
Baltica	-3.04	0.13	-3.13	0.13	0.17
Becker	-1.37	0.10	-1.26	0.09	0.03**
Stella Artois	-1.51	0.19	-1.44	0.18	0.17
Heineken	0.02	0.08	0.09	0.08	0.07*
Royal Guard	-1.17	0.13	-1.13	0.12	0.26
Other Small Brands	2.33	0.04	2.44	0.03	<0.01***
Sample size	1,736		3,932		

Notes:Estimates of the discrete choice demand model using pre-treatment data only (rst 21 weeks). The speci cation follows Equation (2) for all 13 products. Columns (1) and (2) consider the sub-sample of 1,736 consumers who tried at least one small brand product for the rst-time during the treatment period. For this sample, we display the estimated posterior mean and standard deviation of their average utility coef cients. Columns (3) and (4) report the same quantities for the remaining 3,932 households. Column (5) shows the signi cance of the difference between the average coef cients of rst timers and the remaining consumers. This test is performed by determining the fraction of MCMC iterations in which the average of each k^{th} coef cient for the sample of rst timers is greater than the corresponding average for the remaining customers and then computing the minimum between this fraction f_k and its complement 1 f_k. We use the following notation: * $p <$ 0.10, ** $p <$ 0.05, *** $p <$ 0.01 and denotes the probability that the conclusions based on the mean estimates are reversed.

Table 14: Summary Statistics of First-Time Consumers of Small Brands - Low Treatment

	Pre-Treatment (21 weeks) (1)	Treatment (7 weeks) (2)	Post-Treatment (16 weeks) (3)
Panel A: Baltica (350cc can)			
# 1st Timers	-	4	0
# Total Consumers	29	33	33
Fraction of 1st timers	-	0.12	0.00
# of Potential 1st timers	1,319	1,290	1,286
# 1st Timers per Week	-	0.57	0.00
Panel B: Becker (350cc can)			
# 1st Timers	-	1	5
# Total Consumers	41	42	47
Fraction of 1st timers	-	0.02	0.11
# of Potential 1st timers	1,319	1,278	1,277
# 1st Timers per Week	-	0.14	0.31
Panel C: Stella Artois (354cc can)			
# 1st Timers	-	1	1
# Total Consumers	13	14	15
Fraction of 1st timers	-	0.08	0.07
# of Potential 1st timers	1,319	1,306	1,305
# 1st Timers per Week	-	0.14	0.06
Panel D: Heineken (350cc can)			
# 1st Timers	-	3	3
# Total Consumers	46	49	52
Fraction of 1st timers	-	0.06	0.06
# of Potential 1st timers	1,319	1,273	1,270
# 1st Timers per Week	-	0.43	0.19
Panel E: Royal Guard (350cc can)			
# 1st Timers	-	0	0
# Total Consumers	22	22	22
Fraction of 1st timers	-	0.00	0.00
# of Potential 1st timers	1,319	1,297	1,297
# 1st Timers per Week	-	0.00	0.00
Panel F: Other Brands/Formats			
# 1st Timers	-	5	4
# Total Consumers	122	127	131
Fraction of 1st timers	-	0.04	0.03
# of Potential 1st timers	1,319	1,197	1,192
# 1st Timers per Week	-	0.71	0.25

Notes:The table shows the placebo consumers purchasing small brand products in each period for the rst time. Each Panel presents the data for different small brands, and each column shows a speci c period. We de ne new consumers (1st timers) as those who have not purchased the corresponding SKU in our data. We label placebo consumers to those facing a sum of stockouts at the bottom ve percentile of the aggregate exposure to stockouts, ie., consumers who experienced at most three episodes of leading brand unavailability across all products and visits during the treatment period. Column (1) shows the records for the 21 weeks of pre-treatment period; Column (2) for the 7 weeks of the treatment period; and Column (3) for the 16 weeks of the post-treatment period.

