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

Cristián Figueroa† Andrés Musalem§ Carlos Noton‡

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We exploit a natural experiment that exogenously removed the top leading brands from the retail stores for several weeks to study whether prolonged stockouts can erode market shares persistently. Using a 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. Controlling for prices, state dependence and product availability in a choice model with heterogeneous preferences, we find that the less popular brands increase their valuations among those consumers more exposed to stockouts. We interpret our estimates as evidence that changes in the consideration set forced consumers to become increasingly aware of competing products, changing their purchase behavior persistently.

Keywords: stockouts brand loyalty natural experiment consideration sets

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1 Introduction

What would be the consumer choices after several weeks of their preferred leading brands being unavailable? The stockout episodes certainly test the strength of brand loyalty. However, causal effects are elusive since most observed stockouts are correlated with demand shocks such as deep promotions (Anderson et al. (2006); Jing and Lewis (2011); Che et al. (2012); Vulcano et al. (2012)). We study whether exogenous disappearance of the top brands from the shelves can erode their market shares persistently.

We use a natural experiment that exogenously removed the top leading brands from retail stores to evaluate the consequences of widespread stockouts beyond the short run. In 2010 an earthquake caused a significant disruption in the main factory of the top leading beers in Chile. This unanticipated supply shock led to the stockouts of the top brands in all retailers for six weeks. We study this episode using panel data for 5,667 households of a big-box retailer covering transactions during 21 weeks before the earthquake (pre-treatment period); 6 weeks of heavy stockouts (treatment period); and 16 weeks once most brands were available again (post-treatment period).

Using our panel data of consumer purchases before and after the product shortage, we observe that, months after being back on the shelves, the top brands only partially recovered their pre-stockout market shares. In fact, about six percent of the consumers moved away persistently from these leading brands. We use this exogenous variation in product availability to identify the mechanisms of the different economic forces at play, and quantify how stockouts can erode market shares beyond the short run.

Our analysis is based on constructing individual measures of stockout exposure for each product, which is defined as the number of store visits in which the consumer faced a top beer being unavailable.[1] This individual metric of stockout treatment has important advantages. First, the unanticipated supply shock ensures that the treatment is uncorrelated with demand shocks. Second, we capture a considerable variation in the severity of the stockout-treatment across products and consumers that we will exploit for identification. Third, given the accidental nature of the shortage, the stockout episodes were not informative for consumers about the quality of the products nor the quality of the retailer's assortment.

Using household purchases, we estimate a discrete choice model with heterogeneous preferences that incorporates the effect of the stockout exposure on choices in the post-treatment period. In particular, we estimate a non-parametric mixed logit to account for the persistent purchasing behavior consistent with state dependence and unobserved heterogeneity in preferences (Heckman (1981); Dubé et al. (2010)). We follow the approach of Fox et al. (2011, 2016) to avoid parametric assumptions regarding the distribution of the unobserved heterogeneity.

[1] We consider a product to be out-of-stock in a given day if we observe no sales that day. Although this measure could be misleading in slow-rotation products, this seems reasonable for products with market shares between 15 and 30 percent of the beer market.

In the estimation we allow the stockout-treatment to interact with the fixed effects of the four top products. Hence, we let the preferences for the top four brands in the post-stockout period to potentially change among those consumers that were more exposed to stockouts.

Our key finding is that, after controlling for prices, state dependence and product availability, the non-top four products increase their preferences (and market shares) permanently at the expense of the leading brands among the consumers who suffered more extensive exposure to stockouts. In effect, we find that the top four product fixed effects are negatively affected by the stockout treatments leading to a 1-2 percent decrease in market shares in the post-treatment period. Moreover, we find that consumers with lower price sensitivity were more affected by stockouts and decreased their valuations of the top brands relative to their competitors in the outside good. We use our structural estimates to compute the counterfactual long-run market shares after the stockout treatments and find that the outside good increased by 6-8 percent. Also, we quantify the costs as the market share losses of an additional day of stockout which can shed light on the managerial decisions regarding the resources for inventory management to avoid out-of-stocks episodes.

We interpret our estimates as evidence that removing top products from the stores forced consumers to become increasingly aware of competing products, which could end up being the most preferred choices for a substantial share of consumers. The empirical study of consideration sets is remarkably challenging since the endogeneity of the consideration sets typically precludes researchers to disentangle whether consumers have a sizable taste for the leading brands or they have not explored enough the competing products (Roberts and Lattin (1991)). Since rational consumers should include the best products in their consideration sets, identification requires an exogenous change of product availability that is uncorrelated with taste shocks and (perceived) product quality. We overcome this concern since our stockouts are exogenous and unanticipated. Also, another common difficulty is that considerations set are unobservable as researches do not know which products are being inspected by consumers during their shopping trip. Although consideration sets are unobservable in the retail sector, we show that the weekly average of first-time consumers of non-top products more than duplicates during the stockout period. This model-free evidence shows that consumers choose, for the very first time (in our data) the non-top products during the stockout period. The excellent match value of the initially unknown (and probably more expensive) product implied that, at least for a subset of consumers, the new optimal choice was not reverted when leading brands are available.

We also explore the potential connection of the stockout-treatments with alternative sources of brand loyalty. We follow Bronnenberg et al. (2018) who point out that the capital stock of a brand can be explained by switching costs, advertising, habit formation, peer influence, and evolving quality beliefs through learning. First, switching costs in the supermarket industry remained relatively constant across periods and cannot explain the heterogeneous effects of consumer behavior in the post-treatment period. Second, although we have no data on advertising expenditure, we believe that the leading brands have all the incentives to recapture their original market shares through massive advertising. Our evidence seems that for a particular subset of consumers, marketing campaigns were ineffective, so we do not believe that a specific campaign of marketing can explain the persistence of altered market shares. Third, we have no evidence to rule out habit formation or peer influence. However, given the short extension of the stockouts (six weeks) and the fact that the peer influence seems invariant across periods, we think these explanations probably do not play a major role explaining the persistent change in market shares after the stockout period. Fourth, we find unlikely that the stockouts changed the quality beliefs about the leading brands. However, first-time consumers of non-top products might have started to learn about those new products because of the stockouts (Erdem and Keane (1996); Ching et al. (2013); Shin et al. (2012)). We cannot rule out this explanation although it requires a certain level of uncertainty about product quality that seems rather limited in the beer industry in comparison with other industries like, for instance, restaurants, wine, and the automobile industry.

In terms of the existing literature, our paper contributes to two main streams of research. First, our paper relates to the empirical research of the effects of stockouts on purchase behavior. Most of the existent literature focuses on the short-run effects on consumer choice (Vulcano et al. (2012); Musalem et al. (2010)). The few papers seeking to assess longer-run effects use infrequent stockouts that are potentially endogenous (Anderson et al. (2006); Jing and Lewis (2011); Hebblethwaite et al. (2017); Che et al. (2012)). Conlon and Mortimer (2013) implement field experiments in vending machines to randomize assortment and overcome the endogeneity problem. However, they are not able to study long-run effects or state dependence as they cannot track the identity of the consumers. Che et al. (2012) study the effects of stockouts on consumer behavior using individual data from the retail sector. To address the stockout endogeneity, they implement a control function approach using store traffic information and cost data to predict product unavailability. Perhaps restrictive, their exclusion restrictions require the individual demand shocks to be uncorrelated with store traffic. We contribute by studying the consequences of exogenous stockouts of the leading brands using panel data of consumers to account for heterogeneous preferences and state dependence. We also quantify the economic losses for a manufacturer and retailer of setting inventory levels ignoring the long run impact of stockouts on buying behavior.

Second, our paper relates to the stream of empirical research on the interplay between brand loyalty (Bronnenberg et al. (2018); Dubé et al. (2010)) and consideration sets (Nedungadi (1990); Roberts and Lattin (1991); Bronnenberg et al. (2016)). Our paper contributes with a unique and novel natural experiment that provides an exogenous change in availability that allows us to identify different mechanisms 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 of competing products with long-lasting consequences in equilibrium market shares.

The rest of this paper is organized as follows: Section 2 describes the data and the Chilean beer market; Section 3 introduces our theoretical framework to justify long-lasting effects of stockouts in choices, Section 4 presents our econometric model and results; and Section 5 concludes.

2 Data on the Chilean Beer Market

The beer market in Chile is highly concentrated, a common phenomenon across the globe (Adams (2006)). CCU is the major supplier accounting for more than 70 percent of the market and the owner of the top four brands in the market.

Despite the large market shares of top products in Chile and worldwide, the brand quality of beer seems not easily observable and, moreover, it is difficult for consumers to identify brands by taste as shown by evidence from blind contests in different environments (Allison and Uhl (1964); Greer (1998); Tremblay et al. (2005)).

2.1 Data Description

We use brand loyalty card data from a large chain of supermarkets in Chile covering 64 supermarket stores located in major Chilean cities. The point-of-sale (POS) individual-level data include all items in consumers' shopping baskets for the categories of beer, water and soft-drinks that account for a large set of the consumer trips. The records contain prices paid for each item and the date and time of the transaction. We have panel data as the retailer loyalty program uniquely identifies each consumer. Most customers belonging to the same household use a single number to accumulate and redeem loyalty points at a faster rate. This is a common practice in the supermarket industry. According to the retailer, purchases made through its loyalty program account for about 80 percent of its total revenues.