Table 15: Long-run market share estimates conditional on buying

	Baseline	Post Treatment	Absolute Change (2)-(1)	2.5%	97.5%	% Change 100*(3)/(1)
	(1)	(2)	(3)	(4)	(5)	(6)
Cristal Bottle	10.56	9.37	-1.19	-1.42	-0.96	-11.26
Cristal Can	22.34	22.94	0.60	0.39	0.80	2.68
Escudo Bottle	11.88	9.65	-2.23	-2.49	-1.96	-18.75
Escudo Can	26.34	26.58	0.25	-0.10	0.60	0.94
Cristal Other	3.90	4.06	0.16	0.00	0.31	4.05
Escudo Other	4.30	4.90	0.61	0.42	0.79	14.14
Leading Brands	79.32	77.51	-1.80	-2.04	-1.58	-2.27
Baltica	2.19	2.37	0.18	0.15	0.20	7.99
Becker	2.65	2.85	0.20	0.17	0.23	7.53
Stella Artois	0.88	0.95	0.07	0.06	0.08	7.52
Heineken	2.47	2.65	0.18	0.15	0.21	7.21
Royal Guard	1.23	1.33	0.10	0.08	0.11	7.71
Other Brands	11.25	12.34	1.09	0.96	1.22	9.68
Small Brands	20.68	22.49	1.80	1.58	2.04	8.72

Notes: Long-run market shares are calculated using demand estimates and average explanatory variables observed in the data. Column (1) shows the posterior mean of the market shares evaluating the estimated demand function at the average price, state dependence and temperature observed in the Pre-treatment period, imposing full availability. Column (2) shows the same calculation of Column (1) but assuming that all consumers faced the average stockout exposure observed during the Post-Treatment period. Column (3) shows the difference of posterior mean market shares due to stockouts, while Columns (4)-(5) provide the posterior probability intervals for this difference (95% of con dence). Column (6) shows the relative change in the long-run market shares caused by the presence of stockouts.

Table 16: Marginal Changes in Market shares conditional on buying due to an Extra Week of Stockouts

	Baseline	Additional Stockout for Cristal Bottle	Cristal Can	Escudo Bottle	Escudo Can	Cristal Other	Escudo Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cristal Bottle	9.37	6.78	10.21	9.50	9.44	9.39	9.36
Cristal Can	22.94	23.70	16.85	23.15	23.16	22.99	22.92
Escudo Bottle	9.65	9.96	10.16	8.40	9.78	9.66	9.63
Escudo Can	26.59	27.10	28.30	26.97	25.67	26.61	26.52
Cristal Other	4.06	4.25	4.71	4.11	4.10	3.92	4.05
Escudo Other	4.90	5.01	5.21	5.01	5.02	4.91	5.06
Baltica	2.37	2.43	2.55	2.41	2.41	2.37	2.37
Becker	2.85	2.93	3.15	2.88	2.89	2.85	2.84
Stella Artois	0.95	0.97	1.05	0.96	0.97	0.95	0.95
Heineken	2.65	2.72	2.94	2.68	2.70	2.66	2.65
Royal Guard	1.33	1.36	1.47	1.34	1.35	1.33	1.32
Other Small Brands	12.34	12.79	13.38	12.58	12.52	12.36	12.32

Notes: The matrix shows the market shares for each product resulting in the demand function when using baseline parameters plus the post-treatment estimates at the average observed price and state dependence, but adding an additional week of stockout to the observed average stockout treatment. The difference between the baseline market share (in the rst row) is the marginal effect in market shares of an extra week of stockout. The expected effect is a reduction in the same product market share and a weekly increasing in competitor and outside good, that includes not buying beer.

Online Appendix

A Data Construction for Estimation

This section lays out the main steps taken in order to create the sample used in the estimation of the structural model described in section 5. Please note that these steps (particularly steps 1 and 2) apply only to the estimation of the structural demand model. Speci cally, we implement the following steps:

1. We drop 10.51% of the store visits, which correspond to trips with multiple SKU purchases. This step also leads to the removal of 6 households (0.1%) from our dataset because their visits only included multi-SKU purchases. Accordingly, after this step, we are left with 5,668 of the 5,674 consumers.

2. We only model one choice per week for every consumer. In the case of consumers buying the same product in multiple store visits within a week, we only consider the earliest visit in that week (affecting 5.22% of household-week-product combinations). In the case of consumers buying multiple products within a week, we randomly select one choice (affecting 10.29% of household-week combinations).

3. We determine prices using transaction data to create a panel data for each alternative-week-store combination.

4. We build the availability variable that indicates whether each speci c leading brand product was purchased during a particular date in a given store.