We focus on the top four beer products in the Chilean market. The most important products cover the two most important brands, *Cristal* and *Escudo*, and their most popular formats: one liter bottles (1000cc) and individual cans (350cc). We denote Cristal bottle, Cristal can, Escudo bottle and Escudo can as products 1, 2, 3 and 4, respectively.[2]

Also, to ensure mutually exclusive choices, we discard transactions with more than one beer products, which represent a 3.7 percent of all transactions. We consider the store visits of each household in our analysis including those where no beer products were purchased.

The recorded transactions took place between early October 2009 and late July 2010. The dates include 21 weeks before the earthquake (pre-treatment period), 6 weeks of frequent stock-outs (treatment period), and 16 weeks after the shortage episodes were over (post-treatment

[2]We have consider returnable and disposable bottles as the same product, since their prices and content are identical.

period). Figure 1 illustrates the limit dates and names of the different periods that we use in our analysis. Our final sample contains 5,667 consumers, who purchased top 4 beer products for at least 10 times in the pre-Treatment period. The selected households made 128,834 beer transactions in the pre-treatment period and 56,842 transactions during the post-treatment period, showing a strong seasonality.[3]

The average consumer spent approximately 2.54 dollars and purchased 11 items per visit.[4] A store in our sample generated, on average, approximately 2,300 daily transactions (including a product from one of the four categories we analyze). Variation in the total number of transactions and revenue across stores reflects differences in store size and location.

Panel A in Table 1 presents summary statistics for our transaction records. One liter bottles are considerable more expensive than cans, which are more popular.

2.2 Data on Stockouts

CCU is the dominant beer producer in Chile and owns two main bottling plants. The plant close to Santiago suffered severe damages after the earthquake that took place on Feb 27, 2010. As a consequence of this disruption there was a substantial shortage of CCU's leading beer brands.

As captured by our panel data, Table 2 presents the number of stores that faced high and low frequency of stockouts per week. We observe variance across products and periods, with the Treatment Period (i.e., between February 26th, 2010 and April 15th, 2010) concentrating a higher probability of stockout episodes. In addition, the bottle format products were more heavily affected by the production shortage.

Finally, we construct an individual measure of stockout exposure for each of the four top products considered. The product-consumer specific measure is the number of store visits in which the consumer faced a top beer being unavailable. We consider a product to be out-of-stock in a given day if we observe no sales during that day-store pair. The suggested stockout measure could be misleading for slow-rotation products (products that are not sold very often). However, since the considered top 4 products have market shares between 15 and 30 percent of the beer market, our measure is an excellent approximation of product availability.

Figure 2 shows the distribution of the stockout treatment across individuals and products. From this figure we can see how the natural experiment provided us with substantial exogenous variation in product availability that, in turn, will allow us to identify the causal effects of stockouts in the future purchase behavior of treated customers.

Our proposed metric of stockout treatment has significant advantages over previous papers on stockouts. First, our unanticipated supply shock implies that the treatment variable

[3] Fall starts in mid-March in the Southern hemisphere.

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

is uncorrelated with demand shocks, ensuring a necessary exogeneity to identify causal effect. Second, we obtain a considerable variation in the severity of the stockout-treatment across products and consumers that we will exploit for econometric identification. And third, given the nature of the shortage, the stockout episodes were not informative for consumers about the quality of the products nor the quality of the retailer's assortment.

3 Stockouts and Long-term purchases

We rationalize the persistent effects of stockouts on purchase behavior through the existence of 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 first screened and then evaluated for actual purchase. In the first stage, consumers simplify the amount of information, by eliminating alternatives (among those they are aware of) until consumers can deal comprehensively with a smaller set of choices. In the second stage, consumers thoroughly compare the subset of options 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 literature, the consumer is only aware of a subset of all products and, hence, their expected match valuations. Importantly, the consumer has no information on the products outside the awareness set. In terms of the available options in the awareness set, denoted by S^h_{at}, the consumer will decide ex-ante in a first stage how much product information to acquire. This will determine the optimal subset of options that will be inspected in the second stage (Roberts (1989); Roberts and Lattin (1991)). The consideration set, denoted by S^h_{ct}, then solves the following expected utility maximization problem:

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

where $C(S^h_{ct})$ is a product evaluation or search cost associated with assembling the consideration set S^h_{ct} and u^h_{jt} is the utility of alternative j in period t for household h.

We argue that a prolonged stockout of products from the leading brands may change consumers' awareness set. When facing the empty shelves of the most popular products, competing products that might have been previously ignored, are now among the only available alternatives. Thus, some previously unaware consumers may then start to know the characteristics of the less popular brands.

Thus, we claim that the prolonged stockouts may have substantially changed consumer awareness of beer brands. The inclusion of new products in S^h_{at} may have temporary effects if the entrant products are perceived as being 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 products, then the change in purchase behavior can be long-lasting, and in the limit, permanent.

Without additional data or assumptions, it is usually challenging to estimate a model of choice and consideration when the latter is unobserved. For tractability, we will then formulate a discrete choice model focusing on the top 4 products, but allowing the outside good to become more attractive in the post-treatment period for certain consumers as a function their exposure to stockouts from the top 4 products. Hence, we estimate a choice model in which the level of exposure to stockouts affects the valuation of the top 4 brands relative to the outside good. In particular, we include the interaction between the treatment level –measured by the number of days the consumer faced product-specific stockouts– with their respective product-fixed effects.

In the standard baseline model, household h makes discrete choices among J products and an outside option (0) in each trip to the supermarket. To capture inertia (or variety seeking behavior), we let the previous product choice affect current utilities in the standard modeling (Guadagni and Little (1983)). Thus, the utility function before any stockout-treatment is given by:

$$u_{jt}^h \quad = \quad \alpha_j^h + \eta^h \, p_{jt} + \gamma^h \, \mathbb{I}\{s_t^h = j\} + \varepsilon_{jt}^h \tag{2}$$

where p_{jt} is product j price in period t,[5] $\mathbb{I}\{s_t^h = j\}$ is a dummy which equals one if product j is the last produc that was purchased by the consumer, where $s_t^h \in \{1, ..., J\}$ keeps track of the last product choice. ε_{jt}^h is an iid random term with a Type I extreme value distribution function. Consequently, the parameter η^h is the price sensitivity and γ^h is the state dependence coefficient.[6]

The brand intercepts α_j^h represent the persistent form of vertical product differentiation that captures the household's intrinsic brand preferences for product j relative to the outside option. If the prolonged stockouts for the top brands enlarged the awareness set of the consumers with products that are better than the current inside goods, then we should expect the product fixed effects to decrease after the stockout treatment. Moreover, the magnitude of this reduction should be increasing in the stockout-treatment that a consumer was exposed to.

Therefore, we incorporate the potential effects of stockout-treatments in the utility function

[5]Typically, demand estimations are concerned about the potential endogeneity of prices. In our setting, prices are identical across consumers as the retailer follows a national pricing policy eliminating a potential correlation with the individual demand shocks. See a more comprehensive discussion in Chintagunta et al. (2005).

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

for post-treatment periods as follows:

$$\begin{aligned} u_{jt}^{h} &= \alpha_j^h + \tilde{\alpha}_j^h ST_j^h + \eta^h\, p_{jt} + \gamma^h \mathbb{I}\{s_t^h = j\} + \varepsilon_{jt}^h \\ &= X_{jt}^{h'} \boldsymbol{\Lambda}^{\boldsymbol{h}} + \varepsilon_{jt}^h \end{aligned} \tag{3}$$

where the stockout treatment is denoted by ST_j^h and the vector $\boldsymbol{\Lambda}^{\boldsymbol{h}} = (\alpha_1^h, .., \alpha_J^h, \tilde{\alpha}_1^h, .., \tilde{\alpha}_J^h, \eta^h, \gamma^h)$ contains all the parameters of the model.

As detailed in the data section, 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 led to a more valuable outside good, then the changes in product j valuation should be captured by a negative parameter $\tilde{\alpha}_j^h$.[7] There is experimental evidence that consumers' response to stockouts may in some cases be positive (Fitzsimons (2000)). We allow for both positive and negative reactions of the brand fixed effects to the stockout treatment in our heterogeneous model and let the data inform us about the relative weight of each valence among the population of consumers.

4 Estimation and Results

We estimate the model in Equation (3) allowing for a potentially large degree of heterogeneity in preferences to separately identify the persistent unobserved heterogeneity and state dependence. Hence, we follow the approach of Fox et al. (2011, 2016) to estimate the distribution of unobserved taste for products in a non-parametric fashion.

First, we express the probability of a certain sequence of purchases as a function of an arbitrary vector of utility parameters, $\boldsymbol{\Lambda}_r \in S$, where S is a grid that covers the subspace of possible values of the utility parameters. The probability of purchasing product j is the integral over shocks ε that ensures that product j is the one that maximizes the utility conditional on the choice set of each market at time t. Using the distribution of ε, we obtain the standard logit closed-form solution for the individual probability, $\mathbb{P}(y_{jt}^h = 1 \mid \boldsymbol{\Lambda}_r)$, where y_{jt}^h equals one if the household h chooses product j at time t, and zero otherwise.

Using the panel nature of the data, we extend the joint probability for a series of purchases. Thus, the likelihood of household h choosing the observed sequence of choices *conditional on* $\boldsymbol{\Lambda}_r$ is given by:

$$L^h(\boldsymbol{\Lambda}_r) = \prod_{t=1}^{T}\prod_{j=0}^{J} \mathbb{P}(y_{jt}^h = 1 \mid \boldsymbol{\Lambda}_r) = \prod_{t=1}^{T}\prod_{j=0}^{J} \left(\frac{\exp(X_{jt}^{h'}\boldsymbol{\Lambda}_r)}{1 + \sum_{k=1}^{J} a_{kt}^h \exp(X_{kt}^{h'}\boldsymbol{\Lambda}_r)} \right)^{y_{jt}^h} \tag{4}$$

[7] In the empirical section, we also estimate specifications that allow stockouts to alter the state-dependence term.

where, a_{kt}^h is an availability dummy that is equal to one if product k is available at time t for household j. The availability dummy adjusts the choice set allowing only the available products to be chosen.[8]

Second, provided a sufficiently large set of draws of $\mathbf{\Lambda}_r$ satisfactorily covering the grid S, the unconditional choice probability of household h choosing the observed sequence can be approximated by P^h,

$$P^h(\boldsymbol{\theta}) = \sum_{r \in S} \theta_r L^h(\mathbf{\Lambda}_r) \tag{5}$$

where $\boldsymbol{\theta}$ is the vector of weights with $\theta_r \geq 0, \forall r \in S, \sum_{r \in S} \theta_r = 1$. Each θ_r indicates the probability of a household behaving consistently with the vector of parameters, $\mathbf{\Lambda}_r$. Notice that the unconditional probability is only a linear function of θ and that the value of $L^h(\mathbf{\Lambda}_r)$ is fixed for a given set of draws.

Given a random sample of households, $h = \{1, .., H\}$, our estimate of $\boldsymbol{\theta}$, denoted by $\hat{\boldsymbol{\theta}}$, is the argument that maximizes the constrained log-likelihood $LL(\boldsymbol{\theta})$:

$$\hat{\boldsymbol{\theta}} = \arg\max \ LL(\boldsymbol{\theta}) = \arg\max \sum_{h=1}^{H} \ln \left\{ P^h(\boldsymbol{\theta}) \right\} = \arg\max \sum_{h=1}^{H} \ln \left\{ \sum_{r \in S} \theta_r \, L^h(\mathbf{\Lambda}_r) \right\} \tag{6}$$

$$s.t. \ \sum_{r \in S} \theta_r = 1 \tag{7}$$

$$\theta_r \geq 0 \ \ \forall r \in S \tag{8}$$

We maximize the constrained log-likelihood function in Equation (6) subject to the usual constraints of non-negative weights in Equation (7) and that they add-up to one in Equation (8). Notice that the the unconditional probability being linear in θ and that the values of $L^h(\mathbf{\Lambda}_r), r \in S$ are fixed for a given set of draws, greatly simplifies the optimization problem.

Identification: Consistent with the standard requirements of a demand model like ours, we need variation in characteristics (like prices) and the stockout treatment. In our case, the stockout treatment varies across products and individuals allowing us to identify their effect on purchase decisions, including a significant mass of untreated consumers. We also exploit the pre-treatment period that allows identifying the baseline coefficients of product-fixed effects, price coefficient, and state-dependence. Fox et al. (2012) discuss the non-parametric identification of the mixed logit further.

We assume that the relative valuations of the beer products are time-invariant. If certain products are more appealing in different months of the year, then our identification is jeopardized. Nevertheless, we have no reason to believe that the relative valuations of certain beers suffer from any seasonal component.

[8]For simplicity, we assume the same number of observations per household, T, and the same amount of available products, J. We relax this assumption in the empirical estimation.

4.1 Results

We estimate several specifications. Our preferred specification from Equation (3) requires a grid search with 10 dimensions of $\mathbf{\Lambda}$: four baseline brand loyalty parameters and four interactions between the brand dummies and the stockout treatment, plus one price coefficient, and one coefficient for state dependence.[9]

We use $R = 2,500$ Halton draws to cover our subspace of ten dimensions. The literature has emphasized the benefits in terms of coverage of the Halton sequences over other choices for grid search, especially for higher dimensional problems (Train (2009)).

We account for the product availability in our log-likelihood function since stockouts were present even before the earthquake, as shown in Table 2. Thus, we adjust the choice set appropriately for each transaction during the Pre and Post-treatment periods. The stockout treatments are not affected by this inclusion, as we do not use the six weeks treatment period in our ML estimation.

We present the distribution of coefficients based on the estimated weights.[10] Figure 3 shows the estimated probability density function (PDF) and the cumulative probability function (CDF) of the baseline product 1 fixed-effect. In addition, Figure 4 displays the PDF and CDF of the stockout-fixed effect interaction for Product 1. We find a large heterogeneity in tastes for Product 1.

The bottom-right figure shows that more than 50 percent of consumers decrease their valuation for Product 1 when facing stockouts of that product. Similarly, Figures 5-9 show the analogous estimates for the other top products. We conclude that more than 50, 70 and 60 percent of the consumers would decrease their valuations of products 2, 3 and 4, respectively, when facing stockouts of the correspondent products. We can then conclude that products from the Escudo brand (products 3 and 4) are the most affected by the stockouts. These effects are quantitatively important as we will see in the counterfactual exercises.

Similarly, Figure 11 shows the distribution of the price coefficient in the population, stressing that allowing for price heterogeneity is important and that the distribution does not resemble neither a normal nor a log-normal density, as it is commonly assumed in the literature.

Finally, Figure 12 shows the distribution of the state-dependence coefficient and only 55 percent of the consumers display some degree of ”inertia”. Consistently, 45 percent of the population seems to be ”variety seekers”. This is consistent with the substantial heterogeneity in repurchase rates shown in Table 3.

[9]For computational convenience, we normalize the maximum treatment per product to be one (dividing by the maximum exposure observed in the data).

[10]The summary statistics of the distribution of the estimated coefficients is in Table A.8 in the Appendix Section.

4.2 Quantifying the Effects of Stockouts in Market Shares

Using our structural estimates, we can compute the market shares under different scenarios. Notice that these market shares account for prices, availability, state dependence, and the average stockout-treatment that the consumers faced during the treatment period.

First, we compute the Pre-treatment market shares in steady-state. Thus, we evaluate the demand function using baseline parameters at the average observed price and state dependence in the Pre-treatment period, and under full product availability.

Now, we turn into computing the post-treatment market shares in steady-state. Similarly, we use estimated demand function under the same arguments but including the average treatment observed in the data.

Table 4 shows the long-run market shares and the percentage change caused by the observed stockout treatment. We can see in percentage terms, that product 1 (Cristal bottle) decreased by 8 percent while the Escudo products, 3 (bottle) and 4 (can), have a two digits decrease due to the heavy stockouts they suffered. Instead, product 2, Cristal can, increases by two percent, after accounting for the consumers' substitution patterns, prices, availability and state dependence. Recall that Product 2 was the least affected by stockouts during the Treatment period.

These results also imply that the outside good was the biggest winner after the treatment period. The corresponding share increased from 22.8 percent to 28.1 percent. The outside good considers both smaller market share products and also the option of not buying any beer products. We also compute the market shares conditioning on buying beer and find similar results for the increase of the non-top four brands. Later in this section we provide evidence consistent with the non-top products increasing their attractiveness.

Finally, we also compute the marginal impact of an additional stockout day during the treatment period. Table 5 shows the post-treatment market shares for each product when adding one day to the average stockout treatment. We can see that in all scenarios the largest recipient of the substitution is the outside good. The marginal losses range between -1.8 percent for product 3 and -2.6 percent for product 1. We believe this sort of exercises has critical managerial implications in terms to quantify the resources to avoid stockouts in the supermarket industry.

Outside Good: Table 6 shows the weekly average of first-time consumers for each product in different Treatment periods. The figures stress the remarkable peak of new consumers of the non-top 4 products during the heavy-stockout period that is consistent with our theoretical model of awareness and consideration sets.

From Table 1, we also observe that the non-top 4 products are in general more expensive than the temporarily unavailable leading brands. Figure 13 presents the estimated joint distribution the stockout-treatment coefficient, $\tilde{\alpha}_j^h$, and the price coefficient, η_j^h, for each top product j. For example, the top-left figure plots the price sensitivity, η_j^h, of each household h and their correspondent $\tilde{\alpha}_j^h$ that captures the change in valuation of product 1 (Cristal bottle) due to stockouts. The size of the dots captures the frequency of that combination of parameters. The rest of the scatter plots replicate the exercise for product 2 (Cristal can) at top-right, product 3 (Escudo bottle) at bottom-left, and product 4 (Escudo can) at bottom-right.