B Data Details

Table B.1: Summary Statistics for the Full Sample

Panel A: Leading Brands	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Cristal (1L bottle)	1.26	4.3%	4.33%	2.93%
Cristal (350cc can)	0.47	9.9%	8.44%	9.74%
Escudo (1L bottle)	1.25	5.3%	4.90%	3.45%
Escudo (350cc can)	0.47	12.0%	10.98%	12.66%
Other Cristal	0.59	3.7%	4.51%	3.62%
Other Escudo	0.63	4.2%	5.59%	6.19%
All Cristal and Escudo			38.75%	38,59%

Panel B: Small Brands	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Baltica (350cc can)	0.39	5.4%	3.40%	4.20%
Becker (350cc can)	0.41	4.7%	3.37%	5.13%
Stella Artois (354cc can)	0.66	2.7%	3.49%	3.76%
Heineken (350cc can)	0.70	6.3%	8.48%	8.34%
Royal Guard (350cc can)	0.62	2.5%	3.00%	3.19%
Other Beers	0.89	39.0%	39.50%	36.78%
All Non Cristal and Escudo			61.25%	61.41

Av. Trips per household	23.0	No. of households	28,005
Av. Leading Brands per household	10.9	No. of Stores	64

Notes: Column (1) shows the average price for each product, Column (2) shows the percentage of purchases for each product, conditional on a beer purchase. Column (3) and (4) are the sales market shares before the Treatment period and after the Treatment period respectively. We consider 28,005 households that have at least ten beer transactions within the initial 21 weeks of data.

Table B.2: Summary Statistics of Prices and Market Shares (Full Sample)

Panel A: Prices	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
Cristal (1L bottle)	1.30	1.15	1.62	1.24	1.16	1.55	1.30	1.15	1.53
Cristal (350cc can)	0.50	0.44	0.59	0.48	0.44	0.56	0.47	0.43	0.55
Escudo (1L bottle)	1.32	1.15	1.71	1.32	1.17	1.62	1.27	1.13	1.59
Escudo (350cc can)	0.49	0.44	0.59	0.49	0.44	0.59	0.48	0.43	0.58
Other Cristal	0.63	0.50	0.77	0.65	0.52	0.73	0.65	0.51	0.74
Other Escudo	0.71	0.52	0.99	0.69	0.53	0.96	0.70	0.52	0.94
Baltica (350cc can)	0.41	0.36	0.49	0.41	0.37	0.47	0.40	0.34	0.47
Becker (350cc can)	0.45	0.40	0.56	0.46	0.41	0.54	0.41	0.37	0.52
Stella Artois (340cc can)	0.71	0.62	0.93	0.73	0.68	0.89	0.63	0.55	0.86
Heineken (350cc can)	0.72	0.67	0.78	0.72	0.68	0.81	0.71	0.65	0.80
Royal Guard (350cc can)	0.66	0.57	0.82	0.65	0.60	0.78	0.64	0.58	0.77
Other Brands/Formats	1.07	0.43	2.16	1.07	0.42	2.17	1.04	0.40	2.07

Panel B: Market Shares	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
Cristal (1L bottle)	5.77	2.04	11.20	5.91	2.64	9.00	4.08	1.76	9.70
Cristal (350cc can)	9.39	5.30	15.72	18.09	11.17	30.48	11.21	6.01	18.68
Escudo (1L bottle)	6.13	2.14	10.55	1.92	0.77	3.60	4.33	1.95	7.27
Escudo (350cc can)	11.74	8.36	17.69	9.46	4.47	14.82	13.61	9.01	19.77
Other Cristal	6.02	1.33	12.20	3.98	1.28	7.83	4.89	1.22	7.99
Other Escudo	7.32	1.30	15.49	6.16	2.74	9.76	8.19	1.80	15.39
Baltica (350cc can)	3.98	2.01	7.56	3.81	1.77	5.36	4.99	2.52	9.08
Becker (350cc can)	3.68	2.05	5.99	4.89	2.22	8.90	5.75	3.06	10.25
Stella Artois (354cc can)	4.17	1.37	7.47	4.88	1.94	7.17	4.25	1.66	6.48
Heineken (350cc can)	8.91	5.35	12.60	6.89	4.71	10.28	8.69	4.44	12.82
Royal Guard (350cc can)	3.38	1.70	5.49	5.01	2.16	8.54	3.60	1.71	6.45
Other Brands/Formats	41.50	24.69	56.94	37.94	20.90	51.44	37.77	20.88	53.34