Table 7 presents the mass of consumers in each region of the scatter plot and confirm that nearly 35-40 percent of the households are in the (bottom-right) region where consumers display a combination of low-price sensitivity and a negative stockout-treatment coefficient.

We interpret the aforementioned negative correlation as evidence that the top 4 brands may have lost a valuable fraction of their customers. The subset of low-price sensitivity consumers might have been consuming the top four products because of their unawareness of the set of competing products, which they were forced to try during the stockout period. It turns out that, although these smaller products are more expensive, their realized match value was high enough for these consumers to keep choosing them after the top 4 brands were back on the shelves. The set of price-insensitive consumers are of course important for the firms as they could be offered premium versions of the products to increase margins and profits.

4.3 Robustness Checks

We perform several robustness checks to our findings. First, how to perform inference in this approach is still an ongoing and active area of research (Fox et al., 2016). Recall that our ML estimates (with constraints) are the weights $\tilde{\boldsymbol{\theta}}$, although the typical horse-race between different competing specifications impose restrictions over the utility function parameters, Λ. The number of estimates is given by R, the number of draws from the grid S, and therefore, the degrees of freedoms are independent of the values of Λ.[11]

In addition, many of the estimated weights are exactly zero, that is at the boundary of the feasible region. The issue is called a "parameter on the boundary" as the weights θ will often be set to zero in the optimization and the standard assumption of interior solutions in the ML inference are not met. In our case, many parameters are on the boundary, while existing asymptotic theory only allows one parameter at a time to be on the boundary (Andrews (1999)).

Although with some caveats (Andrews (2000)), we implement a bootstrap by re-sampling individuals within our panel of households and construct confidence intervals for the counterfactual market shares.

One potential concern is that the Treatment period is in late summer and that our findings can be explained by seasonality, since the beer sales are larger during the summer relative to the rest of the year. To address this concern we re-estimated the demand model using only observations where at least one beer product was chosen. Our conclusions remain valid: the stockouts have a persistent effect on a decrease in brand valuations for the top brands and the

[11] We explore different model specifications. Although a proper test for model selection is not yet available.

non-top beer products gain a significant market share after the treatment period. However, we acknowledge that if different beers are especially appealing in certain seasons, we may have a confounding factor that we cannot control for. To the best of our knowledge there is no evidence that this is the case.

5 Conclusion

A 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, and product availability, we find that the least popular brands increase their valuations (and market shares) permanently at the expense of the leading brands among the consumers who suffered more extensive exposure to stockouts.

We find evidence that suggests that the prolonged stockouts change the consideration set for a substantial share of consumers, who became aware of competing products with long-lasting purchase behavior. Despite the compelling evidence, we acknowledge that our data comes from a specific retailer and category, which may limit 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 include following the behavior of the same pool of consumers several years after the incident to study permanent consequences. Also, the purchase behavior of the identified first-time consumers could be useful to test competing theories of contained in learning models (Shin et al., 2012).

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6 Figures

Figure 1: Timeline

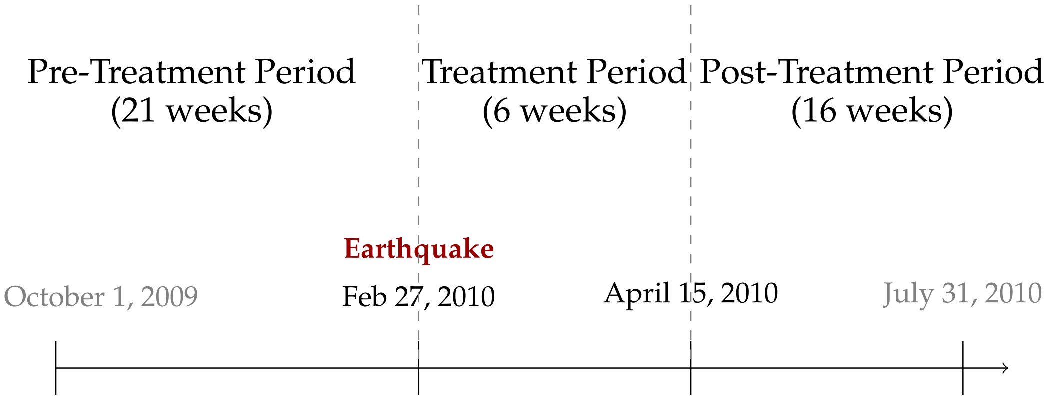
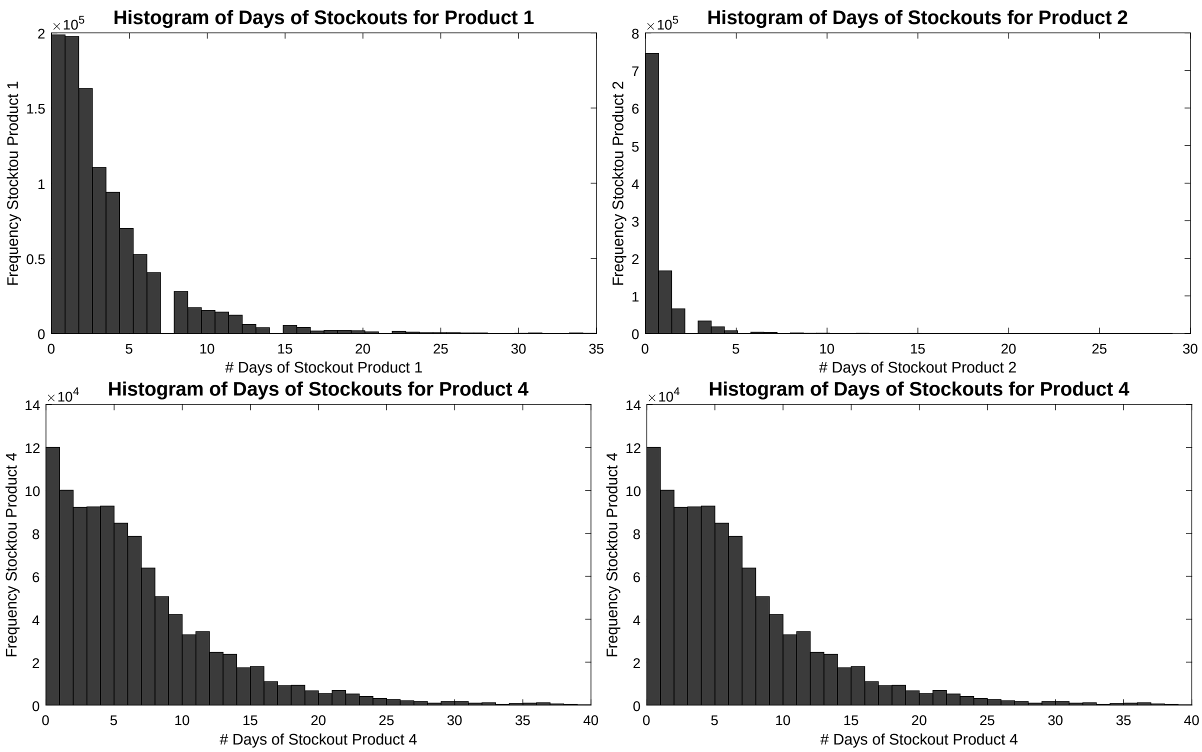


Figure 2: Histogram of Stockout Treatment across Products and Individuals



Notes: Each histogram shows the distribution of the days with stockouts that each consumer faced during the 6 weeks of the Treatment period. An stockout is defined 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: Estimated Distribution of Baseline Product 1-Fixed Effects

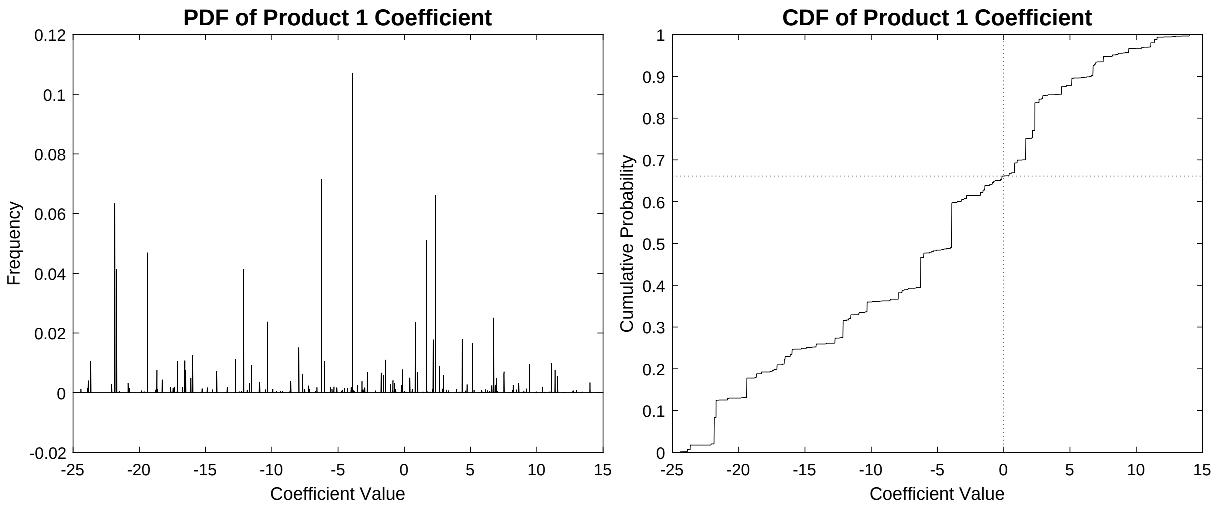
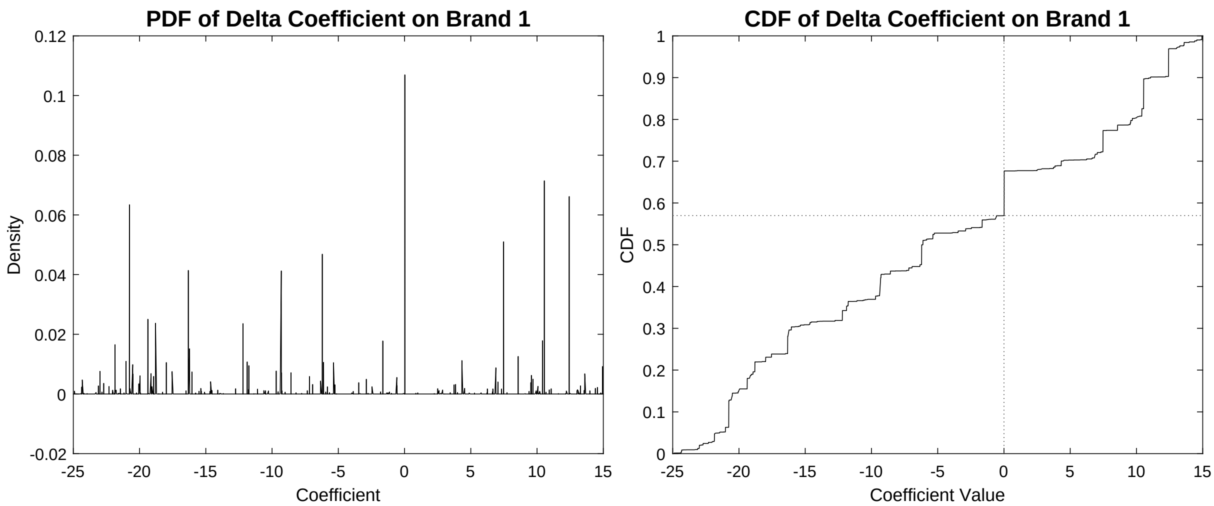


Figure 4: Estimated Distribution of Post-Treatment Product 1-Fixed Effects



Notes: Top figures describe the estimated distribution of baseline Product 1 fixed-effect (Cristal 1L bottle). Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). Bottom figures are the PDF and CDF of the post-treatment fixed-effect of Product 1 that interacts with the individual stockout-treatment of Product 1. The grid ranges from -25 to +15.

Figure 5: Estimated Distribution of Baseline Product 2-Fixed Effects

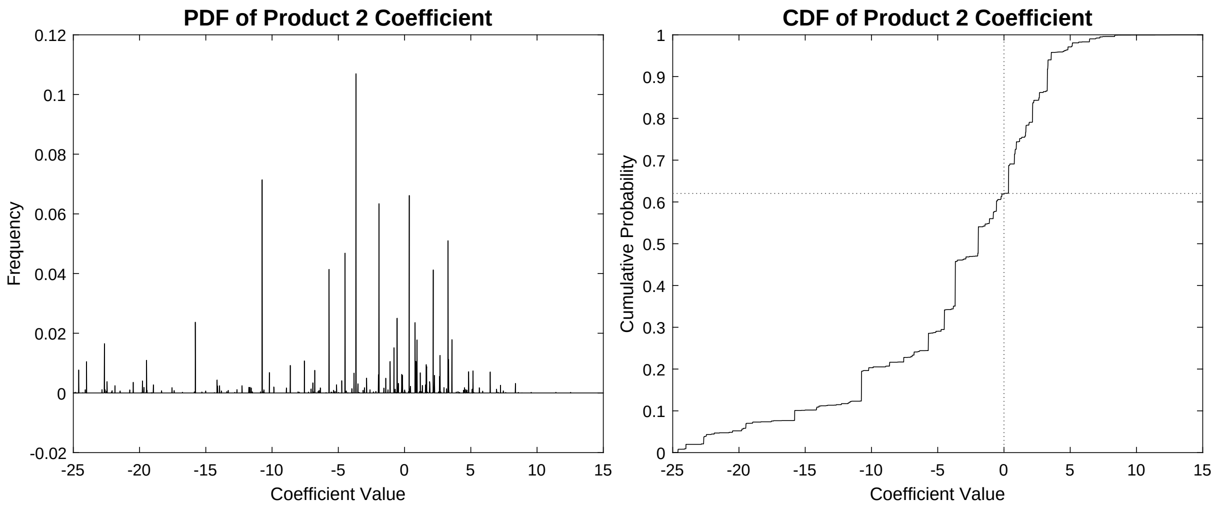
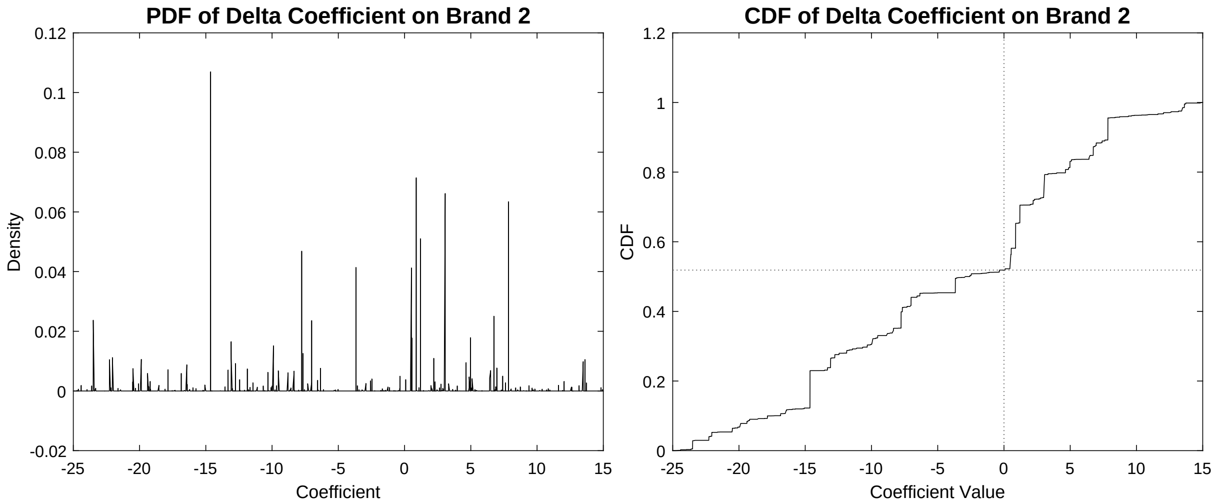


Figure 6: Estimated Distribution of Post-Treatment Product 2 -Fixed Effects



Notes: Top figures describe the estimated distribution of baseline Product 2 fixed-effect (Cristal can). Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). Bottom figures are the PDF and CDF of the post-treatment fixed-effect of Product 2 that interacts with the individual stockout-treatment of Product 2. The grid ranges from -25 to +15.