Panel C: Incidence	Pre Treatment			Treatment			Post-Treatment		
	Mean	p5	p95	Mean	p5	p95	Mean	p5	p95
Cristal (1L bottle)	6.11	2.13	12.16	6.45	2.98	11.96	4.34	1.87	9.32
Cristal (350cc can)	10.38	6.77	15.30	18.85	12.31	29.77	11.42	7.41	17.89
Escudo (1L bottle)	6.88	2.86	12.06	2.24	0.97	4.21	5.03	2.31	8.08
Escudo (350cc can)	12.21	8.76	18.10	9.68	5.52	15.08	13.67	8.68	20.71
Other Cristal	5.10	1.25	8.44	3.52	1.07	6.35	4.39	1.35	7.67
Other Escudo	5.19	1.32	11.23	4.61	2.38	7.76	6.39	1.64	11.14
Baltica (350cc can)	5.62	2.93	10.33	5.48	2.87	8.51	7.32	3.65	12.32
Becker (350cc can)	4.43	2.68	6.50	5.82	2.53	8.68	6.50	3.84	9.94
Stella Artois (354cc can)	3.19	1.16	5.62	3.89	1.78	5.49	3.45	1.33	5.26
Heineken (350cc can)	6.79	3.66	9.38	5.46	3.81	8.09	6.65	3.66	10.20
Royal Guard (350cc can)	2.75	1.30	4.55	4.12	1.89	7.17	2.87	1.53	4.91
Other Brands/Formats	42.40	28.65	54.36	38.25	22.58	49.28	38.77	23.83	51.75

Notes: The table shows the mean prices across transactions (top Panel A), the average value market shares calculated across stores (middle Panel B), and the incidence rate calculated as the average presence in consumer's trip across stores (bottom Panel C). For each period described in Figure 1, we report the mean and the percentiles 5 and 95 of the corresponding distribution. The statistics above consider the full sample of 28,005 households with at least ten beer transactions within the pre-treatment period.

C Robustness Check

Table C.1: Effects of Pre-Treatment Stockouts on the First-Time Purchase Probability of Small Brands

	Pre-Treatment Period (February)		Treatment Period (7 weeks)		Post-Treatment Period (16 weeks)	
Panel A: OLS						
Pre-Treatment Stockouts	0.129	0.011	-0.151	0.019	0.144	0.179
	(0.106)	(0.161)	(0.128)	(0.163)	(0.134)	(0.149)
Constant	0.109***	0.115***	0.292***	0.336***	0.131***	0.120***
	(0.016)	(0.012)	(0.024)	(0.020)	(0.015)	(0.009)
R-squared	0.01	0.05	0.00	0.05	0.00	0.06
Panel B: Logit						
Pre-Treatment Stockouts	0.948	0.124	-0.728	0.113	1.222	2.011
	(0.690)	(1.127)	(0.649)	(0.822)	(0.968)	(1.337)
Constant	-2.021***	-1.987***	-0.876***	-0.686***	-1.815***	-1.901***
	(0.108)	(0.079)	(0.006)	(0.092)	(0.183)	(0.137)
Log-Likelihood	-584.38	-549.49	-892.91	-860.01	-520.98	-472.76
Store FE	N	Y	N	Y	N	Y
Number of Observations	1,430	1,367	1,430	1,425	1,430	1,261

Notes: The table shows the logit estimates of stockouts during the pre-treatment period on the probability of a first-time purchase in small brand products (any brand different from Cristal and Escudo). We us the stockout variable as the sum of visits with unavailable leading brands from October 2009 to January 2010 (pre-treatment). The stockout measure is consumer-specific, as described in Subsection 2.2. As a normalization, we divide the stockout variable by the maximum value. Columns (2) and (4) add store fixed effects. As some stores have no variation in stockouts, we must drop some observations when including store fixed effects. Cluster-robust standard errors (at the store level) in parenthesis. P-values notation: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