Figure 7: Estimated Distribution of Baseline Product 3-Fixed Effects

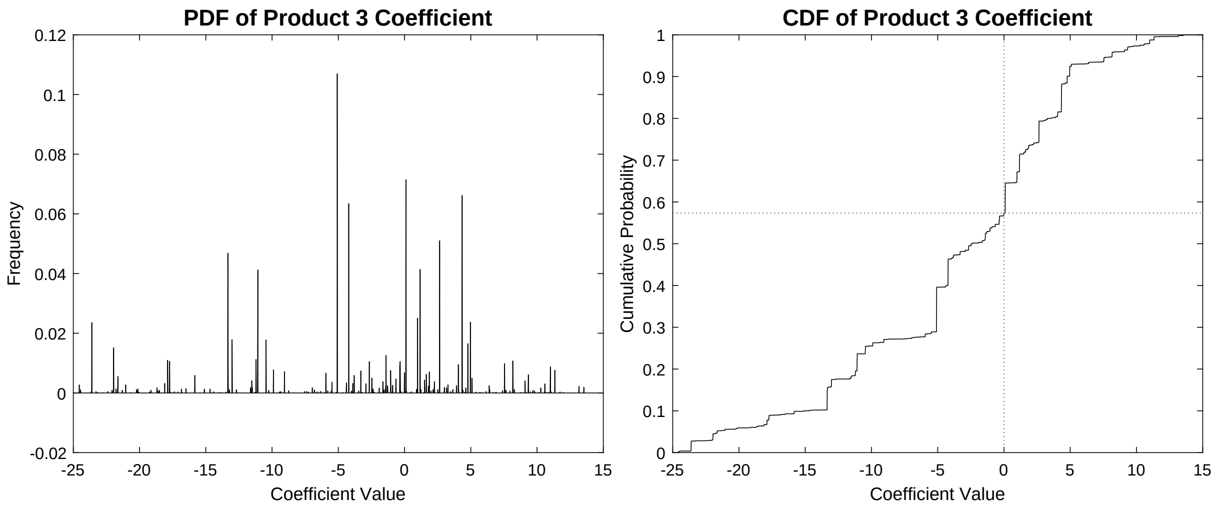
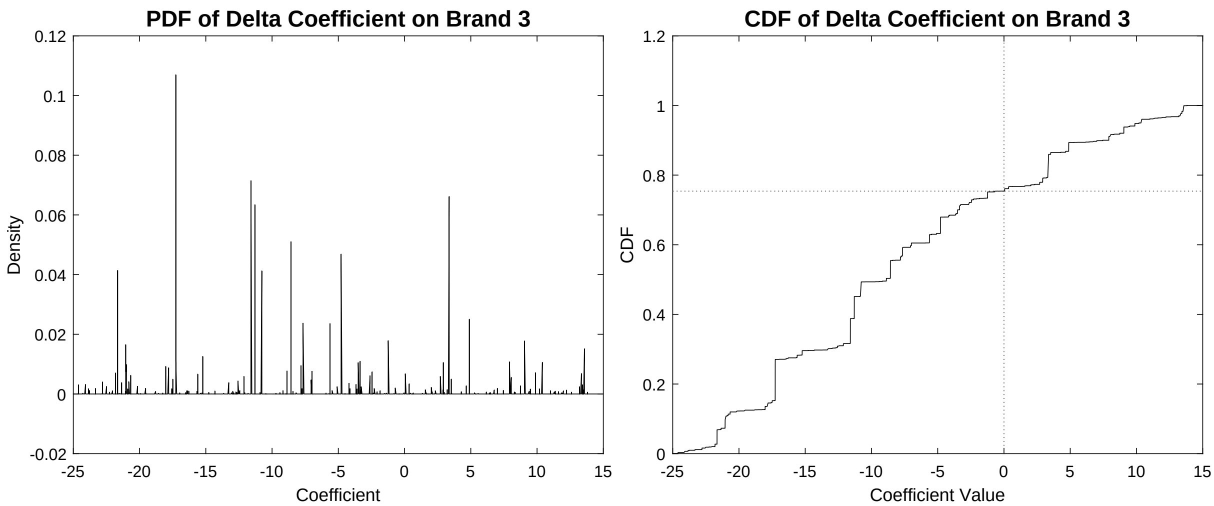


Figure 8: Estimated Distribution of Post-Treatment Product 3-Fixed Effects



Notes: Top figures describe the estimated distribution of baseline Product 3 fixed-effect (Escudo 1L bottle). Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). Bottom figures are the PDF and CDF of the post-treatment fixed-effect of Product 3 that interacts with the individual stockout-treatment of Product 3. The grid ranges from -25 to +15.

Figure 9: Estimated Distribution of Baseline Product 4-Fixed Effects

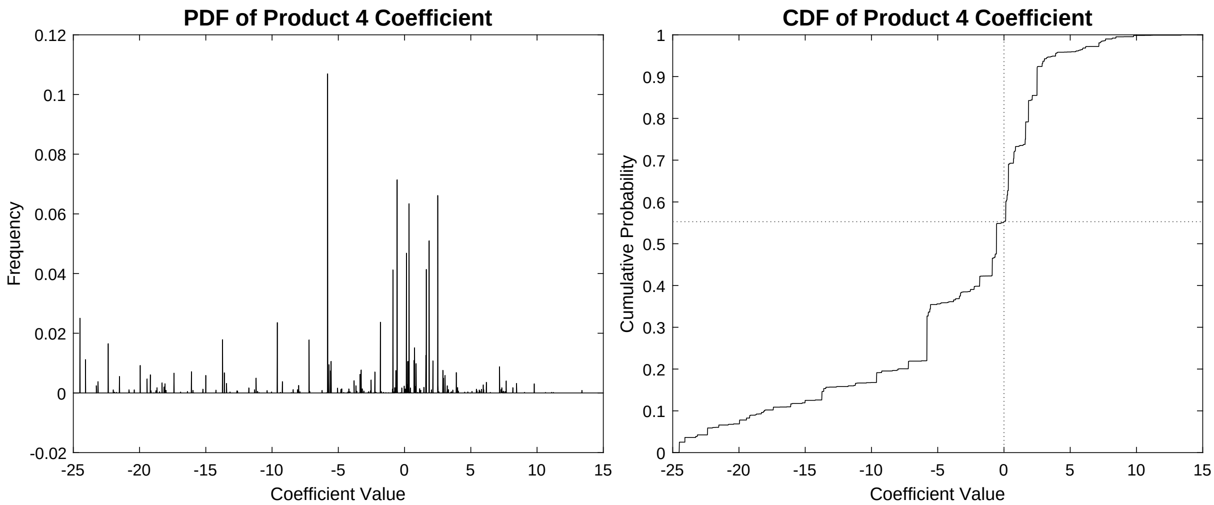
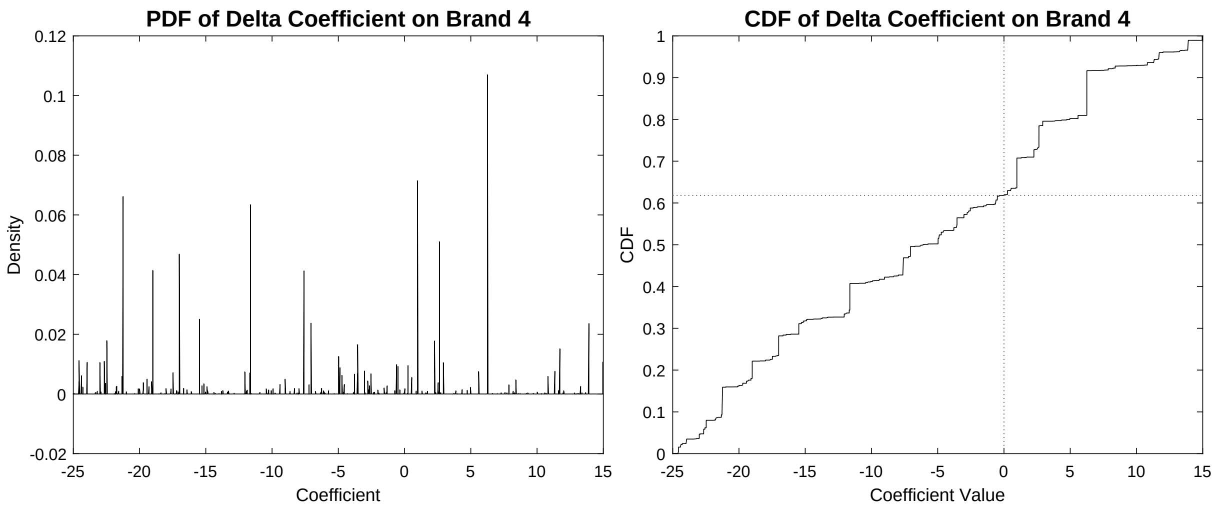
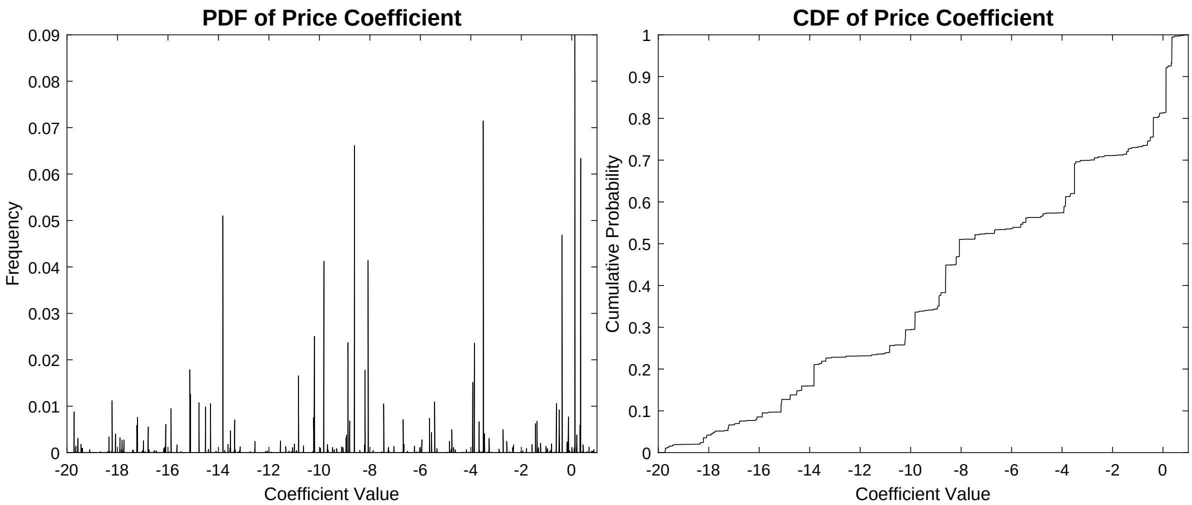


Figure 10: Estimated Distribution of Post-Treatment Product 4-Fixed Effects



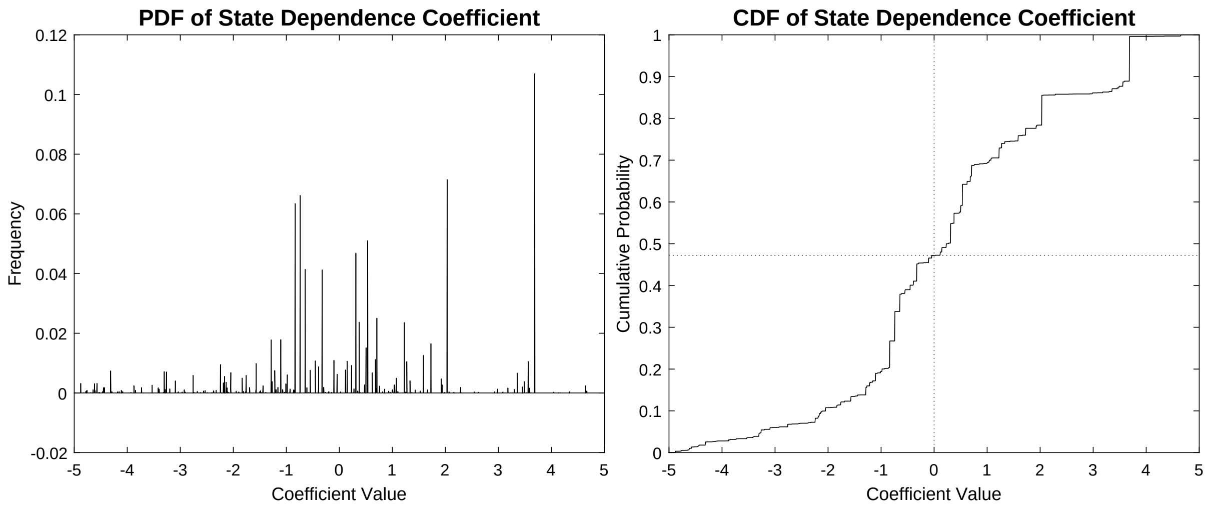
Notes: Top figures describe the estimated distribution of baseline Product 4 fixed-effect (Escudo can). Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). Bottom figures are the PDF and CDF of the post-treatment fixed-effect of Product 4 that interacts with the individual stockout-treatment of Product 4. The grid ranges from -25 to +15.

Figure 11: Estimated Distribution of Price Coefficient



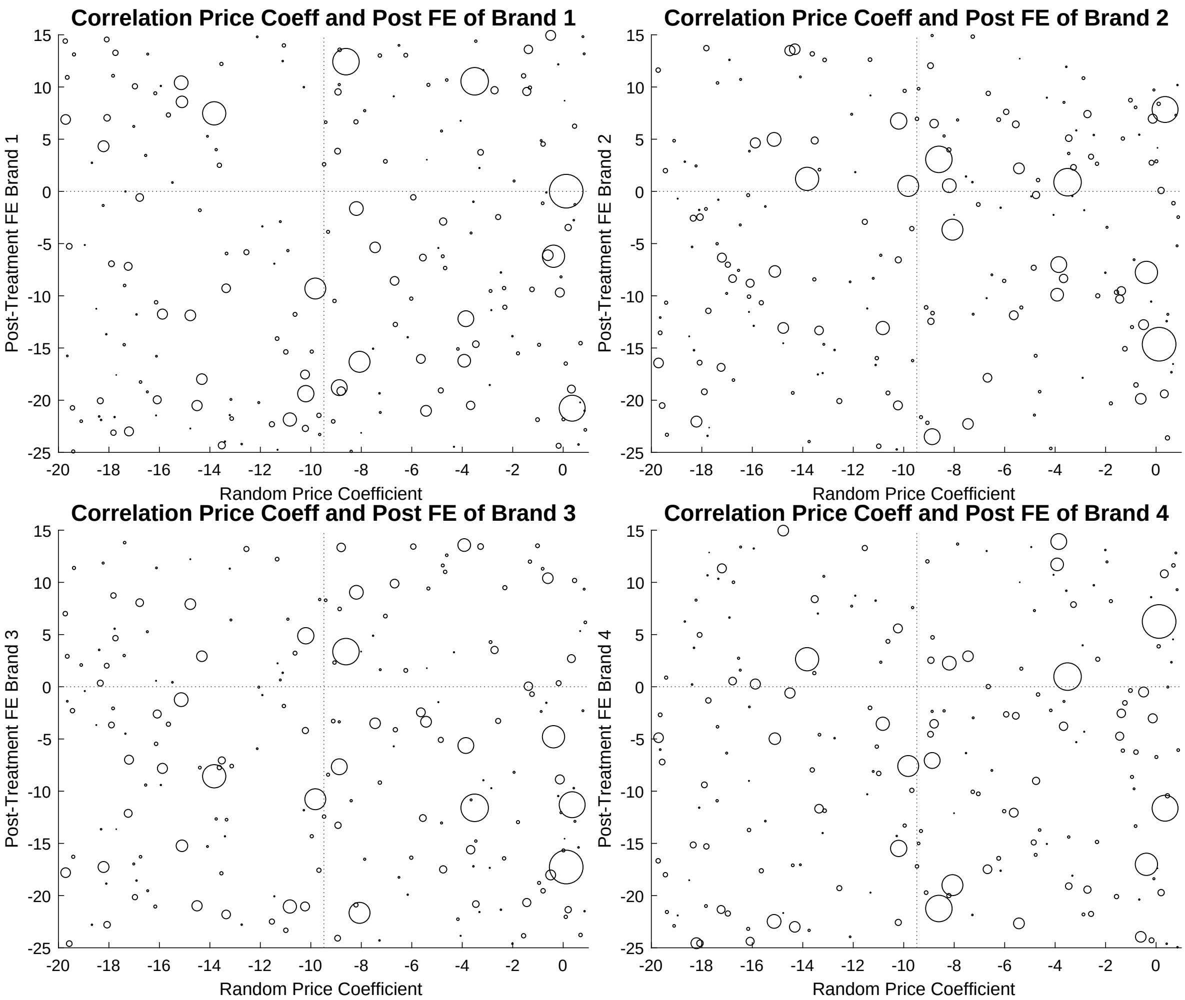
Notes: Top describe the estimated distribution of the baseline price coefficient. Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). The price coefficient does not change after the Treatment period. The grid ranges from -20 to +1.

Figure 12: Estimated Distribution of State-Dependence Coefficient



Notes: Top figures describe the estimated distribution of baseline state-dependence (SD) coefficient. Top left is the probability distribution function (PDF), and top-right the probability distribution function (CDF). The grid ranges from -5 to +5.

Figure 13: *Correlation Between Price Coef and Brand Dummies Post Treat*



Notes: Top-left figure describes the estimated joint distribution of the Post-Treatment coefficient times Treatment for Product 1 (Cristal 1L bottle) and the price coefficient. The same exercise is replicated for: Product 2 (Cristal can) at Top-right, Product 3 (Escudo bottle) at Bottom-left, and Product 4 (Escudo can) at Bottom-right.The negative correlation indicates that less-price-sensitive consumers decrease their valuations of the top-product relative to the outside good. The size of the dots capture the frequency of that combination of parameters. Table 7 presents the mass of consumers in each region of the scatter plot where near 40 percent of the households are in the bottom-right region of each scatter plot, where consumers with low-price sensitivity also have a negative stockout-treatment coefficient.

7 Tables

Table 1: Summary Statistics

Panel A: Top 4 Beer Products	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Product 1: Cristal (1L bottle)	1.29	9.3%	10.77%	7.07%
Product 2: Cristal (350cc can)	0.49	20.7%	19.91%	19.02%
Product 3: Escudo (1L bottle)	1.29	10.6%	11.09%	7.69%
Product 4: Escudo (350cc can)	0.49	24.9%	24.02%	25.67%
Non-Top 4 Beers		34.4%	34.22%	40.55%

Panel B: Other Products	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Stella Artois (354cc can)	0.70	0.7%	0.68%	1.28%
Royal Guard (350cc can)	0.67	1.1%	1.10%	1.77%
Kunstmann (350cc bottle)	1.41	0.4%	0.45%	0.77%
Heineken (330cc bottle)	0.86	0.3%	0.40%	0.43%
Heineken (350cc can)	0.72	2.5%	2.86%	3.64%
Becker (350cc can)	0.44	2.8%	1.91%	3.42%
Corona (710cc bottle)	2.07	0.2%	0.22%	0.33%
Other Non Cristal-Escudo beers	1.04	15.1%	11.95%	14.79%

Panel C: Other Cristal and Escudo	Average Price (US Dollars) (1)	Trips (2)	Market Share (Pre-Treatment) (3)	Market Share (Post-Treatment) (4)
Other Cristal	1.96	5.9%	7.84%	6.49%
Other Escudo	1.77	5.6%	6.80%	7.65%
Average store visits per household	31.0		No. of households	5667
Average top 4 purchases per household	21.5		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, and the outside option is defined as buying any non-top 4 beer. Column (3) and (4) are the sales market shares before the Treatment period and after the Treatment period respectively. We only consider the 5667 households that have at least ten beer transactions within the initial 21 weeks of data.