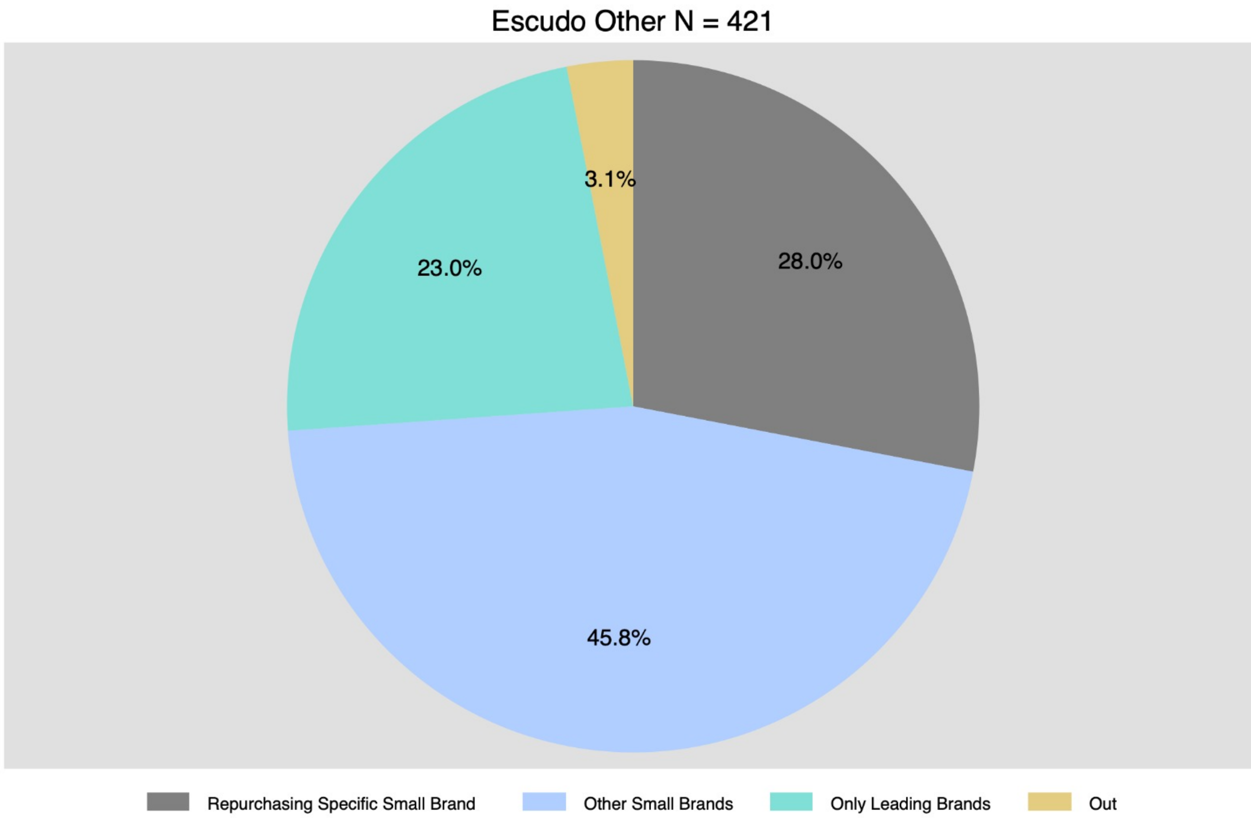
D Analysis of Escudo Other formats

In this appendix section, we explore whether the less popular formats within the leading brand Escudo can display the same change in consumer behavior documented for the small brands products. In effect, from the summary statistics in Table 1, we see that the market share actually increased after the frequent stockout period from 7 to 8.2 percent.

Figure D.1 shows that 421 consumers purchased the Escudo Other format for the first time in our data during the stockout period. This pattern is similar to those shown in Figure 4. Also, similar to the purchase behavior of first timers of small brands depicted in Figure 5, the consumers who have tried "Escudo Other" during the pre-treatment period, were not majorly affected by the stockouts of that product, as shown in Figure D.2.

Whether the product awareness mechanism we introduced in the theoretical section is taking place at the brand or brand-format level is not theoretically clear. We think, this interesting feature can help us to rationalize the estimated positive effect for the Escudo Other product. Arguably, the frequent stockouts of Escudo bottle and Escudo might explain the behavior of the 421 first-time purchasers of Escudo Other formats, leading to the same persistent phenomenon we documented for the small brands.

Figure D.1: Purchase behavior of Treatment First-timers of Escudo Others over time



Notes: The figure shows the purchase behavior over time of the subset of consumers who purchased Other Escudo for the first time during the treatment period. The figure shows that 72 percent of these first-timers do not repurchase Escudo Other during the post-treatment period, whereas 28 percent kept buying Escudo Other during the post-treatment period.