Table 2: Number of Stores under Different Level of Stockouts

	Pre-Treatment (1)	Treatment (2)	Post-Treatment (3)
Product 1: 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
Product 2: 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
Product 3: 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
Product 4: 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

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. From this Table we conclude that product 3 and 4 were heavily treated, while product 2 remained mostly untreated. In most cases, the stockouts kept occurring during the post-treatment period, implying the need to account for availability in the estimation.

Table 3: Repurchase Rates

Product	Purchase Frequency	Repurchase Frequency (Pre-Treatment)		Repurchase Frequency (Post-Treatment)	
	Mean (1)	Mean (2)	Std Dev (3)	Mean (4)	Std.Dev (5)
Product 1: Cristal (bottle)	14%	43%	40%	47%	43%
Product 2: Cristal (can)	32%	56%	40%	65%	42%
Product 3: Escudo (bottle)	16%	42%	40%	47%	43%
Product 4: Escudo (can)	38%	59%	39%	71%	40%

Notes: Column (1) shows the fraction of visits in which a customer purchase a given beer within the top four products; Column (2) and (4) show repurchase probability that is the average probability of purchasing each of the top 4 products, conditional on buying that product in the previous store visit, during the Pre-Treatment and Post-Treatment period, respectively. Column (3) and (5) show the standard deviations of the aforementioned repurchase probability for each period.

Table 4: Long-run market share estimates

Panel A: Unconditional Market Shares	Product 1 Cristal bottle (1)	Product 2 Cristal can (2)	Product 3 Escudo bottle (3)	Product 4 Escudo can (4)	Outside Good (5)
Pre-Treatment	6.7	14.7	6.6	20.3	51.6
Post-Treatment	4.8	14.9	5.5	14.0	60.8
Difference	-1.9	0.1	-1.1	-6.3	9.2

Panel B: Market Shares Conditional on Buying Beer	Product 1 Cristal bottle (1)	Product 2 Cristal can (2)	Product 3 Escudo bottle (3)	Product 4 Escudo can (4)	Outside Good (5)
Pre-Treatment	11.8	23.8	12.3	29.3	22.8
Post-Treatment	10.9	24.4	10.5	26.1	28.1
Difference	-0.9	0.6	-1.8	-3.2	5.3

Notes: Both Panels show long-run market shares based on the estimates and the stockout-treatment observed in the data. Panel A shows the unconditional market shares where the outside good consider buying a non-top 4 beer and not buying beer. Panel B shows the market shares conditional on buying beer, thus, the outside good only consider buying a non-top 4 beer. The first row in each Panel labelled Pre-Treatment is the market shares for each product resulting in the demand function using baseline parameters at the average observed price and state dependence in the Pre-treatment period. The second row labelled Post-Treatment is the market shares for each product resulting in the demand function using the baseline plus Post-Treatment estimates at the average observed price and state dependence in the Pre-treatment period; and the average treatment observed in the Post-Treatment period. The third row is the percentage change in long-run market shares due to the observed stockout treatment.

Table 5: Marginal Changes in Market shares due to an Extra Day of Stockouts

	Product 1 Cristal bottle (1)	Product 2 Cristal can (2)	Product 3 Escudo bottle (3)	Product 4 Escudo can (4)	Outside Good (5)
Base Line	4.8	14.9	5.5	14.0	60.8
Additional Stockout in:					
Product 1: Cristal (bottle)	**4.4**	14.9	5.5	14.0	61.2
Product 2: Cristal (can)	4.7	**14.2**	5.5	14.0	61.5
Product 3: Escudo (bottle)	4.8	14.9	**5.4**	14.1	60.9
Product 4: Escudo (can)	4.8	14.9	5.5	**13.5**	61.3
Percentage Own Change	0.4	0.6	0.1	0.5	

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 day of stockout to the observed average stockout treatment. The difference between the base line market share (in the first row) is the marginal effect in market shares of an extra day 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 6: Weekly Average of First-Time Consumers of Non-Top 4 Products

	Pre-Treatment Period (1)	Treatment Period (2)	Post-Treatment Period (3)
Stella Artois (354cc can)	18.62	44.29	10.45
Royal Guard (350cc can)	27.43	64.86	10.77
Kunstmann (350cc bottle)	13.10	35.86	7.87
Heineken (330cc bottle)	10.86	14.86	5.03
Heineken (350cc can)	56.05	54.29	14.84
Becker (350cc can)	38.81	57.29	14.00
Corona (710cc bottle)	7.81	11.57	4.13

Notes: Each column shows the weekly average of first-time consumer for each product in the Pre-treatment period (Column (1)), Treatment period (Column (2)) and Post-Treatment period (column (3)). The figures stress the remarkable peak of new consumers of the non-top 4 products during the heavy stockout period.

Table 7: Price Sensitivity and Stockout Treatment Effect

Correlation Region	Top-Left (1)	Top-Right (2)	Bottom-Left (3)	Bottom-Right (4)
Product 1: Cristal (bottle)	18,47	28.60	16.84	36.09
Product 2: Cristal (can)	18.37	29.14	16.94	35.55
Product 3: Escudo (bottle)	4.07	24.10	31.24	40.59
Product 4: Escudo (can)	15.59	21.32	19.71	43.37

Notes: Each cell shows the mass of the consumers that display certain correlation between high and low price coefficient and the coefficient of the stockout treatment for each product. The largest mass is in the Lower-Right quadrant that contains the low-price sensitive population and also a negative effect of stockout treatment as shown in Figure 13. Upper-left contains high-price sensitivity and an increase in the brand valuation; Upper-right contains low-price sensitivity and an increase in the brand valuation; Lower-left contains high-price sensitivity and a decrease in the brand valuation.

Table A.8: Summary Statistics of Estimated Coefficients

	Product 1 FE (1)	Product 2 FE (2)	Product 3 FE (3)	Product 4 FE (4)	Price Coefficient (5)	State Dependence Coefficient (6)	Treatment X FE Product 1 (7)	Treatment X FE Product 2 (8)	Treatment X FE Product 3 (9)	Treatment X FE Product 4 (10)
Mean	-6.10	-3.82	-3.83	-3.59	-7.07	0.24	-4.79	-4.38	-7.76	-6.36
Std Dev	9.88	7.21	8.47	7.74	5.93	1.97	12.04	9.67	9.85	11.19

Notes: The first row shows the estimated weighted average of each respective coefficient in the utility function in Equation 3. The second row shows the correspondent standard deviation. These statistics are computed using the estimated $R = 2,500$ weights, from which $1,617$ were set to zero in the optimization stage. FE denotes fixed effect.

Table A.9: Price and Trips per Period

	Pre Treatment		Treatment		Post Treatment	
All Products	Average Price	Trips	Average Price	Trips	Average Price	Trips
Cristal (1L bottle)	1.29	10.5%	1.23	9.9%	1.29	6.7%
Cristal (350cc can)	0.50	21.0%	0.48	27.3%	0.47	20.1%
Escudo (1L bottle)	1.31	11.7%	1.31	3.6%	1.25	8.2%
Escudo (350cc can)	0.50	24.5%	0.50	15.2%	0.49	25.7%
Heineken (350cc can)	0.72	2.3%	0.74	3.1%	0.72	2.8%
Stella Artois (354cc can)	0.74	0.5%	0.76	1.5%	0.64	1.0%
Royal Guard (350cc can)	0.68	1.0%	0.66	2.8%	0.66	1.5%
Heineken (330cc bottle)	0.86	0.3%	0.89	0.4%	0.85	0.3%
Kunstmann (350cc bottle)	1.42	0.3%	1.41	1.1%	1.39	0.6%
Becker (350cc can)	0.46	2.3%	0.47	3.6%	0.42	3.8%
Corona (710cc bottle)	2.13	0.2%	2.07	0.3%	1.99	0.3%
Other Non Cristal-Escudo beers	1.08	14.2%	1.09	20.4%	0.95	17.2%
Other Cristal	2.08	6.1%	1.69	4.5%	1.62	5.3%
Other Escudo	2.00	5.1%	1.38	6.2%	1.36	6.6%

Table A.10: Marginal Changes in Market shares due to an Extra Day of Stockouts conditional on buying beer

	Product 1 Cristal bottle (1)	Product 2 Cristal can (2)	Product 3 Escudo bottle (3)	Product 4 Escudo can (4)	Outside Good (5)
Base Line	4.8	14.9	5.5	14.0	60.8
Additional Stockout in:					
Product 1: Cristal (bottle)	**4.4**	14.9	5.5	14.0	61.2
Product 2: Cristal (can)	4.7	**14.2**	5.5	14.0	61.5
Product 3: Escudo (bottle)	4.8	14.9	**5.4**	14.1	60.9
Product 4: Escudo (can)	4.8	14.9	5.5	**13.5**	61.3
Marginal Effect	0.4	0.7	0.1	0.5	

Notes: The matrix shows the market shares, conditional on buying beer, 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 day of stockout to the observed average stockout treatment. The difference between the base line market share (in the first row) is the marginal effect in market shares of an extra day 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.